TECHNISCHE UNIVERSITÄT MÜNCHEN

T U M S C H O O L O F M A N A G E M E N T

# ENTREPRENEURSHIP POLICY, VENTURE CAPITAL AND INNOVATION

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# Abstract

Policies to stimulate innovation-driven entrepreneurship have become widely used by governments worldwide to foster long-run economic growth. Venture capital (VC) investors play an integral role in these policies, as they provide liquidity and expertise to early-stage ventures. This thesis examines different policy instruments and provides new empirical insights into their effectiveness in increasing access to VC and bringing about radical innovation. The thesis first investigates the link between startup subsidies and firms' access to follow-on financing from VC investors, explicitly distinguishing between the types of investors attracted by them. It then looks at the effects of investor subsidies on the level of managerial support that startups receive from their investors, providing the first empirical evidence for the case of Germany. Further, the thesis provides evidence on the causal effect of external equity financing and innovation activities in startups, explicitly distinguishing between innovation inputs (R&D) and innovation outputs (market novelties). Lastly, the thesis considers potential limits to venture capital financed innovation and growth. A discrete choice experiment on a large sample of German founders shows that entrepreneurs' valuation of control may pose a critical barrier to venture capitalists' investment model.

# Contents


**Acknowledgments** ii

**Abstract** iv

## I Chapters 1

### 1 Introduction 1

1.1 Motivation . . . 1
1.2 Innovation-driven entrepreneurship and venture capital . . . 3
1.3 Existing literature on entrepreneurship policies, venture capital, and innovation . . . 4
1.4 Contribution of the thesis . . . 6
1.5 Outline of the thesis . . . 10

### 2 Startup Subsidies and the Sources of Venture Capital 11

2.1 Introduction . . . 11
2.2 Public subsidies and Venture Capital . . . 13
2.3 Data . . . 15
2.4 Empirical methodology . . . 21
2.4.1 Estimation . . . 21
2.4.2 Matching . . . 22
2.5 Results . . . 24
2.6 Discussion . . . 26
2.7 Conclusion . . . 27

### 3 Financing and Advising Early Stage Startups 29

3.1 Introduction . . . 29
3.2 The case of angel investor subsidies . . . 32
3.2.1 Angel investor subsidies and financing . . . 32
3.2.2 Angel investor subsidies and managerial support . . . 33
3.2.3 The Angel investor subsidy program in Germany . . . 35
3.3 Empirical strategy . . . 37
3.3.1 Difference-in-Differences Estimation . . . 38
3.3.2 Covariate balancing . . . 39
3.3.3 Treatment and control groups . . . 40
3.3.4 Identification of subsidy effect . . . 41
3.4 Data . . . 43
3.4.1 Sample description . . . 43

3.4.2 Variable description . . . 44
3.4.3 Descriptive statistics . . . 46
3.5 Results . . . 48
3.5.1 Angel financing . . . 48
3.5.2 Angel financing amounts . . . 51
3.5.3 Managerial support . . . 52
3.5.4 Composition of investor types and portfolios . . . 52
3.5.5 Syndication of angel investors . . . 56
3.5.6 Robustness test: Technological shocks and pre-treatment trends . . . 58
3.6 Conclusion . . . 59
**4 Outside Equity and Startup Innovation** **61**
4.1 Introduction . . . 61
4.2 Literature . . . 63
4.3 Equity financing and innovation . . . 65
4.4 Empirical approach . . . 67
4.4.1 Econometric model . . . 67
4.4.2 Identification . . . 68
4.4.3 Wald Difference-in-Differences estimator . . . 72
4.5 Data. . . . 73
4.5.1 Data sources and sample . . . 73
4.5.2 Variable definitions . . . 73
4.5.3 Descriptive results . . . 75
4.6 Results . . . 78
4.6.1 Reduced form regressions . . . 78
4.6.2 Two-stage least squares regressions . . . 81
4.6.3 Robustness tests . . . 84
4.7 Discussion and Conclusion . . . 85
**5 The Private Value of Entrepreneurial Control** **87**
5.1 Introduction . . . 87
5.2 Conceptual background . . . 89
5.2.1 Entrepreneurs' preferences for control and independence . . . 89
5.2.2 VC value-adding activities . . . 90
5.2.3 A toy model . . . 91
5.3 Experimental design . . . 92
5.3.1 General motivation . . . 92
5.3.2 Experimental procedure . . . 93
5.4 Data . . . 95
5.4.1 Population and sample . . . 95
5.4.2 Description of sample . . . 96
5.5 Empirical analysis . . . 97
5.5.1 Estimation . . . 97
5.6 Results . . . 101
5.6.1 Robustness tests and further analysis . . . 103

5.7 Conclusion . . . . . 106
**6 Conclusion** **109**
6.1 Summary and implications of results . . . . . 109
6.2 Prospects for future research . . . . . 111

**II Appendix** **114**
**A Startup Subsidies and the Sources of Venture Capital** **114**
A.1 Detailed description of matching algorithm . . . . . 115
A.2 Additional Tables and Figures . . . . . 117
**B Financing and Advising Early Stage Startups** **127**
B.1 Innovative industries . . . . . 128
B.2 Descriptives . . . . . 129
B.3 Covariate balancing results . . . . . 134
B.4 Results . . . . . 139
B.4.1 Angel financing . . . . . 139
B.4.2 Managerial support . . . . . 140
B.4.3 Robustness tests . . . . . 141
**C Outside Equity and Startup Innovation** **143**
C.1 The INVEST program for angel investments . . . . . 144
C.2 Derivation of equilibrium conditions . . . . . 147
C.3 List of industries . . . . . 148
C.4 Description of data and sample . . . . . 150
C.5 Description of variables . . . . . 153
C.5.1 Measuring key variables . . . . . 154
C.6 Results . . . . . 159
C.6.1 First stage and time trends . . . . . 159
C.6.2 Robustness tests . . . . . 163
**D The Private Value of Entrepreneurial Control** **179**
**Bibliography** **185**

# List of Figures


2.1 Change in sources of VC . . . . . . . . . . . . . . . . . . . . . . . . . . . . 18
2.2 Description of databases . . . . . . . . . . . . . . . . . . . . . . . . . . . . 19
2.3 VC investments by founding cohorts . . . . . . . . . . . . . . . . . . . . . . 21
2.4 Illustration of matching algorithm . . . . . . . . . . . . . . . . . . . . . . . 23

3.1 Share of equity-financed startups by eligibility . . . . . . . . . . . . . . . . . 42
3.2 First startup investments by investors in sample . . . . . . . . . . . . . . . . 55
3.3 Average portfolio size of incumbent investors . . . . . . . . . . . . . . . . . 56

4.1 Change in investments and incorporations over time relative to the year 2012 . 70
4.2 Share of equity-financed startups by eligibility . . . . . . . . . . . . . . . . . 71
4.3 Distribution of equity financing and R&D expenditures (in thsd. Euros) . . . . . 77
4.4 Relation between equity financing and innovation inputs . . . . . . . . . . . . 78
4.5 Marginal change in equity financing between groups relative to the year 2012 . 81

5.1 Distribution of willingness to pay for control . . . . . . . . . . . . . . . . . . 105

A.1 Number of strata by size of strata . . . . . . . . . . . . . . . . . . . . . . . 115
A.2 Estimated probability for subsidy receipt before and after matching observations 126

B.1 Distribution of financing volumes in eligible industries over time . . . . . . . . . 132
B.2 Distribution of syndicate sizes . . . . . . . . . . . . . . . . . . . . . . . . . 132
B.3 Likert scale ratings in eligible and non-eligible firms . . . . . . . . . . . . . . 133

C.1 Distribution of equity financing share . . . . . . . . . . . . . . . . . . . . . 155
C.2 Change in incorporations by industries . . . . . . . . . . . . . . . . . . . . . 157
C.3 Change in direct investments from individuals by industries . . . . . . . . . . . 158
C.4 Share of equity-financed startups by industries . . . . . . . . . . . . . . . . . 159

D.1 Sampling approach . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 180
D.2 Response analysis - Distribution of responses by state of completion . . . . . . 181

# List of Tables

2.1 Summary statistics of variables . . . . . 20
2.2 Difference in means of control variables (before and after matching) . . . . . 25
2.3 Estimation results . . . . . 26

3.1 Summary of different treatment and control groups . . . . . 41
3.2 Distribution of VC financed and non-financed startups . . . . . 44
3.3 Summary statistics of outcomes . . . . . 47
3.4 Summary statistics of control variables . . . . . 49
3.5 Estimated effect of investor subsidy on financing decision . . . . . 50
3.6 Estimated effect of investor subsidy on financing volumes . . . . . 51
3.7 Effect on managerial support activities . . . . . 53
3.8 Distribution of investors and startups in MUP . . . . . 54
3.9 Syndication of angel investors . . . . . 57

4.1 Summary statistics . . . . . 74
4.2 Comparison of founding cohorts relative to program introduction . . . . . 76
4.3 OLS - Association between equity financing and innovation inputs . . . . . 79
4.4 OLS - Association between equity financing and innovation outputs . . . . . 80
4.5 Two-Stage Least Squares - Effect of equity financing on innovation inputs . . . 83
4.6 Two-Stage Least Squares - Effect of equity financing on innovation outputs . . 84

5.1 Attributes and levels . . . . . 95
5.2 Description of sample and respondents . . . . . 98
5.3 Marginal effects of changes in attribute levels . . . . . 102
5.4 Willingness to pay for attributes . . . . . 104

A.1 Description of variables . . . . . 117
A.2 Sector classification . . . . . 118
A.3 Distribution of sources of VC by data source . . . . . 118
A.4 Share of VC sources within industries in database . . . . . 119
A.5 Industry distribution by data source . . . . . 119
A.6 Correlation matrix of main variables . . . . . 120
A.7 Distribution of subsidies and VC by industry . . . . . 121
A.8 Results for unbalanced pooled models . . . . . 121
A.9 Results for balanced pooled models . . . . . 122
A.10 Results for balanced within estimation models . . . . . 123
A.11 Robustness test . . . . . 123
A.12 Results for unbalanced seemingly unrelated regression . . . . . 124
A.13 Results for unbalanced seemingly unrelated regression . . . . . 125
A.14 Correlations of seemingly unrelated regression results (after balancing) . . . . 125
A.15 $\text{Chi}^2$-tests for equality of subsidy coefficients . . . . . 126

B.1 NACE codes of eligible industries . . . 128
B.2 Sector classification . . . 128
B.3 Overview on different samples used in the analysis . . . 129
B.4 Number of observations by industries and groups . . . 129
B.5 Description of variables . . . 130
B.6 Correlation matrix of main variables for Sample D . . . 131
B.7 Balancing results Sample E: Angel or VCF financed, only eligible industries . . 134
B.8 Balancing results Sample A: All firms . . . 135
B.9 Balancing results Sample B: Angel investor deal flow . . . 136
B.10 Balancing results Sample C: Angel or VCF financed . . . 137
B.11 Balancing results Sample D: Angel financed . . . 138
B.12 Financing amounts accounting for syndicate size . . . 139
B.13 Effect on managerial support activities (a) . . . 140
B.14 Technological shocks and pre-treatment trends on financing volumes . . . 141
B.15 Financing decision and pre-treatment trends using SUR model . . . 142
B.16 Transformed coefficients for SUR model . . . 142

C.1 Industries in sample . . . 148
C.2 NACE codes of eligible industries . . . 148
C.3 NACE codes of non-eligible industries . . . 149
C.4 Number of observations per firm by founding cohorts . . . 150
C.5 Full panel distribution by founding cohort and first year sampled . . . 151
C.6 Full panel distribution by founding cohort and eligibility . . . 151
C.7 Full panel distribution by reference year and eligibility . . . 152
C.8 Number of firms and observations per firm by industries . . . 152
C.9 Description of variables . . . 153
C.10 Distribution of investment and operating cost (in thsd. Euros) . . . 154
C.11 First stage results of program effects on equity financing . . . 160
C.12 First stage trends: OLS - Equity financing . . . 161
C.13 First stage trends: OLS - Equity financing in levels . . . 162
C.14 Robustness tests innovation inputs: OLS - R&D activity . . . 163
C.15 Robustness tests innovation inputs: OLS - R&D expenditures . . . 164
C.16 Robustness tests innovation inputs: OLS - R&D employment . . . 165
C.17 Robustness tests innovation outputs: OLS - Global market novelty . . . 166
C.18 Robustness tests innovation outputs: OLS - Domestic market novelty . . . 167
C.19 Robustness tests innovation outputs: OLS - Regional market novelty . . . 168
C.20 Robustness tests innovation outputs: OLS - Patent applications . . . 169
C.21 Robustness tests innovation inputs: 2SLS - R&D activity . . . 170
C.22 Robustness tests innovation inputs: 2SLS - R&D expenditures . . . 171
C.23 Robustness tests innovation inputs: 2SLS - R&D employment . . . 172
C.24 Robustness tests innovation outputs: 2SLS - Global market novelty . . . 173
C.25 Robustness tests innovation outputs: 2SLS - Domestic market novelty . . . 174
C.26 Robustness tests innovation outputs: 2SLS - Regional market novelty . . . 175
C.27 Robustness tests innovation outputs: 2SLS - Patent applications . . . 176
C.28 Robustness tests first stage trends: OLS - Equity financing . . . 177
C.29 Robustness tests first stage trends: OLS- Equity financing in levels . . . 178

D.1 Correlations of random coefficients . . . . . . . . . . . . . . . . . . . . . . . . . 182
D.2 Robustness checks: Willingness to pay with fixed vs. random price coefficient . 183
D.3 Heterogeneity of willingness to pay . . . . . . . . . . . . . . . . . . . . . . . . . 184

# I

# Chapters

# 1. Introduction

## 1.1. Motivation

In 1984, Herbert Giersch – founding member of the German Council of Economic Experts - posited in an article for the American Economic Review that “the fourth quarter [of the twentieth century] has a fair chance of becoming the age of Schumpeter.” What he referred to was a refocusing of public policy in developed economies on technological change through innovation-driven entrepreneurship. Schumpeter was the first to describe the process through which entrepreneurial activity induces a continuing process of innovation and creative destruction that results in long-term economic development. The idea of innovative entrepreneurship as the linchpin of economic growth found widespread acceptance among economists and remains an essential basis for economic policy today. This is reflected by the number of high-quality academic publications on this topic in recent years (Botelho et al., 2021), as well as the surge in policy initiatives around the globe to promote innovative entrepreneurship (Bai et al., 2021).

Access to financing is essential for turning new technologies and innovative ideas into commercially successful businesses and products. Innovation-driven entrepreneurs heavily rely on developed capital markets (King and Levine, 1993a; King and Levine, 1993b), i.e., institutions and individuals willing to finance their ideas. Venture capital (VC) is considered a critical source of funding for innovation-driven entrepreneurship and is an essential element of highly developed capital markets (Aghion, Howitt, et al., 2018). Professional venture capitalists engage beyond financing and often provide nascent entrepreneurs with valuable managerial support. These support activities are equally crucial for ventures’ success as access to capital (Quas et al., 2020). For the U.S., where the venture capital market is highly developed, recent empirical studies provide evidence that the support activities of venture capital firms have a positive causal effect on the success of innovative ventures (Bernstein, Giroud, et al., 2016; Ewens and Marx, 2017; Sørensen, 2007). Positive causal performance effects have also been shown for groups of professional angel investors, i.e., private individuals who directly invest their wealth in entrepreneurial ventures, both in the U.S. (Kerr, Lerner, et al., 2011) and Europe (Lerner, Schoar, et al., 2018). Yet, many policymakers consider the size of their domestic venture capital market to be insufficient.[1]

[1]For example, the European Commission has stated in its EU 2020 strategy as one of its goals to "[make] an efficient European venture capital market a reality, thereby greatly facilitating direct business access to capital

Entrepreneurship policies that promote innovation-driven entrepreneurship are typically focused on easing access to early-stage capital markets, particularly access to venture capital. Programs to stimulate the venture capital market are not new, but the global public budgets committed to such programs have constantly increased over the past decades. According to data from Bai et al. (2021), the global annual budget for such programs between 2010 and 2019 averaged around 156 billion US Dollars, or about 0.2% of the world's GDP, exceeding annual disbursements by private venture capital funds. After the great recession of 2007/08, numerous new programs have been launched to stimulate domestic markets for seed and early-stage financing by venture capitalists (OECD, 2011). More recently, the European Union has started major support programs for innovative startups as part of the Green New Deal to narrow the gap with the US venture capital market (Wallace, 2020). Government support programs comprise a variety of different instruments. Direct support measures to stimulate the venture capital market range from governmental venture capital funds - either directly owned by the government or sponsored through funds-of-funds - and incentives for private individuals to allocate more of their assets to venture capital investments. In addition, some instruments may ease access to venture capital indirectly. These instruments comprise startup subsidies, research and development grants, accelerators, incubators, and venture competitions.

The economic argument in favor of such programs is typically based on the notion of *information frictions* in early-stage capital markets (Amit, Glosten, et al., 1990; Stiglitz and Weiss, 1981), and *knowledge spillovers* of innovations (Arrow, 1972; Lerner, 2002) which prevent efficient investment levels in innovation-driven companies. Yet, economists also have concerns about the effectiveness of government support programs (Da Rin, Nicodano, et al., 2006; Lerner, 1998, 2002). In particular critics argue that public initiatives may lead to a *crowding-out* of private investments (Cumming and MacIntosh, 2006) or fail to address to right firms or investors (Lerner, 1998, 2010). Considering the importance of these programs and the fact that they constitute a non-trivial part of public budgets, it is necessary to understand which instruments are most effective at supporting nascent firms and stimulating innovative entrepreneurship. Evidence-based economic research - to which this thesis contributes - may help to shed light on this.

Before providing an overview of the existing literature and how this thesis contributes to it, it is helpful to outline the current understanding of innovative entrepreneurship in the academic literature, distinguish it from other models of entrepreneurship, and motivate the importance of venture capital markets and government intervention in this context.

markets and exploring incentives for private sector funds that make financing available for startup companies and innovative SMEs." See also Tykvová et al. (2012).

## 1.2. Innovation-driven entrepreneurship and venture capital

There seems to be no clear consensus among academics and policymakers on how the concept of innovation-driven entrepreneurship should be defined (Audretsch, 2019; Guzman and Stern, 2015). Some authors narrowly delineate innovative entrepreneurship from other models of innovation and entrepreneurship, which are also discussed in the economic literature (Botelho et al., 2021; Kerr, Nanda, and Rhodes-Kropf, 2014; Lerner, 2010). These authors view innovative entrepreneurship as a phenomenon that occurs primarily in *new firms* rather than in small or medium-sized firms in general. Especially in *emergent knowledge-intensive industries* - with the highest growth potential - new firms play an essential role for major innovations (Acs and Audretsch, 1988). In addition, the concept of innovation in this context is rather narrowly viewed. Innovative entrepreneurship is typically associated with *radical* or *disruptive* innovations. Both types of innovation are characterized by a high degree of novelty and have the potential to create *new markets* (Hopp et al., 2018). Disruptive innovations also have the potential to completely replace existing technologies and push incumbents out of the market (Christensen, 2013). Unlike other entrepreneurship models, innovation-driven entrepreneurship is associated with a high degree of *Knightian uncertainty* because the business models and markets in which these entrepreneurs operate are often unproven (Botelho et al., 2021). This delineation of innovative entrepreneurship, which is used in substantial parts of the recent academic literature, directs attention to a fairly confined group of *pioneering firms*. Many policymakers and parts of the academic community view the concept of innovative entrepreneurship more broadly, often including existing small businesses and incremental innovations in their definition (Audretsch, 2019). The focus of the present thesis will be on *young* firms. Acknowledging that other types of innovative entrepreneurship exist and may occur in established firms and existing industries, the perspective taken in this thesis is that innovation-driven entrepreneurship is a phenomenon occurring in new firms in emergent markets pursuing radical innovations.

Although innovative entrepreneurs are a central element of it, innovative entrepreneurship should not be viewed as an endeavor of a single individual or company. Rather it is a joint effort of distinct actors who must interact in a complex environment through formal and informal governance structures (Zingales, 2000) that blur the boundaries of the firm (Lindsey, 2008). Within the network of distinct actors,[2] venture capitalists constitute an important nexus. On a basic level, venture capitalists provide capital to nascent firms through equity-based financing instruments. This form of financing gives investors the right to acquire shares in the company. The investors' goal is to sell these shares within a limited time horizon at a profit in a so-called

[2] These actors comprise universities and research institutions, corporations, suppliers, potential customers, lawyers, and larger financial intermediaries like investment banks.

*exit*-event.[3] Equity-linked instruments have several advantages for projects characterized by a high degree of *Knightian uncertainty* and low chances of success (Kerr, Nanda, and Rhodes-Kropf, 2014; Winton and Yerramilli, 2008). First, equity provides investors with comprehensive information and monitoring rights, making assessing the operations of the ventures they finance easier. Second, equity provides investors with future cash-flow rights in the firm. If the venture is successful, investors take a pro-rata share of the equity they have acquired. This gives investors an incentive to get actively involved in the venture beyond the original financing and add value to it (Casamatta, 2003). Yet, equity-based financing instruments alone are unlikely to be a sufficient condition for venture capitalists to lead innovation-driven entrepreneurs to success. To be able to add value, investors need to have some level of *industry* or *entrepreneurial experience* themselves (Bottazzi et al., 2008), as well as links to other actors in the market (Conti and Graham, 2020; Hochberg et al., 2007). In this respect, however, investors differ from one another (Bottazzi et al., 2008). Differences exist not only in terms of investors' skills but also in their objectives (Tykvová, 2017). As a result, the venture capital market is characterized by a high degree of heterogeneity on the supply side. This is reflected in the diversity of different sources of venture capital. Traditionally, these include specialized intermediaries - referred to as *venture capital firms* -, as well as private individuals - also known as *angel investors* -, large corporations, universities, governments and also banks (Andrieu, 2011; Gompers and Lerner, 2001). In recent years, the relative prevalence of specific types of investors has shifted (Cumming and Zhang, 2018), and a variety of new actors have entered the scene (Block, Colombo, et al., 2017) with different goals and likely to differ in their ability to support startup companies.

An assessment of the effectiveness of entrepreneurship policies should, therefore, not be limited to the quantity of venture capital provided but also consider its quality, i.e., whether the additional venture capital provided is 'smart money' adding value to innovative ventures.

## 1.3. Existing literature on entrepreneurship policies, venture capital, and innovation

Research on entrepreneurship policies provides mixed evidence of their effectiveness. Whether they are successful seems to depend mainly on the design of specific programs (Alperovych, Groh, et al., 2020; Bai et al., 2021; Lerner, 2010). Private sector involvement is seen as a critical success factor (Alperovych, Hübner, et al., 2015; Bertoni and Tykvová, 2015; Brander et al., 2014; Cumming, Grilli, et al., 2017; Grilli and Murtinu, 2014). Yet, the mechanisms that make private sector involvement a vital success factor are not fully understood. Concretely, it is not

[3] Exit-events can be initial public offerings (IPOs), trade sales to incumbents (acquisitions) or other investors (secondary market transactions).

clear whether private actor involvement is necessary to identify successful ventures *ex-ante* by screening investment opportunities (Bai et al., 2021) or whether early-stage financing from the public sector alone is sufficient to reduce information frictions for *private* actors and increases allocation efficiency of *private* funds. Providing a conclusive answer to this question is not trivial, as government programs may target firms associated with higher Knightian uncertainty, i.e., firms with unproven technology or inexperienced founding teams (Bertoni, Colombo, and Quas, 2017). Comparing the effectiveness of governmental venture capital funds with private actors may be misleading when governments and private actors take different types of risks. The fact that many public initiatives do not seem to generate crowding-out effects (Brander et al., 2014; Leleux and Surlemont, 2003) indicates that governmental venture capitalists are supporting founders and technologies that private actors are not venturing into.

Various studies indicate that different types of government support programs other than governmental venture capital may also reduce information frictions and attract follow-on venture capital. These programs include public accelerators (Gonzalez-Uribe and Leatherbee, 2017) and venture competitions (Howell, 2020), as well as startup grants and research and development grants (Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott, Lins, et al., 2017; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Li et al., 2018; Martí and Quas, 2017; Santoleri et al., 2020; Söderblom et al., 2015; Zhao and Ziedonis, 2020). Yet, these studies do not explicitly consider the type of venture capital that is attracted. In light of the lack of explicit consideration of the sources of venture capital in these studies, the extent to which public subsidy programs for startups attract *private* capital is still unclear.

Given the importance that previous research attributes to the involvement of private actors in selecting the right ventures (Bai et al., 2021; Lerner, 2002, 2010), many governments set up support programs that give more discretionary power to private investors. This type of program design views the role of the public sector primarily as directing additional funding to startups rather than selecting specific technologies or eliminating information frictions in the first place. One type of such program is subsidies for angel investors. The academic literature on angel investor subsidies is limited compared to the literature dealing with the effectiveness of direct startup subsidies and public venture capital funds. Given that these programs have been introduced in various countries in recent years, empirical evidence of their effectiveness is still needed.

One of the main objectives of government support programs is to stimulate radical innovation. There is broad consensus among economists that outside equity financing plays a vital role in such kind of innovation (Da Rin, Hellmann, et al., 2013; Kerr and Nanda, 2015; Lerner and Nanda, 2020). Recent literature discusses how experimentation in entrepreneurship brings about radical innovations (Kerr, Nanda, and Rhodes-Kropf, 2014). In entrepreneurship, experimentation involves experimenting with entirely new technologies and markets (Lindholm-Dahlstrand et al., 2018). Venture capitalists' investment model is particularly suited to finance entrepreneurial experimentation (Nanda and Rhodes-Kropf, 2017a). Yet some critical questions on the role that venture capitalists play in the process of entrepreneurial experimentation remain open. So far, it is not clear whether external equity from private sources is used to finance the *creation* of new technologies or whether it is instead used for *commercialization* and therefore experimenting with new markets.

The venture capital market offers innovation and growth-oriented founders an opportunity to realize their ideas. The relatively lower significance of the venture capital market in Europe (as measured by the share in GDP) has led many policymakers to believe that there is an equity gap for startups.[4] Accordingly, a large body of literature addresses how to effectively increase the supply of venture capital and bridge the equity gap. Compared to this, little work has explored demand-side effects that contribute to the relatively small size of the venture capital market (Croce et al., 2018). An extensive literature posits that there are non-monetary returns to entrepreneurship that relate to valuing independent work and control over their firms' decisions (Åstebro, 2012; Hyytinen et al., 2013; Moskowitz and Vissing-Jørgensen, 2002). Since venture capital agreements often grant investors extensive control rights, many founders may perceive the cost attached to venture capital financing as excessively high, limiting the potential of venture capital-financed innovation and growth in the broader economy. The magnitude of entrepreneurs' control preferences is not yet known, which is why their limiting potential is still unclear.

## 1.4. Contribution of the thesis

### Chapter 2: Startup Subsidies and the Sources of Venture Capital

The second chapter builds on the extensive literature on the role of startup subsidies for follow-on financing from venture capital investors (Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Söderblom et al., 2015; Zhao and Ziedonis, 2020). These papers argue that startup subsidies reduce uncertainty based on theories about information frictions in capital markets (Amit, Glosten, et al., 1990; Stiglitz and Weiss, 1981) and signaling theory (Spence, 1973) about the quality of startups and ease of access to capital. The existing literature treats venture capital as a generic source of financing and does not distinguish between the type of venture capital attracted through startup subsidies. Based on research by Bianchi et al. (2019) and Connelly et al. (2010), I argue that the information value of startup subsidies depends on the nature of the signal

[4]The notion of capital shortage has long been the subject of controversy in the economics literature (see, for example, Eisner (1977)).

receiver, i.e., the investor. I then test whether different types of venture capital investors value startup subsidies differently. Understanding this relation is relevant because different types of venture capitalists are associated with varying performance effects for startups (Tykvová, 2017) and may lead to different conclusions about their effectiveness in crowding-in private venture capital.

To test this hypothesis, I construct a matching procedure that combines coarsened exact matching and propensity score matching to achieve balanced covariates between subsidized and non-subsidized firms while maintaining a sufficient sample size for efficient estimation. The resulting weights of the matching procedure are then used in different types of generalized linear regression models. The data to estimate my model come from the first twelve waves of the IAB/ZEW Startup Panel, covering founding cohorts 2005 to 2018 of German startups. For information on venture capital investors, I construct a unique data set based on data from Bureau van Dijk's Zephyr Database, Majunke Consulting, and the Mannheim Enterprise Panel (MEP). For each transaction, I classify investor types using information from the primary databases and additional information through web research. The final sample contains 9,743 startups in knowledge-intensive sectors, of which 262 receive venture capital from different types of venture capital investors.

The results confirm previous studies showing a positive link between startup subsidies and follow-on financing from venture capitalists and support the view that startup subsidies reduce information frictions. Yet, the value of startup subsidies differs across investor types. After accounting for firms' selection into subsidies, the results remain only for angel investors and governmental venture capital funds.

### Chapter 3: Financing and Advising Early Stage Startups: The Effects of Angel Investor Subsidies

The third chapter focuses on a policy instrument used in various countries over the past decade but has remained largely unaddressed by empirical economic research: subsidies for angel investors. Subsidies for angel investors aim to attract additional smart money from individuals to mitigate potential funding problems of innovative entrepreneurs (Lerner, 1998). Consequently, these programs should be viewed as a measure to create active venture capital markets (Da Rin, Nicodano, et al., 2006). Building on theoretical arguments by Keuschnigg (2004) and Lerner (1998), I investigate whether subsidies for angel investors induce a trade-off for public policy. In particular, I test whether increasing the supply of venture capital by subsidizing angel investors reduces the average level of management support for startups and thus adversely affects the quality of investments. In addition, I examine possible mechanisms to explain my results.

To investigate these relations, I look at the case of Germany, where the subsidy program "IN-

VEST - Zuschuss für Wagniskapital" was introduced in 2013. The program partially reimburses private investors for making equity investments in young companies in Germany. Using the program's eligibility criteria for startups and investors, I test my hypothesis in a Difference-in-Differences framework. The data I use comes from two special IAB/ZEW Startup Panel surveys on the activity of angel investors and venture capital firms conducted in 2012 and 2018. In addition to detailed information on startups, the special surveys provide information on investors' financing and support activities. The final sample contains 12,853 firms, of which 980 receive investments from private investors or venture capital firms.

The results provide evidence that angel investor subsidies increase the supply of early-stage capital in terms of the likelihood of receiving financing and the amounts raised. Conversely, I do not find strong evidence for an adverse effect on managerial support, which stands in contrast to my initial hypothesis derived from the literature. To explore the mechanisms driving this result, I augment the data with ownership information from the Mannheim Enterprise Panel, allowing me to look at the investment history of investors in my sample. While I find an increased entry from angel investors after the introduction of the policy, I also see increases in syndicate sizes with other angel investors. Syndication between experienced and new investors may allow startups to raise larger financing amounts while maintaining access to investors' managerial expertise and networks.

### Chapter 4: Outside Equity and Startup R&D: Evidence from the German INVEST Program

Investigating the link between outside equity and innovation empirically is challenging because information on the innovation activity of young entrepreneurial firms is minimal. The existing literature almost exclusively uses patents as a proxy for innovative activity. Relying solely on patents as an indicator of innovation activity is particularly problematic in the context of startups. On the one hand, most innovations are not patented, often due to strategic considerations. Moreover, it can be assumed that the propensity to patent is affected by financing intentions: companies file patents to attract investors. Analyzing research and development (R&D) expenditures has its own challenges because of the endogenous nature of R&D: firms already spending more on R&D may be more attractive to venture capital investors. Looking at correlations between external equity and R&D expenditures may, therefore, lead to wrong conclusions.

In Chapter 4, I study the relation between startups' financing decisions and their innovation activity based on the model by Kortum and Lerner (2000). The model allows me to consider the relative salience of public and private sources for firms' innovation activity. Data from the IAB/ZEW Startup Panel allows me to separately consider innovation inputs (R&D) and outputs (market novelties). To account for the endogenous nature of financing choices for investment decisions, I use the introduction of the INVEST program as an exogenous shift to the cost of outside equity. Using variation over time between eligible and non-eligible firms, I estimate the model using a Wald Difference-in-Differences approach.

The results indicate a strong positive correlation between outside equity and innovation in terms of investments into R&D and the introduction of global market novelties. Yet when accounting for the endogenous nature of financing choices using the introduction of the INVEST program as an instrument for the cost of outside equity, I find that the effect of outside equity on R&D investments drops in size and is no longer significant. Conversely, the effect on global market novelties increases in size and remains highly significant.

### Chapter 5: The Private Value of Entrepreneurial Control

Chapter 5 examines entrepreneurs' private control benefits in a venture capital setting. Building on the extant literature on the importance of control rights to mitigate agency issues in venture capitalists' investment model (Ewens, Gorbenko, et al., 2021; Kaplan and Stromberg, 2003; Tykvová, 2007) and the literature on non-pecuniary benefits to entrepreneurship (Moskowitz and Vissing-Jørgensen, 2002), I estimate entrepreneurs' valuation of control in an experimental setting. A high valuation of control rights among innovation-driven entrepreneurs makes it comparatively difficult for venture capital investors to leverage their investment model. Understanding the value entrepreneurs attach to control therefore gives us an indication of the limits of venture capitalists' investment model.

To estimate the value of control for entrepreneurs in a venture capital setting, I design a discrete choice experiment in which entrepreneurs are confronted with a series of hypothetical investment proposals from venture capital investors. The investment levels of offers are fixed, but offers have varying levels of cash-flow rights, control rights, and value-adding activities that investors provide. The discrete choice experiment is conducted with entrepreneurs in Germany (n=317). The sample is drawn from the IAB/ZEW Startup Panel, a stratified random sample of the population of German startups. This allows me to make a statement on the broader population of German entrepreneurs that may consider venture capital financing.

The estimated value of entrepreneurial control is about 38% of firms' equity value. That is, entrepreneurs are willing to pay an equivalent of 38% of their firms' equity value to prevent investors from taking control of the venture. Control is also valued much higher than investors' support activities, for which entrepreneurs are willing to pay an equivalent of 3 to 12% of the firm equity value, depending on which type of support investors provide.

Yet, there seem to be important differences between entrepreneurs. Those who already have received financing from a venture capital firm are more willing to give up control. These differences do not seem to be driven by growth orientation but rather by entrepreneurs' idiosyncratic preferences.

## 1.5. Outline of the thesis

The thesis is structured as follows: Chapters 2 to 5 contain the main body of my research. Supplementary materials and further analysis for each chapter are included in the appendix. Chapters 3 and 4 are connected, but each chapter can be read independently. Chapter 6 summarizes the scientific contribution of the thesis and the main findings. It is concluded by outlining avenues for further research that could follow this thesis.

# 2. Startup Subsidies and the Sources of Venture Capital

## 2.1. Introduction

Access to managerial and financial resources is crucial for the success of entrepreneurial firms. Yet, uncertainty about their technological viability, managerial capacity, and ability to compete with other firms (Ostgaard and Birley, 1994) makes it challenging for them to secure external resources. Public support programs for entrepreneurial firms aim to help them to overcome such constraints (Brown and Earle, 2017; Duruflé et al., 2016; Hellmann and Thiele, 2019; Wilson and Silva, 2013). Research suggests that in addition to direct access to seed funding through subsidies, there are also indirect positive effects of public startup subsidies on (follow-on) financing provided by other lenders (Hottenrott, Lins, et al., 2017; Li et al., 2018; Martí and Quas, 2017) or investors (Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Söderblom et al., 2015; Zhao and Ziedonis, 2020).[1]

The evidence on the link between startup subsidies and access to external resources is not limited to specific countries, as these studies show similar patterns for several knowledge-based economies. In these studies, a particular focus has been put on VC investments. VC investors provide financing to startups as well as managerial support (Hellmann and Puri, 2002), which is an essential driver of success for entrepreneurial firms (Conti and Graham, 2020; Ewens and Marx, 2017). As such, VC investors are considered an essential element of ecosystems conducive to the birth and growth of new and innovative firms (Popov and Roosenboom, 2013; Samila and Sorenson, 2011).

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This Chapter is based on Berger and Hottenrott (2021)

[1] Other studies have investigated the link between public R&D subsidies and access to financing for established companies and also find that when information asymmetries are large, subsidy recipients are more likely to have better access to long-term debt (Meuleman and De Maeseneire, 2012) and face a lower cost of debt (Demeulemeester and Hottenrott, 2015).

Existing research studying the link between public subsidies and VC has regarded VC as a generic financing type. This resulted in the notion that public startup subsidies are an initiator and facilitator for startups' success in raising private sector VC per-se. However, VC providers are a heterogeneous class of investors who differ substantially in their investment approaches (Bottazzi et al., 2008; Conti, Thursby, and Thursby, 2013). Importantly, there are significant performance differences between entrepreneurial firms funded by different investor types in terms of innovation performance (Bertoni and Tykvová, 2015; Chemmanur et al., 2014; Dutta and Folta, 2016) and exits (Brander et al., 2014; Colombo and Murtinu, 2016; Cumming, Grilli, et al., 2017; Cumming and Zhang, 2018). While entrepreneurial firms financed by independent venture capital investors and corporate venture capital show very similar performance patterns in sales growth and exits (Colombo and Murtinu, 2016), those financed by angel investors and governmental venture capital investors differ substantially (Brander et al., 2014; Cumming, Grilli, et al., 2017; Cumming and Zhang, 2018). Performance differences also emerge for innovations (Bertoni and Tykvová, 2015; Chemmanur et al., 2014; Dutta and Folta, 2016). Yet, we know little about the role of public subsidies in the decision-making of different types of venture capital investors.

This study aims to contribute to our understanding of the link between startup subsidies and VC, focusing on the heterogeneity of VC investors. Conceptually, we build on insights by Bianchi et al. (2019) suggesting that public subsidies carry information - both about technological prospects and initial resource endowments - and the value of this information depends on the nature of the signal receiver. Drawing on the attention-based view, Bianchi et al. (2019) show that the relative salience of subsidy-related signals varies depending on the type of signal receiver. Building on these insights, this study aims to re-examine the previously documented link between public subsidies and follow-on financing in the context of newly founded firms. We analyze the extent to which public support affects the likelihood of attracting different sources of Venture Capital (VC) financing while differentiating between Government Venture Capital (GVC), Independent Venture Capital (IVC), Corporate Venture Capital (CVC), and Angel Investors (Angel).

Using detailed data from 9,743 startups founded between 2005 and 2018 in knowledge-intensive sectors in Germany, we show that there is indeed a positive correlation between public subsidies and all sources of VC. However, when we apply an econometric matching approach that combines propensity score matching (PSM) with coarsened exact matching (CEM) to achieve comparability between subsidized and non-subsidized ventures based on founder and firm characteristics that likely drive both public funding and VC, the follow-on financing effect is mainly linked to GVC and Angel financing. This result suggests that public startup subsidies do not per-se facilitate follow-on financing and that IVC investors, in particular, do not appear to rely on the information value carried by public subsidies.

Our results have important implications for both entrepreneurial firms and public policy. By participating in public funding programs, founders may initialize further funding, but not with the same likelihood for all sources. The type of VC, however, may determine the extent to which entrepreneurial firms have access to managerial, financial, and social capital in the long run.

## 2.2. Public subsidies and Venture Capital

Promoting entrepreneurial activity is high on the policy agenda around the globe, and the support of new firms usually involves providing startup financing (Bai et al., 2021; Lerner and Nanda, 2020). At the same time, VC has become increasingly important in financing new firms, including in countries that traditionally had comparably low levels of VC (Bertoni and Tykvová, 2015; Caselli and Negri, 2018; OECD, 2011). Research on the decision-making of VC investors shows that they base their funding decisions on objective and verifiable indicators of venture development (Bapna, 2019; Eckhardt et al., 2006; Lerner, 2002; Shepherd, 1999) and initial resource endowments affect the likelihood that new ventures attract VC financing (Shane and Stuart, 2002). Public startup subsidies also provide objective and verifiable information and, in addition, contribute to a firm's initial endowment.

Indeed previous research documents that new firms that receive subsidies are more likely to also successfully raise VC funding in a wide range of countries and for different policy designs. Lerner (2000), Howell (2017) and Islam et al. (2018) study firms funded by the United States Small Business Innovation Research (SBIR) program and Feldman and Kelley (2006) focus on firms that received public financial support from the Advanced Technology Program (ATP) at the National Institute of Standards and Technology (NIST). Cumming (2007) shows similar effects for an Australian program, and Conti (2018) shows that public startup support in Israel has a higher likelihood of VC. Giraudo et al. (2019) confirm this also for Italian startups, and Söderblom et al. (2015) provide evidence for young firms in Sweden. Zhao and Ziedonis (2020) and Hottenrott and Richstein (2020) show that participating in loan-based programs in the United States and Germany increases the likelihood of VC. While both Howell (2017) for the U.S. and Söderblom et al. (2015) for Sweden state that their measure for VC contains various sources of VC (including angel investors), the heterogeneity of sources of VC is not part of their analyses.

This line of research suggests that publicly financed startups appeal to VC investors. There may be at least two reasons for this. First, public subsidies provide quality certification. Second, they fund risky early-stage activities. Bianchi et al. (2019) refer to the former as a *pointing signal* which indicates a quality attribute that distinguishes the recipient firm from its competitors. In addition, the monetary amount raised through a subsidy may serve as an *activating signal* in the sense that it activates the quality attribute of the recipient. Drawing on the attention-based view (Ocasio, 2011), they show that the relative salience of these signals varies depending on the type of signal receiver. Transferring this logic to the setting of VC providers, the information value that investors extract from public subsidies may depend on the investor type.

Funding agencies aim to support firms with high innovation potential, particularly firms whose innovations create knowledge spillovers and social returns in their programs. Most funding agencies base their funding decisions on expert reviews and assessments, which may convey valuable information about firms' technologies, their regulation, and their longer-run prospects (Lerner, 2000). Thus, the information value attached to a subsidy could also be related to regulatory uncertainty and societal returns to firms' activities. Such information should be more valuable to investors who acquire less information about startups ex-ante. Maxwell et al. (2011), for example, show that angel investors base their investment decisions on heuristic assessments, which is in line with earlier findings that they are less likely to acquire information through formal due diligence or networks (Fiet, 1995; Osnabrugge, 2000). Moreover, both GVC and angels pursue goals other than pure economic profit by investing in firms that fit their mission and their desire to contribute to society (Alperovych, Groh, et al., 2020; Hsu et al., 2013).[2] Especially GVC and angels may therefore understand the award of a public subsidy as a signal of these prospects.

In line with the second channel in which subsidies affect VC investments through the provision of seed financing, Howell (2017) argues that firms in the energy sector use the awarded money to advance their project, thereby reducing technological uncertainty. Thus, they reach a proof-of-concept stage, making them more attractive to VCs. Similarly, Hottenrott and Richstein (2020) find that when firms receive grants combined with publicly backed loans, the VC probability is higher than in the case of grants alone. Therefore, it may not be certification alone but also the funding amount that attracts investors. However, the importance of this channel may depend on the relative size of the subsidy compared to the overall investment amount. Since GVC and angels are known to typically invest smaller amounts (Cumming and Zhang, 2018; Lerner, 1998), the initial endowment may matter more to them.

IVCs spend much of their time screening investment projects (Gompers, Gornall, et al., 2020; Kaplan and Strömberg, 2001, 2004), fulfilling their due diligence obligations to their limited partners. General partners and investment managers typically come from various backgrounds, including science, engineering, and finance (Bottazzi et al., 2008). From there, IVC should be able to arrive at an informed assessment regarding complex technological and market-related questions. For them, the information value of public subsidies should be relatively low. Also, societal returns should matter less for IVC investors, as their main goal is to maximize the return on investment (Hsu et al., 2013).

[2] Angel investors prefer investment proposals characterized by the moderate use of positive language, moderate levels of promotion of innovation, supplication, and blasting of competition, and high levels of opinion conformity which differs from preferences of other investors (Parhankangas and Ehrlich, 2014).

Yet, the cash inflow from the subsidy may still increase firms' attractiveness to IVC investors as it allows the financing of uncertain early-stage investments and help to build up tangible as well as intangible assets. Besides the financial resources, there could also be learning effects related to receiving subsidies which result in more advanced business plans contributing to firms' success in acquiring funding from IVCs (Martí and Quas, 2017).

The decisions of CVC funds typically rely to a large extent on the corporate's internal expert knowledge. Moreover, the economic profit of the venture may not be the most important aspect of the CVC objective function. The CVC may pursue strategic goals (Riyanto and Schwienbacher, 2006), which reduces the information value of subsidies and the importance of reducing uncertainty through proof-of-concept (Bianchi et al., 2019). Smaller CVC funds may still use public funding programs as screening devices, helping them identify promising newcomers.

While these arguments suggest that subsidized startups may be more likely to raise VC financing, there could also be crowding out between public subsidies and any type of VC if receiving one kind of financing reduces the need to raise another. Startups could perceive public startup support as an alternative to GVC (and vice versa) as both financing instruments target startups in the seed phase (Bertoni and Tykvová, 2015). In addition, as a result of public subsidies, startups could become less attractive for GVC if they are already advanced in their business development and no longer fit the criteria for GVC (Alperovych, Groh, et al., 2020).

Previous analyses, however, do not distinguish between the sources of VC, leaving the question open whether a specific type of investor drives the observed link between the subsidy and VC or whether there is considerable heterogeneity in the link depending on the source of VC. We hypothesize that there are differences depending on the information value the subsidy provides for the respective investor and the relative importance of the financial resources attached.

## 2.3. Data

For the analysis, we use detailed firm-level and transaction-level data for startups founded in Germany from 2005 to 2018. The information comes from four primary databases. In the following, we briefly describe the databases and our data collection.

### Data on startups

Our primary data source is the IAB/ZEW Startup Panel,[3] which is based on a representative annual survey among startups in Germany, administered by the Institute for Employment Research

[3] See Fryges, Gottschalk, and Kohn (2009) for details.

and ZEW - Leibniz Centre for European Economic Research. The sample of startups that enter the survey is drawn as a stratified random sample[4] from the Mannheim Enterprise Panel (MEP),[5] a comprehensive database of the universe of German firms. When startups enter the survey, they are at least one year and at most three years old and remain in the sample until a maximum age of seven. The IAB/ZEW Startup Panel covers information on the founders and the activities of the company. Importantly for our analysis, it contains detailed information on public subsidies for startup companies. Founders are asked to indicate whether they have received public subsidies through grants, subsidized loans, or guarantees. Grants are by far the most common type of support (28% of all firms), while subsidized loans and particularly guarantees are rarer (15% and 6%, respectively). It should be noted, however, that of those firms that receive a grant, 52% also receive a subsidized loan. Moreover, loans and guarantees typically overlap (81% of those with a guarantee also receive a subsidized loan). Previous research shows that both grants and subsidized loans facilitate additional spending in startups, are similar in promoting follow-on financing, and contribute to firm performance (Brown and Earle, 2017; Hottenrott and Richstein, 2020; Huergo and Moreno, 2017; Zhao and Ziedonis, 2020). For these reasons and because the exclusive categories are small when combined with Venture Capital information, we consider these forms of subsidies jointly for this study.

To control for founder and firm characteristics, we use the information on founder demographics, including founders' gender, educational background, founding experience, and industry experience, as well as whether a team founded the firm. In addition, we include firms' founding year, their sector of activity, and their location. The innovation potential is proxied by an indicator for R&D activity and by Intellectual Property (IP) in terms of patents.[6]. In addition, we include a variable indicating whether firms were founded to realize a specific business idea (as opposed to those starting a business out of the desire for independence or out of necessity).

### Venture capital transactions

We use transaction data from two primary sources to identify startups that receive venture capital investments. The first is Bureau van Dijk's Zephyr database which contains information on worldwide M&A transactions, including venture capital transactions. We use the information on minority stake acquisitions through venture capital financing from 2005 to 2019, where the target company is located in Germany. Besides other sources of transaction information, Zephyr has been used in a recent large-scale research project on venture capital in Europe to identify, i.a. German venture capital transactions (Bertoni and Martí, 2011). Following this approach,

[4]See Table A.2 in the appendix for the sector classification.

[5]The MEP is based on data from Creditreform - Germany's largest credit rating agency - and maintained and administered by the ZEW - Leibniz Centre for European Economic Research in Mannheim. For more details on the MEP, see Bersch et al. (2014).

[6]Patents are a signal to investors in Conti, Thursby, and Thursby (2013) and Haeussler et al. (2014), for example.

we complement the Zephyr data with information from another data source since Zephyr has limited coverage for German venture capital transactions. In particular, we use data provided by Majunke Consulting, a private equity boutique that collects information on M&A, private equity, and venture capital transactions in the DACH region.[7] Majunke's VC data started in 2005, and the data set contains all information collected by Majunke up until 2019. We match the information on acquirers (i.e., venture investors) and target companies (startups) with the MEP. To do so, we apply a fuzzy string matching algorithm to company names and addresses.[8] The resulting matches are then manually cross-validated by research assistants. Using this approach, we identified 99% of firms from the Zephyr database and 98% from Majunke's data in the MEP. Once the transaction information is merged with the MEP, we can link the data to the survey information in the IAB/ZEW Startup Panel based on a unique company identifier.

### Classification of investors

We classified investors based on the primary origin of their funds. Specifically, we differentiate between Angel, i.e., individuals, who invest their own money, IVC, whose sources come from a pool of wealthy individuals, institutional investors, and other private sector sources, GVC[9] where the public sector provides funds, and CVC, where a corporation operates the fund. For the classification, we used information from the primary databases when available. If not available, we manually researched this information using investors' websites, Crunchbase, Bloomberg, and ownership information from the MEP.

The distribution of deals across investor types indicates that Angel, IVC, and GVC account for relatively similar shares in the total of deals, with only CVC being less frequent (see Table A.3 in the appendix). Moving from the deal level to the firm level, we see that the shares of Angel, GVC, and CVC increase, reflecting that IVCs have more funding rounds per firm.[10]

The empirical setting for the following study is Germany, for which Figure 2.1 shows that VC financing increased substantially from 2005 to 2019 (left panel). It also illustrates that there is a mix of VC providers and that the different sources of VC have become equally important over time (right panel). The importance of Angel and CVC increased more than financing provided by GVC and IVC, and while IVC remained the most frequent source of VC, Angel financing caught up from the least (in 2005) to the second most frequent source of VC in 2019. This development is not specific to Germany, but similar trends have been witnessed in other countries (OECD,

[7] The DACH region comprises Germany (D), Austria (A) and Switzerland (CH).

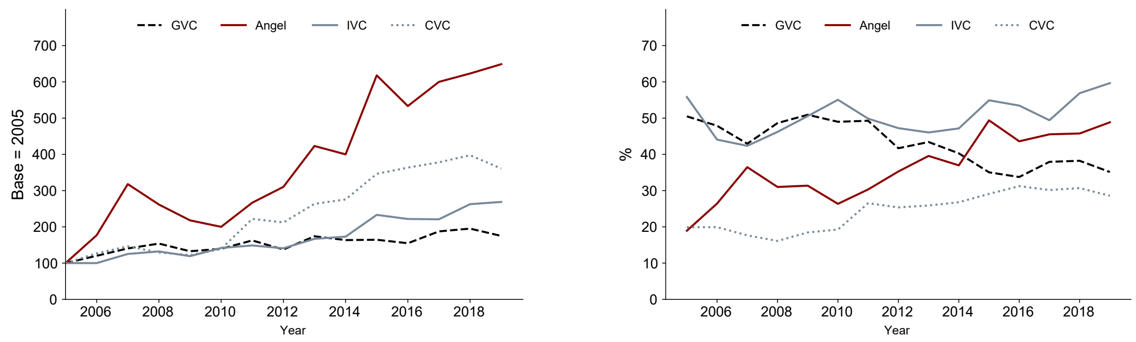
[8] For the fuzzy string matching we used Thorsten Doherr's SearchEngine: https://github.com/ThorstenDoherr/searchengine

[9] We classify VC deals related to public banks, such as the *Kreditanstalt für Wiederaufbau (KfW)*, as GVC.

[10] See Table A.3 in the appendix for a comparison of the distribution of investor types according to the different data sources. The Majunke information provides better coverage of all deals, particularly for angel investments, than Zephyr.

**Figure 2.1.: Change in sources of VC**

**(a) by number of deals** **(b) by share of total deals**




**Source:** Bureau van Dijk, Majunke Consulting. Mannheim Enterprise Panel. Own calculations.

2011; Wilson and Silva, 2013).

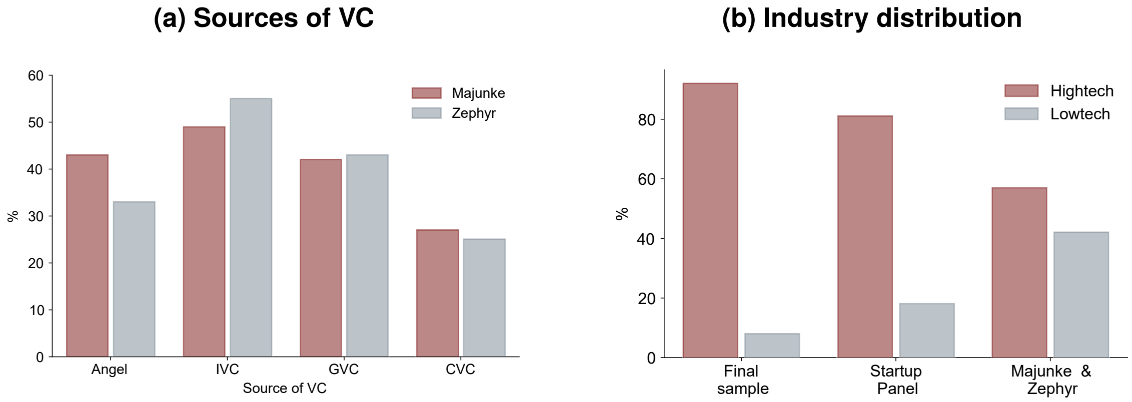
### Sample for analysis

By 2019 the IAB/ZEW Startup Panel contained information on about 18,000 firms in knowledge-intensive sectors and about 11,000 firms in non-knowledge-intensive sectors. These firms are almost always owner-managed (98%), i.e., at least one owner is part of the management team. In the following, we focus on potentially relevant firms for venture capital investors. Research on the venture capital market shows consistently that venture capital investments are concentrated in specific sectors and focus on certain types of startups (Lerner and Nanda, 2020). This is also true for startup subsidies. Therefore, we restrict the sample to knowledge-intensive sectors. We discard startups operating in the construction, retail, and consumer-oriented services industries. We exclude startups working as franchises or joint ventures and keep only startups that are limited liability companies or incorporations.

Our raw sample consists of 10,531 firms. After we eliminated firms with missing values in one of the explanatory variables that enter the matching, the final sample covers information from 9,743 firms, of which 35% received startup subsidies and 2.7% some form of VC. The resulting data structure is such that we analyze firm-year observations where we have time-varying observations on subsidy status for up to seven years after founding as we obtain the subsidy information from the survey. The VC information is available until 2019 for all firms since it is independent of the survey.

We check the composition of our final sample in terms of investor types against the initial information obtained from the Majunke and Zephyr databases. Figure 2.2 shows that the coverage of Angel deals is higher in the Majunke database (and slightly higher for CVC), whereas IVC tends to have better coverage in the Zephyr database (see also Table A.3). This

**Figure 2.2.: Description of databases**




**Source:** Bureau van Dijk, Majunke Consulting. Mannheim Enterprise Panel. Own calculations.

stresses the importance of collecting deal-level information from both Majunke and Zephyr. The coverage of GVC is comparable in both databases. We also check the sector composition in the transaction database versus the full Startup Panel and our final sample. This comparison reflects the stratification of the Startup Panel (stratified by industry), which allows better coverage of high-tech firms. Therefore, the relatively high representation of angel deals results from better coverage of those transactions in our transaction database (compared to Zephyr) and the result of the sector composition in the Startup Panel.[11] Despite the selection criteria applied as described above, the final sample is quite comparable to the full Startup Panel (see Table A.5 in the appendix).

Table 2.1 provides descriptive statistics of the variables used in the analysis and Table A.1 describes the construction of the variables in more detail.[12]

When looking at VC-funding in subsidized versus non-subsidized firms, we see that in more recent founding cohorts, a larger share of subsidized firms received VC (Figure 2.3). At the same time, the importance of some VC types - particularly Angel financing, which we hypothesized to be more sensitive to startup subsidies - increased as well (Figure 2.1). Table 2.2 presents differences between the group of subsidized and non-subsidized startups in terms of founder and firm characteristics and shows that the groups differ considerably in their observable characteristics, pointing to the importance of accounting for these differences in the following analysis.

[11] See Table A.4 in the appendix for the distribution of VC deals across sectors in the transaction data.

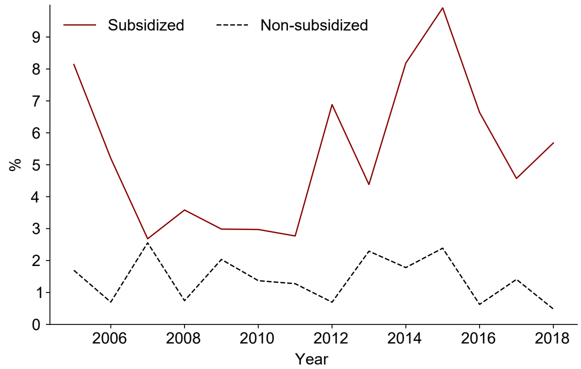
[12] Table A.6 shows pair-wise correlations between the main variables used in the following analysis. Table A.7 shows the distribution of subsidies and VC investments over sectors illustrating that both are most common in hightech manufacturing but also occur in other industries.

**Table 2.1.: Summary statistics of variables**

| | Firm obs. | Mean | Std. Err. | Min. | Max. |
|---|---|---|---|---|---|
| Subsidy(T) | 9743 | 0.351 | 0.477 | 0 | 1 |
| **Venture Capital** | | | | | |
| VC(T) | 9743 | 0.027 | 0.162 | 0 | 1 |
| GVC(T) | 9743 | 0.018 | 0.134 | 0 | 1 |
| BA(T) | 9743 | 0.013 | 0.113 | 0 | 1 |
| IVC(T) | 9743 | 0.012 | 0.109 | 0 | 1 |
| CVC(T) | 9743 | 0.006 | 0.080 | 0 | 1 |
| Startup age at VC(1) | 262 | 1.634 | 1.730 | 0 | 10 |
| **Founders** | | | | | |
| Founder age | 9743 | 41.573 | 9.744 | 17 | 95 |
| Team | 9743 | 0.474 | 0.499 | 0 | 1 |
| Academic | 9743 | 0.694 | 0.461 | 0 | 1 |
| Female | 9743 | 0.167 | 0.373 | 0 | 1 |
| Industry experience | 9743 | 13.462 | 9.969 | 0 | 59 |
| Founding experience | 9743 | 0.568 | 0.495 | 0 | 1 |
| Failure experience | 9743 | 0.198 | 0.399 | 0 | 1 |
| Opportunity-driven | 9743 | 0.486 | 0.500 | 0 | 1 |
| R&D(T) | 9743 | 0.543 | 0.498 | 0 | 1 |
| Patent | 9743 | 0.058 | 0.234 | 0 | 1 |
| **Industry** | | | | | |
| Hightech manufacturing | 9743 | 0.201 | 0.401 | 0 | 1 |
| Hightech services & software | 9743 | 0.455 | 0.498 | 0 | 1 |
| Lowtech manufacturing | 9743 | 0.131 | 0.337 | 0 | 1 |
| B2B & knowledge-int. services | 9743 | 0.213 | 0.409 | 0 | 1 |
| **Founding cohort** | | | | | |
| 2005-07 | 9743 | 0.133 | 0.340 | 0 | 1 |
| 2008-10 | 9743 | 0.197 | 0.398 | 0 | 1 |
| 2011-13 | 9743 | 0.234 | 0.423 | 0 | 1 |
| 2014-16 | 9743 | 0.294 | 0.456 | 0 | 1 |
| 2017-18 | 9743 | 0.142 | 0.349 | 0 | 1 |
| **Region** | | | | | |
| West Germany | 9743 | 0.824 | 0.381 | 0 | 1 |
| Berlin | 9743 | 0.062 | 0.240 | 0 | 1 |
| East Germany | 9743 | 0.114 | 0.318 | 0 | 1 |

**Note**: Firm obs. refers to the number of firms observed in the sample. The observation period per firm varies depending on the founding year and the corresponding years in which we observe the firm (the minimum number of observation periods is one year, the maximum is 12 years, and the median is five years). Subsidy(T) comprises different types of public subsidies, including grants (77% of subs. firms), subsidized loans (43% of subs. firms), and public guarantees (18% of subs. firms).

**Figure 2.3.: VC investments by founding cohorts**




**Source:** Bureau van Dijk, Majunke Consulting, IAB/ZEW Startup Panel. Own calculations.

# 2.4. Empirical methodology

## 2.4.1. Estimation

To investigate the link between subsidies and venture capital, we estimate linear probability models such that

$$XVC_{it} = \alpha + \beta Subsidy_{it} + \gamma X_{it} + \tau_t + \phi_i + u_{it} \tag{2.1}$$

where $XVC_{it}$ is an indicator variable that switches to 1 in the year when startups receive their first venture capital investment from one of the investor types in $XVC = \{GVC, Angel, IVC, CVC\}$. $Subsidy_{it}$ is an indicator variable that switches to 1 in the year when startups receive their first public subsidy, $X_{it}$ is a set of control variables, and $\tau_t$ and $\phi_i$ are the year and company-specific fixed factors, of which the latter are unobserved.

We estimate pooled models and a within-estimator that accounts for unobserved time-constant firm characteristics. Since few firms in our sample receive VC financing before applying for startup grants, we focus on cases where the subsidy precedes the equity investment.

The critical variable of interest - subsidy receipt - is not randomly assigned to firms. A correlation between subsidy receipt and VC financing could be due to common drivers of both outcomes rather than a causal link between the two. Firms seeking subsidies typically have less internal funds and limited access to external capital, which is arguably the main reason they seek public support. More innovative firms may select both into subsidy schemes and are, at the same time, more attractive targets for VCs.

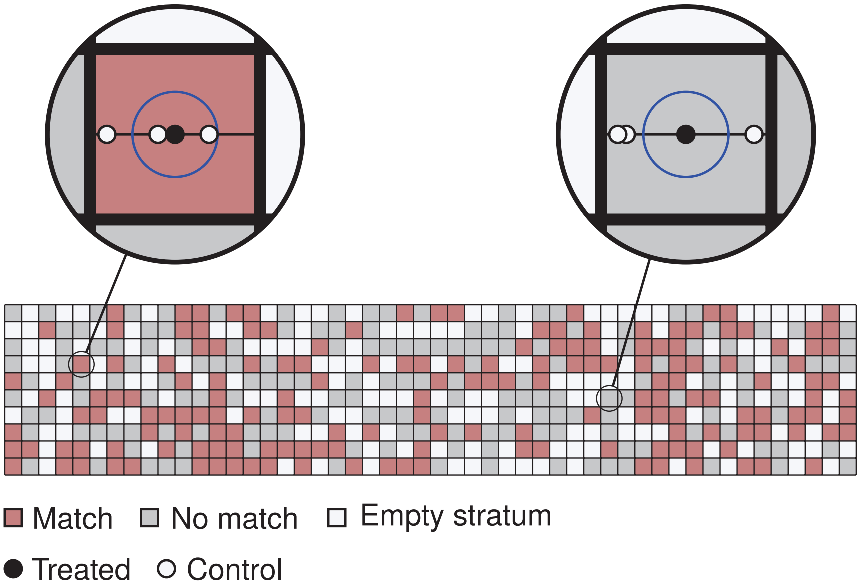
### 2.4.2. Matching

To address the selection into the group of subsidized firms, we perform matching techniques suited for causal analysis in non-experimental research designs (Rubin, 2005). In particular, we employ a matching procedure that combines propensity score matching (PSM) and coarsened exact matching (CEM) (Iacus et al., 2012). The idea of matching is to find reasonably comparable observations, thereby adjusting the distribution of pretreatment covariates by re-weighting and often potentially excluding observations. The goal is to quasi-randomize the treatment assignment by ex-post balancing treatment and control group in terms of relevant characteristics that explain selection into treatment. Observations that are unique and not comparable to others based on their observable characteristics are discarded; as for these observations, no counterfactual can be constructed. While exact matching has several desirable properties, like an intuitive interpretation, and an upper bound on the level of imbalance in the matched sample (Iacus et al., 2011), i.e., the degree of variation between different specifications, it also has some downsides. Most notably, exact matching often leads to small estimation samples due to empty cells, as it discards any observation that is not within the set of strata defined by coarsened pretreatment covariates of treated observations. This may lead to inefficient estimations. PSM does not have this constraint, but when used alone, it does often not ensure balance in terms of all covariates between groups.

Our matching algorithm proceeds in the following way: First, we narrow down a set of control observations that must have been active in the year when treated observations received their first subsidy. For those observations, we estimate the propensity score for being treated, i.e., the treatment probability, using the complete set of covariates displayed in the upper panel of Table 2.2. Note that these variables cover a set of founder characteristics (such as the biological age, gender, industry experience, entrepreneurial experience, academic background, and the motivation to start the business) since previous research illustrated the role of founder and team attributes in the VC selection process (Bernstein, Korteweg, et al., 2017). Second, we define exact matching requirements. In particular, we require that firms are from the same founding cohort, the same industry, are located in a similar region, have the same age when entering the survey, and operate in the same year. This results in 6,048 distinct strata[13] of which 2,757 have at least one observation in our sample. We perform caliper matching on the estimated propensity score within each stratum of the exact matching. This ensures that within each stratum, only those observations with comparable treatment probabilities based on the full set of covariates are matched. For 1,533 strata, we identify at least one tuple of caliper matches. Strata for which the sample contains more observations have a higher likelihood of finding a match. Strata consisting of only one observation cannot be matched by definition.

[13] We have three regions, four industry groups, fourteen founding cohorts, three age groups, and 12 observation-periods, which gives $3 \times 4 \times 14 \times 3 \times 12 = 6,048$ strata.

**Figure 2.4.: Illustration of matching algorithm**




**Note:** Figure 2.4 illustrates the matching algorithm. Cells represent the 6,048 strata based on company characteristics, including founding cohort, observation year, region, industry, and age when entering the survey. White cells represent empty strata for which the sample does not include any observations. The colored cells represent the 2,757 filled strata for which the sample contains at least one observation. The algorithm performs a caliper matching within each stratum based on the propensity score. The propensity score is calculated using firm and founder characteristics as described in Table 2.1. There are two cases to consider. Case 1 (red): when treated observations (black) have control observations (white) within their caliper neighborhood (blue), they are assigned as a match. Case 2 (gray): No match is assigned when control observations are outside the caliper. Of the 2,375 colored cells with at least two observations, 1,533 have matching partners within their caliper.

The advantage of this empirical approach is that it is applicable to different data structures and has relatively modest data requirements. Furthermore, it allows us to make a more general statement about the average treatment effect of startup subsidies on follow-on financing from different sources of VC. It is not confined to specific program designs, typically limited to the estimation of local average treatment effects.[14] The limitation of this approach is that it is based on the selection-on-observables assumption, which does not rule out the possibility of omitted variable bias. However, if observed variables are highly correlated with our unobserved variables that affect the outcome, the bias arising from omitted variables is reduced (Lechner and Wunsch, 2013). Given VCs place a high weight on founding team characteristics when making their investment decisions (Gompers, Gornall, et al., 2020), and we have plenty of information about founders in our data set, we are confident that we can reduce potential bias from omitted variables. In addition, firm fixed effects (included in estimations based on the matched sample)

[14] This is the case for studies that use instrumental variables or regression discontinuity designs (RDD). Furthermore, RDDs often require detailed information about the evaluation process of the firms that apply for support programs. Such information is often not available or not comparable across schemes. Especially in the case of public support schemes, the names of rejected applicants are usually not provided by funding agencies to protect unsuccessful applicants from experiencing negative consequences from their rejected applications.

will account for the remaining time-invariant unobservable characteristics. [15] If the matching procedure reduces the difference in the covariate distribution (including unobserved factors) between treatment and control firms, our results can be interpreted as an average treatment effect. Figure A.2 shows the distributions of the propensity scores after matching, and Table 2.2 shows that the differences between treated and control firms in terms of the key characteristics are significantly reduced after matching.

## 2.5. Results

Table 2.3 shows the main estimation results. Panel A shows the results for the unbalanced sample, and Panels B and C show pooled OLS and fixed effects models on the balanced sample, respectively. The coefficient of the subsidy variable gives the percentage point change in the probability of receiving VC. In all three panels, the results confirm the previously reported link between public startup subsidies and VC. The first column in Panel B indicates that this relationship is robust to accounting for the non-randomness of the subsidy receipt as it persists in the balanced sample. In particular, receiving a public subsidy doubles the probability of receiving VC to 0.0050 relative to the baseline probability of receiving VC for non-recipients which is 0.0024 in *any given period*.[16]

Looking at the different sources of VC in Panel B, we observe that subsidized firms are significantly more likely to receive GVC or Angel investments but not more likely to receive CVC and IVC. This is in contrast to the models on the unbalanced sample (Panel A), in which we observe positive correlations with all four sources of VC. This result is also robust to the within estimation (Panel C) which additionally accounts for unobserved heterogeneity among firms (Tables A.8-A.10 in the appendix show the full estimation results with and without matching).

We also estimate the four equations jointly in seemingly unrelated regression (SUR) models. This allows us to account for the co-occurrence of several VC types. In particular public-private co-investments in which GVC funds invest jointly with other investors are quite common in Germany (Bascha and Walz, 2007) and Europe more generally (Alperovych, Groh, et al., 2020). The findings are robust to this alternative estimations method (see Tables A.12 and A.13 in the appendix for detailed regression results and Table A.14 for error correlation across equations). In this specification, we test whether the coefficients for subsidy receipt are significantly different

[15] See Arkhangelsky and Imbens (2018) for details on the virtue of combining propensity score matching and FE models.

[16] The marginal effect of 0.0026 refers to the difference in the predicted probability of VC in both groups. The percentage increase is calculated as Prob(VC|Subsidy)/Prob(VC|No Subsidy) = $(0.0050/0.0024 - 1) \times 100 \approx 109$.

**Table 2.2.: Difference in means of control variables (before and after matching)**

| | Panel A: unbalanced | | | | | |
|---|---|---|---|---|---|---|
| | Subsidized N=3,422 | | Non-subsidized N=6,321 | | | |
| | Mean | Std. Err. | Mean | Std. Err. | Δ | t |
| **Controls** | | | | | | |
| Founder age (log) | 3.680 | 0.216 | 3.710 | 0.252 | 0.029 | 6.051*** |
| Team | 0.537 | 0.499 | 0.440 | 0.496 | −0.097 | −9.191*** |
| Academic | 0.716 | 0.451 | 0.682 | 0.466 | −0.034 | −3.489*** |
| Female | 0.170 | 0.375 | 0.166 | 0.372 | −0.004 | −0.522 |
| Industry experience | 12.950 | 9.290 | 13.739 | 10.309 | 0.789 | 3.849*** |
| Founding experience | 0.498 | 0.500 | 0.606 | 0.489 | 0.107 | 10.196*** |
| Failure experience | 0.175 | 0.380 | 0.211 | 0.408 | 0.036 | 4.348*** |
| Opportunity-driven | 0.493 | 0.500 | 0.483 | 0.500 | −0.010 | −0.987 |
| R&D | 0.520 | 0.500 | 0.403 | 0.491 | −0.117 | −11.110*** |
| Patent | 0.071 | 0.257 | 0.051 | 0.220 | −0.020 | −3.867*** |
| | Panel B: balanced | | | | | |
| | Subsidized N=2,206 | | Non-subsidized N=1,657 | | | |
| | Mean | Std. Err. | Mean | Std. Err. | Δ | t |
| **Controls** | | | | | | |
| Founder age (log) | 3.690 | 0.214 | 3.696 | 0.243 | −0.006 | −0.713 |
| Team | 0.519 | 0.500 | 0.496 | 0.500 | 0.023 | 1.188 |
| Academic | 0.710 | 0.454 | 0.712 | 0.453 | −0.001 | −0.080 |
| Female | 0.163 | 0.369 | 0.166 | 0.372 | −0.003 | −0.221 |
| Industry experience | 13.559 | 9.298 | 13.882 | 10.271 | −0.323 | −0.833 |
| Founding experience | 0.519 | 0.500 | 0.524 | 0.500 | −0.005 | −0.237 |
| Failure experience | 0.183 | 0.386 | 0.165 | 0.372 | 0.017 | 1.255 |
| Opportunity-driven | 0.482 | 0.500 | 0.477 | 0.500 | 0.005 | 0.262 |
| R&D | 0.537 | 0.499 | 0.554 | 0.497 | −0.017 | −0.919 |
| Patent | 0.066 | 0.248 | 0.068 | 0.253 | −0.003 | −0.282 |
| Propensity score | 0.256 | 0.150 | 0.255 | 0.149 | 0.001 | 0.217 |

**Note**: Panel A shows the means and differences in means (Δ) for subsidized and non-subsidized startups before balancing covariates. Panel B shows the means and differences in means (Δ) after balancing. Differences in means are the estimated coefficients of a weighted univariate regression of the control variable on the treatment status. The regression weights are the balancing weights obtained from the matching procedure. The standard errors and t-values are calculated under the assumption of heteroskedasticity. The stars *** indicate a statistically significant difference in means with $p<0.01$.

in the GVC versus the Angel equation and find that the coefficients are not statistically different ($\chi^2(1) = 1.02$, p-value = 0.31). In contrast, both GVC and Angel differ significantly from IVC and CVC (see Table A.15 in the appendix for all pair-wise comparisons).

Note that we only know the exact year of the first subsidy receipt for companies first surveyed in their founding year. From these companies, we know that 85% of startups that receive a subsidy receive it in their year of business activity. For the group of firms for which the founding year and the first reference year are not equal, we assume that they receive their first subsidy in the founding year. We, therefore, conduct robustness tests to check whether this assumption is material to the results and re-estimate all models only, including firms that we observe from the first year onward. The results from these models confirm the initial results (see Table A.11, Panels A and B).

**Table 2.3.: Estimation results**

| | Panel A: POLS (unbalanced) | | | | |
|---|---|---|---|---|---|
| | VC | GVC | Angel | IVC | CVC |
| Subsidy(t) | 0.0034*** (0.0006) | 0.0028*** (0.0005) | 0.0016*** (0.0004) | 0.0011*** (0.0004) | 0.0007** (0.0003) |
| Firm-year obs. | 55,051 | 55,330 | 55,659 | 55,589 | 55,837 |
| | Panel B: POLS (balanced) | | | | |
| | VC | GVC | Angel | IVC | CVC |
| Subsidy(t) | 0.0026*** (0.0008) | 0.0021*** (0.0007) | 0.0015*** (0.0005) | 0.0003 (0.0006) | 0.0007* (0.0004) |
| Firm-year obs. | 24,978 | 25,104 | 25,285 | 25,212 | 25,323 |
| | Panel C: Within (balanced) | | | | |
| | VC | GVC | Angel | IVC | CVC |
| Subsidy(t) | 0.0058** (0.0025) | 0.0044** (0.0021) | 0.0031* (0.0018) | 0.0013 (0.0017) | 0.0011 (0.0010) |
| Firm obs. | 3,953 | 3,955 | 3,963 | 3,961 | 3,961 |
| Firm-year obs. | 24,978 | 25,104 | 25,285 | 25,212 | 25,323 |
| | | Panel D: SUR (balanced) | | | |
| | | GVC | Angel | IVC | CVC |
| Subsidy(t) | | 0.0023*** (0.0008) | 0.0016*** (0.0006) | 0.0002 (0.0006) | 0.0007* (0.0004) |
| Firm-year obs. | | 25,410 | | | |

**Note**: Panels A and B and D include year, industry, and region fixed effects. Panel C includes year and firm fixed effects. Observations are at the firm-year level. Estimated coefficients are presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

## 2.6. Discussion

Venture capitalists' decision-making is a central subject of investigation in entrepreneurship and management research (Gompers, Gornall, et al., 2020). Recent research suggests that startup subsidies play an essential role in their decision-making. Several studies show that firms that receive public seed funding are more likely to raise VC. This holds for different policy programs, countries, and industries. So far, however, studies have not considered the heterogeneity of investor types in the subsidy-VC link, although their objectives, screening processes, and investment strategies differ substantially (Bertoni and Tykvová, 2015; Brander et al., 2014).

Using detailed transaction-level data, we classify investors by the source of their funds into government VC (GVC), independent VC (IVC), corporate VC (CVC), and angel investors (Angel), and re-examine the subsidy-VC link, explicitly distinguishing between these investor types. Our results confirm the positive relationship between public startup subsidies and subsequent VC financing documented in earlier studies. This relationship also holds when accounting for selection effects and common drivers of both subsidies and VC financing. Yet, the results show that the notion that subsidies facilitate follow-on financing by VC investors does not hold for all investor types. We show that the positive relationship is driven by GVC and Angel financing, not IVC.

We propose several explanations for this finding. In line with the attention-based view, the information value attached to the subsidy may depend on the signal receiver's degree of ex-ante information acquisition. Higher engagement in ex-ante information acquisition should reduce subsidies' information value. Information attached to the subsidy pertains to both startups' technological aspects and their initial endowment. As an alternative explanation for the case of GVC, there could be an inherent link between a subsidy and GVC investment. Subsidies could be provided with the explicit invitation of the funder to seek GVC. In addition, when pitching for GVC, firms that have previously dealt with public agencies may have an advantage either through learning about their expectations or simply through (personal) connections. Such connections to government funding bodies could be reflected in the subsequent receipt of different forms of public financing. Exploring this channel further could also be interesting in light of the discussion on path dependency in public support resulting in publicly funded startups relying on public subsidies at later stages of their life cycle (Aschhoff, 2009; Koski and Pajarinen, 2010).

## 2.7. Conclusion

These results have implications for both entrepreneurs and policymakers as the investor type affects longer-run firm performance. The follow-on financing from GVC and Angel may contribute to startup subsidies' previously documented beneficial effects. Small amounts of public seed funding have been shown to result in measurable average performance effects in startups (Autio and Rannikko, 2016; Conti, 2018; Hottenrott and Richstein, 2020; Howell, 2017;

Söderblom et al., 2015). Yet, it is not clear what the counterfactual financing would have been.

Relative to IVC, both GVC and Angel (but not CVC) show smaller performance effects in terms of innovation (Bertoni and Tykvová, 2015; Chemmanur et al., 2014; Dutta and Folta, 2016) and exits (Brander et al., 2014; Colombo and Murtinu, 2016; Cumming, Grilli, et al., 2017; Cumming and Zhang, 2018). However, there is some evidence that initial financing from GVC increases the likelihood of receiving IVC (Guerini and Quas, 2016), but for initial angel financing, the evidence is mixed. There may be substitution effects resulting in less IVC (or other VC) financing raised later on (Hellmann, Schure, et al., 2021; Kerr, Lerner, et al., 2011) or a crowding-in of further VC (Lerner, Schoar, et al., 2018). Thus, public startup subsidies may or may not initiate a funding cascade. We therefore strongly encourage further research on the interplay between private and public sources of startup financing and, in particular, the role of public subsidies as triggers for financing cascades. This may also include the analysis of potential path dependency in the use of public sources of financing.

Future research should also focus on the mechanisms behind these findings presented here. Further analyses may address some of the limitations of this study. First, we still know little about the mechanisms behind the presented findings. Information on the subsidy amount could help disentangle "pointing signals" from "activating signals", which we could not separate due to data limitations. Second, studying heterogeneity in the subsidy-VC link based on founder and firm characteristics could be insightful as those characteristics may be related to the degree of information friction. Moreover, a closer analysis of factors beyond the individual firm, such as inter-firm alliances (Hoenig and Henkel, 2015), could reveal boundary conditions under which startup subsidies trigger follow-on financing (or not).

Finally, like most studies on angel investors' activities, our data may not capture all relevant deals, as many may happen below the radar. Therefore, we encourage research on identifying the extent of visible versus invisible business angel investments using alternative data sources that directly collect such information from startups. Studying these issues in more detail would help policymakers to design effective entrepreneurship policy programs which benefit founders.

# 3. Financing and Advising Early Stage Startups: The Effect of Angel Investor Subsidies

## 3.1. Introduction

After the financial crisis of 2007/08, policymakers worldwide were concerned about a decline in innovative entrepreneurship (Wilson and Silva, 2013). Limited access to essential resources, primarily financial, human, and social capital, is considered one of the main drivers of this development, as it is widely regarded as one of the major barriers to innovative entrepreneurship (Hall and Lerner, 2010; Kerr and Nanda, 2009). Young innovative firms are particularly affected, as they are subject to a liability of newness (Stinchcombe, 1965). Countries have enacted various policy measures to improve access to essential resources for young and innovative companies. One type of program that has recently received particular attention is subsidies for angel investors (European Commission, 2017). Angel investors are wealthy individuals who invest their money directly in entrepreneurial firms. From what we know about them, professional angel investors approach investments similarly to venture capital firms (VCF), supporting their portfolio companies with money and management support (Ehrlich et al., 1994; Politis, 2008). Management support may range from informal managerial advice to strategic support on the board, developing and commercializing products, and providing access to the investors' network. These activities are equally important for developing entrepreneurial companies as access to finance (Quas et al., 2020). The extent to which young and innovative companies can raise capital and commercialize their ideas largely depends on the availability of investors who provide "smart money" in an economy (Popov and Roosenboom, 2013). Yet only a fraction of newly founded ventures is funded by such investors.[1]

[*] This Chapter is based on Berger and Gottschalk (2021)

[1] Berger, Egeln, et al. (2020) report that in Germany, only 4% of high-tech startups receive funding from Venture Capital funds and about 10% from angel investors.

Subsidies to angel investors aim to stimulate investment activity to increase access to financial and managerial resources for young and innovative companies. Compared to other policy measures targeted at raising investments in entrepreneurial companies, direct subsidies have a relatively low administrative burden and short approval times, which adds to their attractiveness. Still, there have long been concerns that subsidies to angel investors could distort investment incentives and fail to deliver on their promises to entrepreneurial companies (Lerner, 1998). In particular, there have been concerns that investment subsidies may negatively affect the level of managerial support companies receive (Keuschnigg and Nielsen, 2003). So far, the empirical evidence about such policy effects is very limited.

Denes et al. (2020) study the effect of angel investors subsidies, using the staggered introduction of tax credits for angel investors in U.S. states. Their results show no discernible impact on relevant economic outcomes such as entrepreneurial activity or successful exits of entrepreneurial companies. The authors explain this result with an increased entry of inexperienced individuals into angel investing and diversion of subsidies by company insiders. The exclusion of company insiders from such programs seems to be a crucial element of their success. For example, González-Uribe and Paravisini (2019) find that subsidizing angel investors through the Small Enterprise Investment Scheme (SEIS) in the U.K. has significantly accelerated the asset formation of entrepreneurial companies. Both studies have in common that they study the effects of angel investor subsidies on financing constraints and company performance, leaving the question of whether angel investor subsidies affect managerial support.

In this paper, we want to contribute to our understanding of the effect that subsidy programs to angel investors have on financial *and* managerial resources provided to entrepreneurial companies by angel investors. We examine whether subsidies to angel investors (i) increase the chances of closing a deal with an angel investor, (ii) increase the amount of capital raised from angel investors, and (iii) have adverse effects on managerial support received by these investors. Our study is based on the case of Germany, an economy where venture capital activity has been moderate relative to other OECD countries but that has recently experienced a surge in investment activity, with its capital city Berlin rising to one of the most important hubs for venture capital investments in Europe (Kraemer-Eis et al., 2016).

For our analysis, we leverage a unique data set from an annual survey of a representative sample of entrepreneurial companies based in Germany. The data contains information on the financial engagement and the level of managerial support provided by angel investors to these companies. While survey designs have some disadvantages, they are useful for cases where information is otherwise difficult to obtain. Managerial support activities by venture capitalists are typically non-contractible and, therefore, not recorded in contracts and other official documents. It has become common practice in the literature to study these activities in surveys (Bottazzi et al., 2008; Gompers, Gornall, et al., 2020). In addition, the financial engagement of angel investors is difficult to observe because many angel investors prefer to remain anonymous (Brettel, 2003; Wetzel Jr., 1983) and may even have economic incentives to stay under the radar (Engineer et al., 2019). The data allows us to compare the engagement of angel investors in entrepreneurial firms before and after the introduction of a major subsidy program for private investors in Germany. Using eligibility criteria for the program allows us to build counterfactuals and quantify the effects of the policy in a Difference-in-Differences framework. To address concerns about confounding factors that could potentially drive our results, we match firms on a wide range of observable characteristics as suggested by Heckman et al. (1997). We also conduct several robustness tests to rule out other potential explanations for our findings.

Our results indicate that after the policy's introduction, the financing availability from angel investors increased significantly. This is true in terms of the share of firms that have access to angel investors' capital and the financing amounts they receive. The probability of closing a deal with an angel investor increased by 37%, while the amount of capital obtained from angel investors increased by 63%. Regarding managerial support, we find negative coefficients for access to networks and development-related tasks. However, these effects are not robust to different specifications. Overall, our findings suggest no apparent adverse effects on support activities. This contrasts our initial hypothesis derived from the literature suggesting a clear negative impact on managerial support (Kanniainen and Keuschnigg, 2003, 2004; Keuschnigg, 2004; Lerner, 1998).

To understand the mechanisms behind this result, we augment the firm-level survey data with ownership data provided by Creditreform, Germany's largest credit rating agency. For all investors with an open equity position in one of the companies in our sample, we can construct their complete investment history. This allows us to look at the entry timing of investors and their portfolio development. Looking at the entry timing of the investors in our sample, we find a significant entry of new investors after the policy was introduced, consistent with findings for the U.S. by Denes et al. (2020). However, we also find that portfolios of existing investors increased. Consistent with these patterns, we find that syndicate sizes of angel investors significantly increased after the introduction of the policy. These findings suggest that although subsidies to angel investors may not directly affect the investment decisions of professional angel investors (Denes et al., 2020; Stedler and Peters, 2003), they could have indirect effects through more syndication with inexperienced investors. This could explain why we do not find adverse effects on managerial support activity. Syndication may allow angels to manage their investments more efficiently and ensure that managerial support to companies is not diluted despite financing more of them.

The study proceeds as follows, in Section 3.2, we derive our hypothesis regarding the sign of the effect of angel investor subsidies on financial and managerial support. We end the section with a presentation of Germany's grant for angel investors. In Section 3.3, we outline our empirical approach to assess the effect of angel investor subsidies on financial and managerial support for startup companies. In Section 3.4, we present the data. Results of our empirical analysis are summarized in Section 3.5, and robustness tests provided in Section 3.5.6. Section 3.6 concludes our analysis.

## 3.2. The case of angel investor subsidies

### 3.2.1. Angel investor subsidies and financing

Financing constraints have been identified as a major barrier to innovative entrepreneurship by both policymakers (Wilson and Silva, 2013) and academics (Kerr and Nanda, 2009). At the most basic level, entrepreneurship is inherently uncertain and requires significant upfront investments, while entrepreneurs are often liquidity constrained (Blanchflower and Oswald, 1998; Evans and Jovanovic, 1989; Praag et al., 2005). This is especially true for young and innovative entrepreneurs who invest a large part of their resources in innovation projects (Hall and Lerner, 2010). In principle, liquidity constraints could be solved via capital markets. However, several arguments have been established in the economics and finance literature that cast doubt on the efficient functioning of the capital market for young and innovative companies.

Financiers often lack the necessary information about a company's founding team and technology to arrive at an informed assessment of its prospects. This is especially true for entrepreneurs without a track record engaging in new technologies. A lack of verifiable information may lead financiers to increase the price or ration the supply of financial capital, adversely affecting the supply of capital to companies (Amit, Glosten, et al., 1990; Stiglitz and Weiss, 1981). Another line of argument speaking for financial constraints is that investments in technological innovations cannot be fully appropriated (Arrow, 1972; Levin, 1988). Technological innovations are often based on intangible assets, such as the knowledge stock of employees (Bertoni, Colombo, and Croce, 2010), so they can easily disseminate to potential competitors. When knowledge disseminates, it leaves the investing party at a severe disadvantage, as rivals do not bear the cost of failure risk. This positive externality on competitors leads many economists to conclude that investment in research and development activities is generally too low in a laissez-faire state of the economy.

Various studies indicate that direct subsidies to entrepreneurial companies help them overcome information frictions and have a positive effect on their innovation activity and long-run financial posture (Berger and Hottenrott, 2020; Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott, Lins, et al., 2017; Hottenrott and Richstein, 2020; Howell, 2017;

Islam et al., 2018; Lerner, 2000; Li et al., 2018; Söderblom et al., 2015; Zhao and Ziedonis, 2020). However, these programs are administratively expensive because funding is typically allocated based on evaluations of project proposals and expert assessments.[2]

Subsidies to angel investors could be a cost-effective alternative to such programs by increasing investors' willingness to provide more venture capital to entrepreneurial companies. Subsidies to angel investors place investment decisions at the investors' discretion but reimburse a portion of the initial investment cost. The reduction in investment cost reduces losses in case the company defaults. In that way, these subsidies increase the expected return on investments in entrepreneurial companies and may create incentives to invest more in entrepreneurial companies (Kanniainen and Keuschnigg, 2003, 2004). As angel investors are considered informed investors, they should be able to make an informed assessment about a company's chances of success (Amit, Brander, et al., 1998). Giving investors the discretion to choose investments could be an efficient way to allocate resources to the most promising companies while increasing the supply of financing.

In contrast to the view that angel investor subsidies increase access to financing, there are reasons to believe that subsidies to angel investors may leave angels' investment decisions unaffected. Unlike direct subsidies to entrepreneurial companies, which may serve as a certifying signal (Kleer, 2010) or reduce technological uncertainty (Howell, 2017), subsidies to angel investors do not close the information gap but only change the distribution of investors' payoffs. Subsidies to angel investors could leave investors' investment decisions unaffected and tempt them to replace their private funds with public funds. Such crowding-out would not change the aggregate supply of financing from angel investors but instead only shift the sources of funds. A priori, it is unclear whether subsidies to angel investors positively affect companies' access to financial resources or are more likely to have no such effect. Given that previous research indicates that subsidies to angel investors positively affect financing, we hypothesize that we will also find *positive* effects on financing.

**Hypothesis 1** *Subsidies for angel investors increase the supply of venture capital at the intensive and the extensive margin.*

### 3.2.2. Angel investor subsidies and managerial support

Management practices matter. This is true across various types of companies, including entrepreneurial companies (Bloom and Reenen, 2010). Bloom, Brynjolfsson, et al. (2019) estimate that management practices account for more than 20% of variation in productivity, which makes

[2] The Hightech Gründerfonds (HTGF), Germany's largest publicly sponsored seed and early-stage investment fund, had management fees of approximately 13.89 Million Euros in 2013 and 2014 alone. Successful applicants waited for 6 to 12 months until a deal was concluded (Geyer et al., 2016).

them one of the most critical performance drivers in organizations. At the same time, there appear to be significant differences in management practices depending, among other things, on companies' ownership structure (Bloom, Sadun, et al., 2015). Entrepreneurial companies still owned by founders score by far the lowest in managerial practices.

An essential benefit of angel investors is their managerial support to budding entrepreneurs. Managerial support comes in various forms (Ehrlich et al., 1994; Politis, 2008) and ranges from informal managerial advice to more formal engagement on the board. Beyond this, angel investors are reported to support companies in developing and commercializing products and giving founders of entrepreneurial companies access to their network. While little is known about the performance effects of different managerial support activities by angel investors at large, it is likely the case that professional angel investors have similar abilities to add value to entrepreneurial firms as VCFs (Lerner, Schoar, et al., 2018).[3] Besides alleviating financial constraints in entrepreneurial companies, professional angel investors likely increase managerial competencies in these companies. However, the extent to which individual angel investors provide managerial support seems to vary widely across investors. Some angel investors seem to pursue a purely passive investment approach. These investors provide only financing, but often through an "informal network led by one (or more) active angels, who find deals, perform the due diligence, informally syndicate the deal among their network, and manage the investments" (Prowse, 1998, p.788).

A central question of our study is how subsidies to angel investors may influence the level of managerial support that entrepreneurial companies receive from angel investors. The current literature provides two channels through which subsidies to angel investors may affect the level of managerial support they provide. The first channel is related to the composition of investors' portfolios (Kanniainen and Keuschnigg, 2003, 2004; Keuschnigg, 2004), and the second is associated with the composition of angel investor types in the market (Lerner, 1998). Providing managerial support to startups is time-consuming and requires intensive care from the investor (Gorman and Sahlman, 1989).[4] Given the natural time constraints investors face, they are forced to distribute their support activities across all companies in their portfolios. This creates a trade-off between the number of companies an individual can invest in and the time that can be effectively spent supporting each of those companies. As subsidies to angel investors lower the marginal cost of making an additional investment, investors may increase the number of investments beyond their optimal level (Boadway and Keen, 2006). Kanniainen and Keuschnigg (2003) argue that adding new companies to an investor's portfolio gives more companies access

[3] The literature on Venture Capital indicates, that various support activities of VCFs have positive effects on their exit performance, including strategic advice on the board (Lerner, 1995), hiring executives (Ewens and Marx, 2017; Hellmann and Puri, 2002), commercialization of products (Hellmann and Puri, 2000), and access to the investors' networks (Conti, 2018; Hochberg et al., 2007; Lindsey, 2008).

[4] Brettel (2003) reports that angel investors in Germany spend on average more than six days a month on their investments.

to venture capital but at the same time lowers the level of managerial advice that each company receives. In their model, the introduction of an investment subsidy reduces the average level of managerial advice companies receive.

Although it is unlikely that marginal changes in investors' portfolio sizes will lead to measurable empirical effects on management support, the model does contain important implications. For example, subsidies to angel investors could change their investment strategy from active to passive. Instead of intensively supporting a few companies, investors might be enticed to diversify risk by investing in many companies with minimal managerial support.[5] The original analysis by Kanniainen and Keuschnigg (2004) uses a static equilibrium perspective. In a follow-up paper, they introduce free entry into the model. They argue that as the level of managerial advice declines in the market, there are opportunities for new investors to exploit and enter the market. With free entry, the sign of the effect of an investment subsidy is no longer clear.

Implicitly, the model with free entry assumes entrant investors have the same skills to support startups as existing investors. Lerner (1998) cautions that subsidies for angel investors may encourage naïve individuals to enter the market. These investors may not possess the necessary skill to provide managerial support to entrepreneurial companies. This conjecture is supported by empirical evidence, which shows that in the U.S., the introduction of tax credits for angel investors has primarily encouraged the entry of non-professional investors (Denes et al., 2020). Increasing the level of non-professional investors in the market may dilute the aggregate level of managerial support for startup companies.

The arguments brought forward by the existing literature suggest that subsidies to angel investors are likely to negatively affect the *average* level of managerial support that entrepreneurial companies receive from them.

**Hypothesis 2** *Subsidies for angel investors decrease the average level of managerial support at the intensive margin.*

### 3.2.3. The Angel investor subsidy program in Germany

In May 2013, the German federal government introduced the investor subsidy program "INVEST - Zuschuss für Wagniskapital." The program has three main objectives: first, it aims to facilitate access to venture capital for young innovative companies and to improve their capital endowment in the long term. Second, individuals with an entrepreneurial orientation are to be attracted to high-risk investments in young innovative companies. And third, existing angel investors are encouraged to invest more frequently and more venture capital in young innovative companies.

[5]Such practices are increasingly common and often termed as 'spray-and-pray' (see for example Ewens, Nanda, et al. (2018) and Lerner and Nanda (2020)).

To encourage individuals to invest, the program reimburses 20% of the investment in young innovative companies as a grant. The grant only applies to equity investments, i.e., investments that provide capital in exchange for a stake in the company. Except for convertible loans - which become eligible once a conversion has taken place - other types of financing instruments are exempt from the program. The equity the company issues must be common stock and bear the full risk and returns from the investment.[6] The investment amount covered by the program is capped at the top and bottom. Investors must invest at least 10,000 Euros per company; per year, investors can claim a maximum of 500,000 Euros of their venture capital investments for the subsidy. Companies can claim a maximum of 3 million Euros in venture capital per year for the support, corresponding to a maximum funding amount of 600,000 Euros per company and year. Thus the program aims to create a more active market for equity financing in Germany, an economy that has traditionally been focused on bank financing (Black and Gilson, 1998).

One of the most critical aspects of the program is that it aims to target young innovative companies. At the same time, the program seeks to keep administrative overhead low and ensure quick approval times.[7] As it is difficult to determine the innovation potential of companies under time and budget constraints, the funding agency applied a heuristic when the program was first introduced. Eligibility was restricted to companies that operate in specific industries that the policy maker considers innovative. The criteria upon which the government decides whether one sector is innovative are not specified, but there seems to be a high degree of congruence with industries' R&D intensity. Since the revision of the program, startups can also provide other proof of innovativeness. However, according to Gottschalk et al. (2016), these additional criteria only applied to 2% of granted applications. Besides the criterion of innovativeness, there are several other criteria for eligibility, such as age and size thresholds. Specifically, companies must be no older than seven years at the time of application; footnoteThe initial program design allowed firms to be at most ten years old. As our sample covers only firms up to a maximum age of seven years, this is immaterial for our sample. and must not have more than 50 employees. Their annual revenues and balance sheet totals must not exceed 10 million Euros.[8] In addition, companies must not be listed on a stock exchange and must be independently owned. Their headquarters must be within the European Economic Area. According to data from the funding agency, the innovation criterion is the most important reason for rejection after incomplete applications.

For investors, the following eligibility criteria apply. Investors must be natural persons or small investment companies of a maximum of 6 persons, whose shareholders must be natural persons

[6] Since 2017, the program has included a tax exemption on capital gains from exiting investments that received a grant.

[7] The administrative cost of the INVEST program was approximately 657,000 between 2013 and 2015 (Keil et al., 2019). The time of the award process was, on average less than two months (Gottschalk et al., 2016).

[8] This is the definition of an SME according to the Official Journal of the European Union (L 124/36 from 20.03.2003).

(so-called angel investor funds or angel investor pools). The funds must originate directly from the individuals who invest in those companies. This requirement excludes Venture Capital Funds (VCFs), as the limited partners of a VCF invest their money indirectly. Also, the typical legal form for limited partnerships that VCFs use in Germany (GmbH & Co. KG) is ineligible for the grant. As the policy wants to stimulate venture capital investments (rather than acquisitions of firms), the maximum equity stake that investors can initially acquire is set at 20%, and investors must hold their shares for at least three years before they are allowed to sell them.

An important aspect of the program is that it aims to exclude company insiders. That means individuals affiliated with the company before the investment are not eligible for the grant. To do so, the program guidelines require that the application for the grant must be made before the conclusion of an investment contract between the investor and the company. The equity must be newly issued, i.e., secondary transactions are not permitted. And finally, the equity issuance must increase the company's financial resources. This excludes, for example, subsequent conversion of existing credit lines or subordinated loans into equity. That way, insiders such as co-founders and existing investors shall be excluded from the subsidy.

By the end of 2018, 6.374 investments received grants. The program has leveraged approximately 513 million Euros in venture capital. This translates to about 13% of early-stage investments in startup companies in Germany during that period.[9] In total, investors of about 1,700 companies were supported by the grant between the start of the program and the end of 2018. To put this into perspective, Berger, Egeln, et al. (2020) estimate that about 3,340 firms in high-tech sectors and under the age of four received an investment from a private individual from 2009 to 2012, i.e., before the program was introduced. In the period from 2015 to 2018 - after the program had been introduced - they estimate this number to be at 5,120 firms. The number of additional firms that receive investments from private investors is in the range of the number of firms whose investors have received the grant.

## 3.3. Empirical strategy

In our analysis, we study the role of angel investor subsidies on firms' access to financial and managerial resources. In particular, we want to know whether angel investor subsidies increase the likelihood of financing from angel investors, whether they increase the financing amounts firms receive from their investors, and whether they change the level of managerial support from angel investors. The structural relation is given by the following equation

$$y_{it} = \delta D_{it} + \tau_t + \gamma_i + \beta X_{it} + u_{it}. \tag{3.1}$$

[9]The calculation is based on the market statistic for Germany by INVEST EUROPE (2019).

We use the conventional indices $i$ and $t$ to denote firms and time, respectively. The outcome $y_{it}$ is either financial or managerial support that startups receive from their investors. The first term on the right-hand side $D_{it}$ is an indicator equal to one for observations affected by the policy. These observations are referred to as being part of the *treatment group*. This is the case if firms and their investors are eligible for the program ($\gamma_i = 1$), and they are observed in the post-policy period ($\tau_t = 1$). Hence, $\gamma_i$ and $\tau_t$ are group and period indicators and jointly determine whether an observation is part of the treatment or control group. $X_{it}$ is a set of control variables, and the last term $u_{it}$ is an error term. Our focus will be on the coefficient $\delta$, which represents the effect of the angel investor grant on outcomes $y_{it}$.

We estimate our model with a Difference-in-Differences approach on a repeated cross-section of firms representing the population of startup companies in Germany. In what follows, we describe our empirical strategy. We first outline the semi-parametric Difference-in-Differences estimator for cross-sectional samples. We then explain how we group firms into treatment and control groups, followed by a discussion on identifying assumptions and interpreting our estimation results.

## 3.3.1. Difference-in-Differences Estimation

Difference-in-Differences designs are commonly applied to quantify the effect of policy interventions when experimental data is unavailable. In our analysis, we want to estimate the parameter $\delta$ to quantify the impact of angel investor subsidies on startups' financial and managerial outcomes. The main idea behind the Difference-in-Differences approach is to mimic an experiment that allows for the comparison of an effect $y_{it}$ for counterfactual observations over time.

As argued earlier, the treatment and control groups must follow parallel paths over time. This assumption is likely to be violated if the treatment and control group differ significantly in relevant variables that are likely to affect the outcome. To account for differences between groups, a common approach is to use non-parametric or semi-parametric matching procedures to balance the distribution of covariates between the treatment and control groups (Abadie, 2005; Heckman et al., 1997). Our approach follows the exposition of Blundell, Dias, et al. (2004). Their approach applies to repeated cross-sectional data and considers the possibility of different control groups. The non-parametric version of the Difference-in-Differences estimator for repeated cross-sections can be written as follows (Blundell and Dias, 2009)

$$\hat{\delta} = \sum_{i \in T_1} \left\{ \left[ y_{it_1} - \sum_{j \in T_0} \tilde{w}^T_{ijt_0} y_{ijt_0} \right] - \left[ \sum_{j \in C_1} \tilde{w}^C_{ijt_1} y_{ijt_1} - \sum_{j \in C_0} \tilde{w}^C_{ijt_0} y_{ijt_0} \right] \right\} w_i. \tag{3.2}$$

Here, $\{T_0, T_1, C_0, C_1\}$ represent the treatment group ($T_t$) and control group ($C_t$) before and after the introduction of the program, and $\tilde{w}^G_{ijt}$ is the weight of firm $j$ in group $G$ and period $t$ when comparing it to firm $i$. Note that in repeated cross-sections, the treated group is compared to both control groups and the treatment group in period $t = 0$. When calculating the weights, each non-treated group is matched separately to the treated group. To calculate the weights, Blundell, Dias, et al. (2004) use propensity score matching. Recently, other convenient matching procedures have been proposed that deal with some of the shortcomings of propensity score matching, particularly the sometimes remaining imbalance in the covariate distribution. To address this, we will use different matching approaches. This also allows us to check whether our results depend on a particular matching approach.

## 3.3.2. Covariate balancing

In the previous paragraph, we emphasized that we need comparable control groups for our treatment group to obtain meaningful estimates. Greater comparability between groups can be achieved by aligning the distribution of observable covariates. Matching methods accomplish this by reweighting and possibly discarding observations. The resulting weights of the matching procedure can then be used in parametric or non-parametric regressions to estimate causal effects under the assumption of ignorability (Rosenbaum and Rubin, 1983). An advantage of balancing covariates is that it reduces the dependence of results on a specific functional form. There is a large number of possible matching methods. Among the most popular procedures is propensity score matching.

The intuition behind propensity score matching is simple. For a given firm $i$, we want to estimate the treatment probability given a set of observable characteristics. Therefore, the propensity score is defined as $p_i = E(D_i = 1|X_i)$, and can be estimated using some generalized linear models such as logit or probit. Based on the estimated propensity score, we want to find for each treated individual $D_i = 1$ similar individuals that are not treated $D_k = 0$. To identify matching tuples, several algorithms have been proposed in the literature. For Difference-in-Differences estimators with repeated cross-sections, Heckman et al. (1997) suggest using a Kernel matching function. The idea of this approach is to use all non-treated observations as controls but give those closest to the treated unit higher weights. When using the Kernel Matching approach, the weights $w_i$ in Equation (3.2) are given by $w_i = \frac{K(\frac{p_i - p_k}{h_n})}{\sum K(\frac{p_i - p_k}{h_n})}$, where $K(\cdot)$ is a kernel function to be defined, and $h_n$ is the selected bandwidth of that function.[10] One shortcoming of matching methods based on the propensity score is that they sometimes perform poorly on the very thing they intend to do, namely increasing covariate balance (King and Nielsen, 2019). While the Kernel function gives some flexibility through appropriate choice of the Kernel function, there is a more convenient way to address this issue.

[10]Note that we estimate the model using the user written Stata command `diff`, and estimate the propensity score using a logistic model and choose a bandwidth of 0.06.

We use entropy balancing to reduce model dependence while ensuring covariate balance (Hainmueller, 2012). Entropy balancing directly calculates weights that minimize the imbalance between the covariate distribution of treated and non-treated individuals. Hainmueller (2012) suggests to use the so-called entropy divergence as objective function, which is defined as $h(w_i) = w_i log(w_i/q_i)$, where $w_i$ are the weights and $q_i$ is a base weight. The objective function $h(\cdot)$ is minimized for the weights $w_i$ subject to balance constraints and a normalizing constraint. The balance constraints are imposed on the moments of the re-weighted control group. Therefore, the moments of the distributions of the treated and re-weighted control group can be matched up to a finite tolerance level. The normalizing constraint ensures that the sum of the weights is unity.[11]

### 3.3.3. Treatment and control groups

We construct treatment and control groups for the Difference-in-Differences approach based on the program's eligibility criteria that we outlined in Section 3.2.3. Investments are eligible for the grant if both the firm and the investor are eligible for the program. Investors' eligibility is based on the sources of funds. Sources of funds must originate directly from the individuals investing in the firm and therefore exclude VCFs. We base firms' eligibility on their industry affiliation. Choosing this approach has three reasons: first, the age and size thresholds of the program guidelines do not provide meaningful cutoffs as angel investors and venture capital firms typically invest in very young and small firms. Looking at an age cutoff of seven years or a size cutoff of 50 employees would provide an average treatment effect for firms that are unlikely to represent the typical angel-financed firm. More importantly, our data covers only firms below the age cutoff and only a few above the size cutoff.[12] Third, the most common reason for rejecting applications immediately after incompleteness is that firms fail to comply with the innovativeness criterion (Gottschalk et al., 2016).

In the following, firms are referred to as part of the *treatment group* if they are eligible for the program and observed in the post-policy period, i.e., after the program has been introduced. The eligibility criteria allow for different grouping choices for the counterfactual observations. On the one hand, we can use companies as a *control group* that are not eligible for funding due to their industry affiliation. These investments are excluded from the subsidy program due to the company's characteristics. On the other hand, we can use companies that have received funding from VCFs. These investments are not eligible for the program due to the investors.

The available data force us to construct control groups from different samples. On the one

[11] The numerical implementation of the matching procedure that calculates the weights is discussed in Hainmueller and Xu (2013).

[12] Only 7 out of the 14,286 firms in the raw data had more than 50 employees when they started their operations, the numbers for sales are similar.

**Table 3.1.: Summary of different treatment and control groups**

| Sample | Treatment | | Control | | Included firms |
|---|---|---|---|---|---|
| | Groups | $N$ | Groups | $N$ | |
| A | Eligible × Post | 3,160 | Non-eligible × Post, Pre | 9,693 | All firms |
| B | Eligible × Post | 966 | Non-eligible × Post, Pre | 1,485 | Angels investors' deal flow |
| C | Eligible × Post × Angel | 290 | Non-eligible × Angel, VCF | 690 | Angel or VCF financed |
| D | Eligible × Post | 290 | Non-eligible × Post, Pre | 562 | Angel financed |
| E | Angel × Post | 290 | Angel × Pre, VCF | 294 | Angel or VCF financed, Eligible firms |

**Note**: Eligible firms in the pre-treatment period are part of the control groups. Treatment status is based on two criteria: the firm's eligibility and the investor's eligibility. In Samples A, B, and D, treatment status is purely based on firm eligibility. In Samples C and D, treatment status is based on investor and firm eligibility. In Sample D, Angel equals one for all firms, and in Sample E, Eligible equals one for all observations.

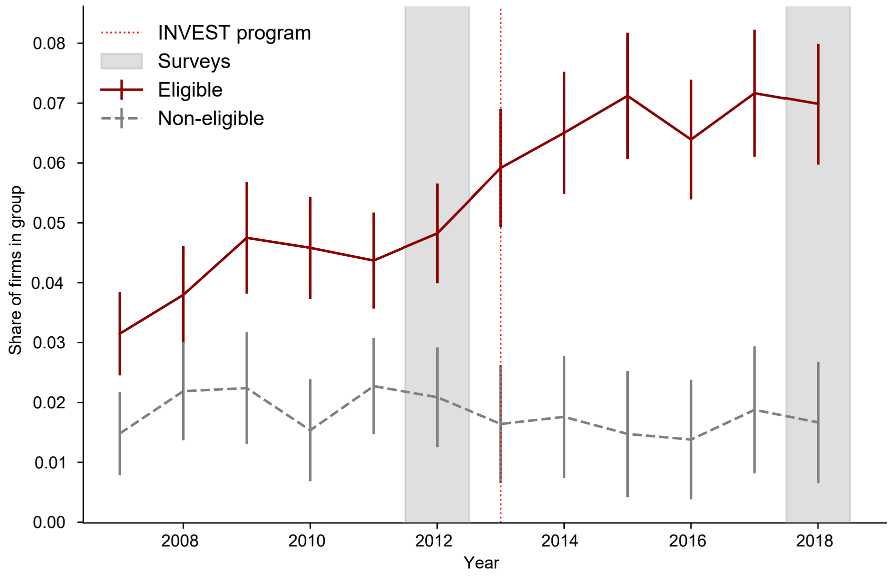
hand, this has to do with the practical implementation of the specific research questions we aim to answer but is also related to limitations regarding the data (see Table B.3 in the appendix for an overview of the different samples). Table 3.1 provides an overview of the different specifications that we use. As mentioned earlier, we refer to a firm as being treated when it is eligible for the program and observed in the post-treatment period, i.e., after the program has been introduced (Eligible × Post). When analyzing effects on financing amounts and the level of managerial support (Samples C, D, and E), firms are referred to as being treated if they are i) eligible for the program, ii) observed in the post-treatment period and iii) financed by angel investors (Eligible × Post × Angel). Firms are control observations in case they are i) observed before the program was introduced (Pre), ii) non-eligible to the program based on their company characteristics (Non-eligible), or iii) not financed by angel investors (VCF).

### 3.3.4. Identification of subsidy effect

Difference-in-Differences approaches allow for identifying causal relationships under the common trend assumption. Before the considered policy intervention, treatment and control groups must follow a similar path over time. Our data allows us to test for pre-treatment trends with a limited sample of firms and outcomes. For some outcomes, we only have a proper control group for two observation periods, which rules out testing for pre-treatment trends in those cases. To interpret our estimates in a causal sense, we want to rule out confounding factors that occurred during the same period and are related to eligibility and financing choices. We proceed in two steps to show that the policy is the primary driver of our results. First, whenever possible, we provide evidence for our claim by testing for common trends before the policy.

Figure 3.1 plots the share of equity-financed firms in eligible and non-eligible sectors over

**Figure 3.1.: Share of equity-financed startups by eligibility**




**Note:** Figure 3.1 shows the share of startups receiving an equity investment in eligible (red) and non-eligible industries (gray) by reference year. The red line shows the time when the subsidy program was introduced. The error bands depict the 95%-confidence interval. The gray shaded areas indicate the two observation periods in our main sample.
Source: IAB/ZEW Startup Panel.

time and clearly indicates that after the introduction of the policy, equity financing in the group of eligible firms increased markedly. It also shows that prior to the policy, the two groups followed similar trends. Since the data in Figure 3.1 does not allow us to distinguish between equity financing from angels and equity financing from VCFs, we provide further evidence focusing only on high-tech firms. This sample contains only firms in *eligible industries* but allows investments to differ in their *investors' eligibility*. For this reduced sample, we have prior information from the *High-tech Startup Survey*, that ZEW conducted jointly with Microsoft in 2007 and which was a predecessor to the IAB/ZEW Startup Panel. This data allows us to test for pre-treatment trends by comparing the propensity to finance with either type of VC (Angel vs. VCF) and their respective financing amounts over time. These tests allow us to mitigate concerns about alternative explanations for our findings - such as the arrival of technological opportunities - and strengthen our claim that the subsidy drives the effects we estimate. Second, we control for a large number of firm-level characteristics with a semi-parametric Difference-in-Differences approach. As suggested by Heckman et al. (1997), this reduces the impact of confounding factors in our estimates.

A limitation of our research approach is that we do not use administrative funding records on actual subsidy receipts. Instead, we classify firms into their respective groups based on their observable subsidy eligibility. Our approach is therefore similar to the approach by González-Uribe and Paravisini (2019), who group firms into "automatic qualifiers" and "non-eligible firms".

In our data, not every angel investment that went into an eligible company has necessarily been matched by public subsidies to the investors. Therefore, our results represent a lower bound of the subsidy effect, as we expect no smaller effect sizes had all eligible investments been matched with additional funds from the subsidy program.

# 3.4. Data

## 3.4.1. Sample description

Our primary data source is the IAB/ZEW Startup Panel. The Startup Panel is based on an annual survey among entrepreneurial companies located in Germany. Companies that enter the survey are drawn from a stratified random sample of the population of newly founded firms in Germany. When firms enter the survey, they are at most three years old. They remain in the survey until they are seven years old. Therefore, the unit of observation in the Startup Panel is entrepreneurial companies in their early life cycle. The data includes a large number of high-tech companies as the sample is stratified by industries (see Tabel B.2 in the appendix for a complete list of sectors contained in the Startup Panel).

In 2012 and 2018, the Startup Panel contained a unique survey on venture capital (VC) financing with a particular focus on funding from angel investors. Our analysis is based on the subset of startups participating in either of the two survey waves in the Startup Panel. Given the sampling procedure of the Startup Panel, almost all companies in our sample appear only once in our data set.[13] Thus, our data set is a repeated cross-sectional sample. The raw data contains information on 13,695 observations. Out of the sample of firms that received angel financing, some indicated that they have received financing from a very large number of investors (in some cases, 100 or more). As these firms are likely to be financed by crowd investments and not angel investors, we decided to discard the top 1% of firms in terms of syndicate size. We also discard observations that contain missing values in at least one of the key variables used in our analysis. This leaves us with a sample of 12,853 observations.

Table 3.2 shows the sample distribution by financing source and eligibility of the investment target. Out of the 12,853 observations, 10,337 neither had contact with an angel investor nor received VC financing (No VC). In total, 2,451 companies were in touch with an angel investor (Angel investor's deal flow), 852 of those firms received financing from angel investors (Angel), 99 firms received financing from both angel investors and VC Firms (Angel & VCF), and 1,437 did not close a deal after having been in contact with an angel investor (No Deal). One hundred twenty-eight firms received financing from a venture capital fund but not from an angel investor

[13] Out of the 980 firms in our main sample, four occurred in both waves.

**Table 3.2.: Distribution of VC financed and non-financed startups**

| | Angel investors' deal flow | | | | | |
|---|---|---|---|---|---|---|
| Year | Angel & VCF | Angel | No deal | VCF | No VC | Full |
| | | | All firms | | | |
| 2012 | 28 | 364 | 510 | 79 | 5,109 | 6,090 |
| 2018 | 71 | 488 | 927 | 49 | 5,228 | 6,763 |
| Total | 99 | 852 | 1,437 | 128 | 10,337 | 12,853 |
| | | | Eligible firms | | | |
| 2012 | 25 | 200 | 374 | 52 | 2,571 | 3,222 |
| 2018 | 63 | 290 | 583 | 42 | 2,182 | 3,160 |
| Total | 88 | 490 | 957 | 94 | 4,753 | 6,382 |
| | | | Non-eligible firms | | | |
| 2012 | 3 | 164 | 136 | 27 | 2,538 | 2,868 |
| 2018 | 8 | 198 | 344 | 7 | 3,046 | 3,603 |
| Total | 11 | 362 | 480 | 34 | 5,584 | 6,471 |

**Note**: Table 3.2 shows the number of startups in our sample by the type of venture capital they receive. Startups receiving finance from angel investors (Angel) and venture capital funds (VCF) are in the first column. Companies in the column *No deal* have not received venture capital but were part of angel investors' deal flow. Companies in Column *No VC* neither received VC from angels nor VCFs, and have not been in contact with angel investors.

(VCF).[14] Because we cannot clearly assign the companies that received financing from both angels and VCFs to either the treatment or control group, we exclude these companies from our analysis. This leaves us with a sample of 980 firms that received either financing from either angel investors or VCFs, but not both, for our analysis of the financing volumes at the intensive margin.

### 3.4.2. Variable description

In this section, we describe our main outcome variables and explain the selection of our control variables before we present descriptive statistics.

**a) Financial outcomes.** Data on financing differentiates between financing obtained from angel investors and VCFs. Firms were asked to indicate the total amount of funding they have raised from either source of VC since their foundation. *Angel Amount* gives the total amount of venture capital a firm has received from angel investors until the observation year. Likewise, *VCF*

[14]Note that 65 firms (51%) of firms in the group VCF were not in contact with an angel, and therefore not part of angels' deal flow.

*Amount* gives the total amount raised from venture capital funds, and the sum of both is given by *Total VC Amount*. In our estimations, we use the natural logarithm of financing amounts.

**b) Managerial outcomes.** We construct the outcomes for managerial support activities from the respective survey items. Startups were asked to rank the degree of managerial support they receive from their angel investors on a five-point Likert scale, from 1 (no engagement) to 5 (very active). Managerial support activities covered by the survey include activity on the *board*, the investors' *network*, general *mentoring*, as well as support in *commercialization* or *development* related tasks within the company. To make the results interpretable, we standardize managerial outcomes. For this, we subtract the average rating for each category in the baseline control group (non-eligible firms in the pre-treatment period) and divide this term by the respective standard deviation. That way, we can interpret the outcomes as standard deviations from the mean of the baseline control group.

**c) Control variables.** Our empirical approach critically depends on the construction of valid counterfactual outcomes. Eligible and non-eligible firms should therefore be comparable over time. Estimates could be biased if firm characteristics between eligible and non-eligible firms changed over time, and at the same time, these changes affected either financial or managerial support. To construct our counterfactual outcomes, we use the rich information on the founder and firm characteristics contained in the Startup Panel. We selected control variables based on an in-depth literature review to identify founder and firm characteristics most relevant in venture capitalists' financing decisions. Thus, we use the control variables based on the founding team and company characteristics.

The first set of control variables is related to firms' organizational and human capital. Organizational and human capital, such as the composition of the founding team and founders' experience, play an important role in the likelihood of receiving venture capital and the raised amount of venture capital. For venture capital investors, the founding team is often cited as the most important selection criterion and seen as the most important success factor of a venture (Gompers, Gornall, et al., 2020).[15] Founders with an academic background and those with previous management experience are more likely to raise external capital (Gimmon and Levie, 2010), and the industry experience of the founding team is one of the most important investment factors for VCFs (Kaplan and Strömberg, 2004). Founders with previous founding experience are more likely to raise venture capital (Hsu, 2007) and raise higher amounts of venture capital (Ko and McKelvie, 2018; Zhang, 2009). When founders have raised venture capital with their previous venture, the effects become larger. To account for the effect of the founding team on the likelihood of receiving venture capital and the amounts raised, we use several control

[15] Although results by Gompers, Gornall, et al. (2020) pertain for VCFs, experimental results by Hsu et al. (2013) suggest no difference in the importance of specific human capital characteristics for VCFs and angels investment decisions.

variables for the founders' organizational and human capital. In particular, we use an indicator for founders' previous *founding experience*, founders' years of *industry experience*, whether one of the founders sold their previous company in a *successful exit*, an indicator for whether the venture was founded by a *team*, and whether the team had an *academic* background. A full description of the variables can be found in Table B.5 in the appendix.

While organizational and human capital are regarded as the most important factors in venture capital investors' funding decisions, other important factors should be accounted for. A large literature documents the positive role of patents as signals for venture capital investors (Conti, Thursby, and Thursby, 2013; Conti, Thursby, and Rothaermel, 2013; Haeussler et al., 2014), as well as startup subsidies (Berger and Hottenrott, 2021; Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Söderblom et al., 2015; Zhao and Ziedonis, 2020). We include controls for whether firms had a *patent at start*. We also include a variable whether firms received a *startup subsidy* within the first three years of existence or any *public subsidy* in the observation year.

A growing literature is reporting on a *gender gap* in venture capital, suggesting that venture capital investors are biased against women (Ewens and Townsend, 2020; Zhang, 2020). Guzman and Kacperczyk (2019) find that gender differences in venture financing can be largely explained by a lower growth orientation of female founders. We account for gender using an indicator of whether a company was founded by *female* founders and proxy growth orientation of the venture by an indicator variable for whether the venture is *opportunity* driven.

Finally, we proxy for the development stage of the venture by the company age of the startup and include regional dummies for East Germany, West Germany, and Berlin. Note that we cannot match on industry affiliation with the two-digit NACE code, as eligibility is based on it. Also, founding cohorts cannot be matched because of insufficient overlap between the two waves. Industry affiliation and founding cohorts are therefore captured by fixed effects. To address concerns that our results are driven by industry affiliation or different time trends, we run robustness tests where we consider only companies in eligible industries but funded by different investor types. For this subset of firms, we also have data to test for pre-treatment trends (see Section 3.5.6).

### 3.4.3. Descriptive statistics

Table 3.3 summarizes the main outcome variables of our analysis. Of the more than 12 thousand companies in our sample, 20% have been in contact with angel investors, 7% have obtained VC from angel investors, and 2% have received financing from VCFs. This is consistent with prior assessments of the market size for angel financing and shows that raising money from

**Table 3.3.: Summary statistics of outcomes**

| | Firm obs. | Mean | Std. Err. | Med. | Min. | Max. |
|---|---|---|---|---|---|---|
| Angel deal flow (Y/N) | 12,853 | 0.19 | 0.39 | 0 | 0 | 1 |
| **Outcomes: Financial** | | | | | | |
| Angel (Y/N) | 12,853 | 0.07 | 0.26 | 0 | 0 | 1 |
| VCF (Y/N) | 12,853 | 0.02 | 0.13 | 0 | 0 | 1 |
| Total VC amount (in thsd. Euros) | 980 | 393.84 | 1,272.25 | 55 | 0 | 25,000 |
| Angel amount (in thsd.) | 852 | 328.24 | 1,226.49 | 50 | 0 | 25,000 |
| VCF amount (in thsd. Euros) | 128 | 830.46 | 1,475.31 | 400 | 5 | 10,000 |
| **Outcomes: Managerial** | | | | | | |
| Board | 852 | 1.59 | 1.24 | 1 | 1 | 5 |
| Network | 852 | 2.31 | 1.45 | 2 | 1 | 5 |
| Mentoring | 852 | 2.49 | 1.48 | 2 | 1 | 5 |
| Commercialization | 852 | 1.62 | 1.20 | 1 | 1 | 5 |
| Development | 852 | 1.46 | 1.06 | 1 | 1 | 5 |
| **Syndication** | | | | | | |
| Syndication (Y/N) | 852 | 0.35 | 0.48 | 0 | 0 | 1 |
| Syndicate size | 360 | 3.96 | 3.32 | 3 | 2 | 20 |

**Note**: Summary statistics for financing amounts only include startups financed by either angels or VCFs, but not both. Information on syndication and managerial outcomes is unavailable for startups that only received funding from VCFs.

angel investors is considerably more common than raising money from VCFs. Looking at the financing amounts raised from either type of investor shows that, on average, VCFs provide much larger financing amounts than angel investors. In our sample, companies raise more than twice the amount from VCFs compared to angel investors. Yet, some angel investors provide large funding amounts of up to 25 million Euros.

In terms of managerial support, the descriptive statistics reveal several important insights. First, angel investors are particularly active in mentoring and providing firms with access to their network. Almost 60% receive some level of informal advice from their investors, and more than half of the companies receive access to their investors' network (see also Figure B.3 in the appendix for a more detailed description). Fewer firms have angel investors that take a formal or active role within the firm. Only some companies have an investor who is formally engaged as an advisor on the board (22%) and is actively involved in commercialization-related tasks (25%) or production-related tasks (19%). This shows that most angel investors focus on opening doors and providing informal advice.

The different support activities are highly correlated with each other. Also, support activities are positively correlated with funding volumes and syndicate sizes, suggesting complementarities (see Table B.6 in the appendix for details). Firms whose founders have more industry experience receive less support, which is consistent with the notion that angel investors provide managerial support to those firms who need it. Interestingly, having had a successful exit with a previous company is not negatively related to managerial support. Even successful founders seem to seek support from investors. Potentially to gain industry-specific knowledge. Overall, Figure B.3 in the appendix suggests that firms in eligible industries receive slightly more support than those in non-eligible industries. We study whether investor subsidies have affected these differences in the following analysis.

Table 3.4 reports summary statistics for the firm characteristics differentiated by the different groups in our sample. The proportion of opportunities-driven companies - our proxy for companies' growth potential - is particularly pronounced for firms that receive financing from VCF and angel investors, where almost three in four firms indicate this. The proportion of firms that receive only financing from angels or VCF is somewhat lower. The share of firms with a female founder with either VCF or angel financing is similar in size to the average company in our sample. Also, founders who receive financing from either angels or VCF seem to be somewhat more experienced in founding a firm than the average founder in our sample but, on average, have less industry experience. Also, companies receiving financing from either angels or VCF are more often founded by a team, have an academic background, and hold patents. Regarding geographical distribution, a comparatively large proportion of companies is based in Berlin. Tables B.7 - B.11 in the appendix contain a comparison of means before and after balancing the control variables for all samples that we use in our empirical analysis.

## 3.5. Results

### 3.5.1. Angel financing

We first look at the effect of introducing the subsidy program on companies' chances of raising money from an angel investor. To do so, we estimate Equation (3.2) with linear probability models. The outcome is equal to one if the company closed a deal with an angel investor and zero otherwise. Table 3.5 shows the results of that estimation. Companies eligible for the program were significantly more likely to close a deal with an angel investor after the introduction of the policy. Relative to the baseline probability of closing a deal with an angel investor - which is at 6.3% (43.4%) in sample A (B) - we observe a marginal increase of 4.2 (15.2) percentage points (p.p.). This suggests a relative increase in the probability of raising money from an angel investor of 67% for all eligible firms and a relative increase of 37% for eligible firms within angel investors' deal flow. The coefficients drop in the matched specifications in columns (3) - (6) but remain significant and large. When entropy balancing our results, we estimate a relative increase of 37% (28%) for all eligible firms (eligible firms in contact with angel investors). This

**Table 3.4.: Summary statistics of control variables**

| | Angel investors' deal flow | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Angel & VCF | | Angel | | No deal | | VCF | | No VC | | Full | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| **Firm characteristics** | | | | | | | | | | | | |
| Oppourtunity | 0.72 | (0.45) | 0.49 | (0.50) | 0.51 | (0.50) | 0.66 | (0.48) | 0.30 | (0.46) | 0.34 | (0.47) |
| Female | 0.15 | (0.36) | 0.19 | (0.39) | 0.15 | (0.36) | 0.19 | (0.39) | 0.19 | (0.40) | 0.19 | (0.39) |
| Founding exp. | 0.66 | (0.48) | 0.49 | (0.50) | 0.56 | (0.50) | 0.51 | (0.50) | 0.38 | (0.49) | 0.41 | (0.49) |
| Team | 0.69 | (0.47) | 0.41 | (0.49) | 0.46 | (0.50) | 0.58 | (0.50) | 0.28 | (0.45) | 0.32 | (0.46) |
| Academic | 0.94 | (0.24) | 0.62 | (0.48) | 0.69 | (0.46) | 0.74 | (0.44) | 0.44 | (0.50) | 0.49 | (0.50) |
| Industry exp. | 12.57 | (9.06) | 14.95 | (10.09) | 15.25 | (10.21) | 16.94 | (9.49) | 17.28 | (10.27) | 16.86 | (10.28) |
| Successful exit | 0.30 | (0.46) | 0.12 | (0.32) | 0.12 | (0.32) | 0.13 | (0.33) | 0.07 | (0.25) | 0.08 | (0.27) |
| Startup age | 2.51 | (1.85) | 2.32 | (1.88) | 2.21 | (1.85) | 3.13 | (2.20) | 2.30 | (1.99) | 2.30 | (1.97) |
| Size at start | 2.82 | (1.63) | 2.88 | (4.20) | 2.56 | (2.46) | 3.03 | (2.81) | 2.36 | (3.67) | 2.42 | (3.58) |
| Patent | 0.08 | (0.27) | 0.07 | (0.25) | 0.07 | (0.25) | 0.14 | (0.35) | 0.02 | (0.15) | 0.03 | (0.18) |
| Public subsidy | 0.45 | (0.50) | 0.20 | (0.40) | 0.20 | (0.40) | 0.47 | (0.50) | 0.13 | (0.33) | 0.15 | (0.35) |
| Startup subsidy | 0.65 | (0.48) | 0.37 | (0.48) | 0.34 | (0.47) | 0.77 | (0.43) | 0.29 | (0.45) | 0.31 | (0.46) |
| **Region** | | | | | | | | | | | | |
| Berlin | 0.16 | (0.37) | 0.07 | (0.25) | 0.07 | (0.25) | 0.04 | (0.19) | 0.04 | (0.19) | 0.04 | (0.20) |
| West | 0.65 | (0.48) | 0.83 | (0.38) | 0.82 | (0.39) | 0.76 | (0.43) | 0.83 | (0.37) | 0.83 | (0.38) |
| East | 0.19 | (0.40) | 0.11 | (0.31) | 0.12 | (0.32) | 0.20 | (0.40) | 0.13 | (0.34) | 0.13 | (0.34) |
| **Industry** | | | | | | | | | | | | |
| Hightech manufacturing | 0.27 | (0.45) | 0.16 | (0.37) | 0.15 | (0.36) | 0.30 | (0.46) | 0.10 | (0.30) | 0.11 | (0.31) |
| Software and techn. services | 0.59 | (0.50) | 0.30 | (0.46) | 0.38 | (0.49) | 0.41 | (0.49) | 0.25 | (0.43) | 0.27 | (0.45) |
| Non-hightech | 0.14 | (0.35) | 0.53 | (0.50) | 0.47 | (0.50) | 0.29 | (0.46) | 0.65 | (0.48) | 0.62 | (0.49) |
| Firm obs. | 99 | | 852 | | 1,437 | | 128 | | 10,337 | | 12,853 | |

**Table 3.5.: Estimated effect of investor subsidy on financing decision**

*Sample A: All firms*

| | Dependent variable: 𝟙[Angel="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Unbalanced | | Entropy balanced | | PS balanced | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Eligible × Post | 0.042*** | 0.040*** | 0.027* | 0.026* | 0.033** | 0.031** |
| | (0.013) | (0.013) | (0.015) | (0.015) | (0.015) | (0.015) |
| Post | 0.001 | -0.008 | 0.016 | 0.006 | 0.012 | 0.005 |
| | (0.006) | (0.012) | (0.010) | (0.019) | (0.010) | (0.018) |
| Eligible | | | | | -0.033*** | -0.023 |
| | | | | | (0.009) | (0.014) |
| Const. | 0.063*** | 0.069*** | 0.065*** | 0.070*** | 0.000 | -0.000 |
| | (0.003) | (0.006) | (0.004) | (0.009) | (0.000) | (0.000) |
| R2 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| Firm obs. | 12,850 | 12,850 | 12,850 | 12,850 | 12,845 | 12,845 |

*Sample B: Angel investor deal flow*

| | Unbalanced | | Entropy balanced | | PS balanced | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Eligible × Post | 0.152*** | 0.147*** | 0.116** | 0.114** | 0.106* | 0.106** |
| | (0.047) | (0.048) | (0.054) | (0.053) | (0.054) | (0.052) |
| Post | -0.138*** | -0.166*** | -0.097* | -0.074 | -0.094* | -0.072 |
| | (0.041) | (0.055) | (0.051) | (0.096) | (0.049) | (0.097) |
| Eligible | | | | | -0.623*** | -0.460*** |
| | | | | | (0.049) | (0.083) |
| Const. | 0.414*** | 0.434*** | 0.416*** | 0.405*** | 0.623*** | 0.695*** |
| | (0.012) | (0.028) | (0.014) | (0.041) | (0.049) | (0.091) |
| R2 | 0.05 | 0.06 | 0.06 | 0.08 | 0.06 | 0.08 |
| Firm obs. | 2,446 | 2,446 | 2,446 | 2,446 | 2,441 | 2,441 |
| **Fixed effects:** | | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | | Yes | | Yes | | Yes |

**Note**: Table 3.5 shows the average effect of the angel investor grant on the likelihood of raising venture capital from an angel investor. Sample A contains all startups in the startup panel, including those not in contact with angel investors. Sample B contains only startups in contact with an angel investor, including those that did not get an investment. *Eligible* startups operate in one of the industries that qualify for the grant, listed in Table B.4 in the appendix. *Post* is the observation period after 2013 when the angel investor grant was introduced. Coefficients are estimated using ordinary least squares. Columns (1) and (2) do not balance the covariate distribution and use unit weights for the calculation of Equation (3.2). Columns (3) and (4) use Entropy Balancing to balance the covariate distribution. Columns (5) and (6) use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The *balancing covariates* include Team, Female, Academic, Opportunity, Industry exp., Founding exp., Successful exit, Patent at start, Startup subsidy, Size at start, Startup age, and Region. See Tables B.8 and B.9 in the appendix for the balancing results.
Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

suggests that - at the extensive margin - the policy positively affects companies' chances of raising financing from angel investors.

## 3.5.2. Angel financing amounts

**Table 3.6.: Estimated effect of investor subsidy on financing volumes**

*Sample C: Angel or VCF financed*

| | Dependent variable: log(total VC amount) | | | | | |
|---|---|---|---|---|---|---|
| | Unbalanced | | Entropy balanced | | PS balanced | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Angel × Eligible × Post | 0.961*** | 0.915*** | 0.631** | 0.629** | 0.654*** | 0.652*** |
| | (0.236) | (0.257) | (0.251) | (0.247) | (0.227) | (0.232) |
| Eligible × Angel | -2.233*** | -2.199*** | -2.071*** | -2.042*** | -1.994*** | -1.987*** |
| | (0.104) | (0.135) | (0.124) | (0.134) | (0.124) | (0.133) |
| Post | 0.538*** | 0.438 | 0.509*** | 0.618 | 0.837*** | 0.960* |
| | (0.130) | (0.445) | (0.131) | (0.540) | (0.144) | (0.540) |
| **Fixed effects:** | | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | | Yes | | Yes | | Yes |
| R2 | 0.30 | 0.31 | 0.28 | 0.30 | 0.32 | 0.33 |
| Firm obs. | 977 | 977 | 977 | 977 | 963 | 963 |

**Note**: Table 3.6 shows the average effect of the angel investor grant on the amount (in logs) of venture capital raised from an angel investor. Sample C contains startups that raised venture capital from angel investors or venture capital funds, but not both. *Eligible*" startups operate in one of the industries that qualify for the grant, listed in Table B.4. *Post* is the observation period after 2013 when the angel investor grant was introduced. *Angel* are startups that raise venture capital from angel investors, but not venture capital funds. Coefficients are estimated using ordinary least squares. Columns (1) and (2) do not balance the covariate distribution and use unit weights for the calculation of Equation (3.2). Columns (3) and (4) use Entropy Balancing to balance the covariate distribution. Columns (5) and (6) use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The *balancing covariates* include Team, Female, Academic, Opportunity, Industry exp., Founding exp., Successful exit, Patent at start, Public subsidy, Size at start, Startup age, LLC/Inc., and Region. See Table B.10 for the balancing results. Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Next, we focus on the amounts of financing raised from angel investors. To do so, we use the sample of firms that have closed a deal with at least one angel investor or a VCF. The outcome is the natural logarithm of total VC raised since the startup was founded up until the observation year. The treatment group comprises firms in the post-treatment period that have raised money from at least one angel investor and are eligible for the subsidy. The results are presented in Table 3.6. All models are estimated using ordinary least squares.

All specifications indicate the subsidy program's economic and statistically significant effect on the amount of money raised from angel investors. In the baseline specification, our results suggest that the program almost doubled the amount of financing raised from angel investors. When accounting for factors that are likely to be correlated with the financing amounts using entropy balancing (Columns (3) and (4)), the coefficient drops to 0.63, which corresponds to an increase in financing volumes by 63%. The results remain qualitatively and quantitatively similar when using propensity score matching. These results suggest that the introduction of the policy also positively affected the financing volumes provided to entrepreneurial companies by angel investors.

### 3.5.3. Managerial support

So far, we have looked at the effect of the policy on financial outcomes. As argued in Section 3.2.2, there are reasons to believe that the introduction of angel investor subsidies could affect the managerial support companies receive from angel investors. Unfortunately, our sample only contains information for managerial support activities by angel investors. Therefore, we cannot use VCFs as a control group here. Instead, we base the analysis for managerial support on the sample of companies that received financing from angel investors but differ in their eligibility for the program. The treatment group is companies eligible for the program, and non-eligible companies serve as the control group.

Table 3.7 contains the main results where we accounted for industry and founding cohort fixed effects. The results indicate ambiguous effects of the policy on managerial outcomes. In the unbalanced sample, the sign on board and network is positive, while mentoring, commercialization, and development have negative signs, none of them being significantly different from zero. When balancing the covariates, the sign on network is reversed, and the coefficients on network and development become significantly different from zero. The entropy balanced results indicate that the introduction of the angel investor subsidies decreases startups' access to investors' networks by 0.27 standard deviations and support in development-related tasks by 0.44 standard deviations. However, these results are not robust to different matching procedures, as none of the coefficients is statistically different from zero at the 10% significance level when applying propensity score matching. From our results, we cannot confidently reject that the policy did not affect managerial support activities. This contrasts our initial conjecture that would have predicted negative effect sizes. To understand the mechanisms behind these results, we will move our analysis to the investor level in the next section.

### 3.5.4. Composition of investor types and portfolios

The main interest of our analysis is to understand the effects of subsidies to angel investors on firms' access to financial and managerial resources. However, we are also interested in understanding where these results originate. To understand the mechanisms behind our findings, we further investigate the prevalence of investor types in the market and their portfolios. This will allow us to assess the extent to which mechanisms suggested by theory play out empirically.

When discussing the hypothetical effects of subsidies in Section 3.2.2 we argued that they should affect both the entry of new investors and the portfolio size of existing investors. To get information on investors and their portfolios, we augment our data with ownership information

**Table 3.7.: Effect on managerial support activities**

*Sample D: Angel financed*

| | Dependent variable: level of support for X | | | | |
|---|---|---|---|---|---|
| | Panel A: Unbalanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.232 | -0.030 | 0.100 | -0.154 | -0.098 |
| | (0.173) | (0.167) | (0.146) | (0.167) | (0.144) |
| Post | 0.422 | 0.087 | 0.140 | 0.414 | 0.636 |
| | (0.357) | (0.258) | (0.260) | (0.376) | (0.399) |
| R2 | 0.09 | 0.11 | 0.11 | 0.09 | 0.08 |
| Firm obs. | 849 | 849 | 849 | 849 | 849 |
| | Panel B: Entropy balanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.223 | -0.046 | -0.267* | -0.074 | -0.441** |
| | (0.265) | (0.216) | (0.150) | (0.225) | (0.176) |
| Post | 0.265 | 0.104 | 0.575** | 0.695* | 1.012* |
| | (0.418) | (0.334) | (0.247) | (0.414) | (0.513) |
| R2 | 0.17 | 0.23 | 0.17 | 0.10 | 0.15 |
| Firm obs. | 849 | 849 | 849 | 849 | 849 |
| | Panel C: Propensity score balanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.198 | -0.130 | -0.103 | -0.077 | -0.251 |
| | (0.244) | (0.190) | (0.131) | (0.202) | (0.182) |
| Eligible | 0.510 | 0.449*** | 0.912*** | 0.945*** | 1.938** |
| | (0.448) | (0.163) | (0.275) | (0.256) | (0.756) |
| Post | 0.491 | 0.251 | 0.404 | 0.613 | 0.922* |
| | (0.425) | (0.323) | (0.281) | (0.444) | (0.517) |
| R2 | 0.14 | 0.17 | 0.15 | 0.11 | 0.14 |
| Firm obs. | 813 | 813 | 813 | 813 | 813 |
| **Fixed effects:** | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | Yes | Yes | Yes | Yes | Yes |

**Note**: Table 3.7 shows the average effect of the angel investor grant on the level of managerial support from angel investors. Sample D contains startups that raised venture capital from angel investors but not venture capital funds. *Eligible* startups operate in one of the industries that qualify for the grant, listed in Table B.4. *Post* is the observation period after 2013 when the angel investor grant was introduced. Coefficients are estimated using ordinary least squares. Models in *Panel A* do not balance the covariate distribution and use unit weights for the calculation of Equation (3.2). Models in *Panel B* use Entropy Balancing to balance the covariate distribution. Models in *Panel C* use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The *balancing covariates* include Team, Female, Academic, Opportunity, Industry exp., Founding exp., Successful exit, Patent at start, Public subsidy, Size at start, Startup age, LLC/Inc., and Region. See Table B.11 for the balancing results.
Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

from the Mannheim Enterprise Panel (MEP). The MEP is a comprehensive firm-level database comprising the universe of German companies and is based on information from Creditreform, Germany's largest credit rating agency.[16] The MEP contains the population of all firms in Germany and forms the sampling basis of the IAB/ZEW Startup Panel. It contains detailed information on company owners, both individuals, and firms with open equity positions in companies. Company owners are uniquely identified in the data, which allows us to construct the investment history for all company owners in our sample. As company owners comprise founders and investors, research assistants manually classified owners into investors and founders. This exercise was conducted using information from the MEP and the special surveys. The survey includes data on angel investors' age, gender, ownership share, and the number of investors per company. We also used the information we found on the web using company websites and secondary sources such as Crunchbase and Bloomberg. Table 3.8 shows the results of this search effort. Of the 1,079 companies in our sample, 368 had at least one open equity position in the MEP. These companies have in total 1,076 investors, of which 748 are angel investors and 329 are venture capital funds.

**Table 3.8.: Distribution of investors and startups in MUP**

| Year | Number of startups | | Number of investors | | |
|---|---|---|---|---|---|
| | VC | Open equity | Total | Angel | VC Fund |
| 2012 | 471 | 119 | 305 | 176 | 129 |
| 2018 | 608 | 249 | 771 | 572 | 200 |
| Total | 1,079 | 368 | 1,076 | 748 | 329 |

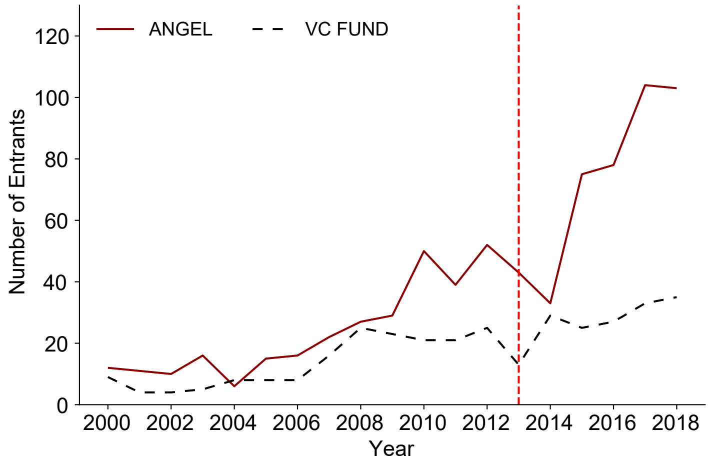
**Note**: *VC* contains the number of startups in the sample indicating to have received financing from VC investors. *Open equity* gives the number of startups in the sample for which we find open equity positions in the MUP. Note that not all startups that receive equity from either angels or VCF have open equity positions, e.g. because they have used convertible notes. *Total* gives the total number of individual investors (either Angel or VC Fund) we identified in the MUP.

We first focus on the composition of investor types. Denes et al. (2020) differentiate between professional and non-professional investors. Their notion of professionalism essentially refers to the prior experience of investors. Having the entire investment history for the 1,086 investors in our sample, we can look at when these investors made their first venture investment into an entrepreneurial company.

Figure 3.2 indicates in which year the 748 angel and 329 VCF investors in our sample made their first investment. Clearly, after the introduction of the policy in 2013, there has been a spike in the entry pattern of angel investors. This is consistent with the findings by Denes et al. (2020) for the U.S. and suggests that subsidies to angel investors spur entry by new investors. An evaluation of the INVEST program reports that 20% of subsidized investors have invested

[16]For more information on the MEP, see Bersch et al. (2014).

**Figure 3.2.: First startup investments by investors in sample**



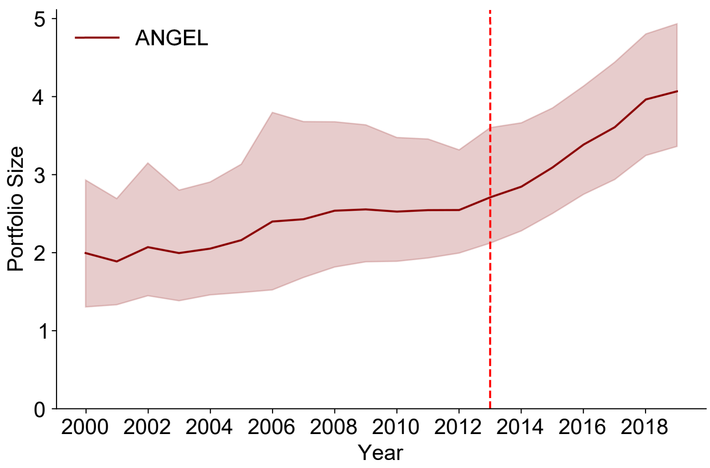

**Note:** The graph shows when investors in the sample made their first startup investment. Startup investment is defined as an investment into a company that is at most seven years old when the investment is made and is not an investment company (this excludes primary NACE 3 codes: Activities of head offices (701), Activities of holding companies (642), Trusts, funds and similar financial entities (643), Fund management activities (663)). Furthermore, the investor must not be part of the executive team.

for the first time due to the program (Gottschalk et al., 2016). Overall, this indicates that the composition of investor types changed as a result of the policy, increasing the share of new investors. Assuming that new investors dispose of lower levels of managerial expertise, one would expect to find an average negative effect of the policy on managerial support activities, considering the observable change in the composition of investors.

The results from the previous section do not confirm that subsidies to angel investors have adverse effects on managerial support. Next, we are focusing on the portfolios of investors that have been investing before the introduction of the subsidy program. Previous research suggests that professional angel investors see subsidies such as tax incentives or grants as non-material for their investment decisions (Denes et al., 2020; Stedler and Peters, 2003). We would therefore expect to find no change in their average portfolio size following the introduction of the policy. Figure 3.3 shows the average portfolio size of angel investors in our sample that has been investing before 2013.

Looking at Figure 3.3, we see that after having remained relatively stable for almost a decade, the average portfolio size of these investors increased markedly after the policy was introduced. This is in contrast to the survey results among professional investors, which suggest that, from the perspective of these investors, the effort to obtain subsidies is disproportionate to their benefits (Denes et al., 2020). The following section will explain how these seemingly conflicting results are reconciled with existing research findings.

**Figure 3.3.: Average portfolio size of incumbent investors**




**Note:** The graph shows the average size of incumbent investors' startup portfolios. An incumbent investor is defined as having started investing before 2013. Startup investment is defined as an investment into a company that is at most seven years old when the investment is made and is not an investment company (this excludes primary NACE 3 codes: Activities of head offices (701), Activities of holding companies (642), Trusts, funds and similar financial entities (643), Fund management activities (663)). Furthermore, the investor must not be part of the executive team. The red shaded area indicates the 95%-confidence interval.

## 3.5.5. Syndication of angel investors

Prior literature documents that angel investors syndicate their investment in groups (e.g. Bonini et al., 2018; Lerner, Schoar, et al., 2018). Syndicating investment in groups increases angel investors' access to information and deal flow. It also allows individual syndicate members to reduce their involvement by accessing the groups' shared skills and resources (Bonini et al., 2018). This will enable individuals to invest more and commit more of their wealth to entrepreneurial companies. Prowse (1998) reports that not all individuals in those groups are actively engaged. Only some individuals operate as lead investors, structure and monitor the deals. More syndication among angel investors provides an intuitive explanation for the investment patterns we find. While subsidies might be more critical for the investment decisions of inexperienced investors, they may leverage the activity of experienced investors by increasing their investment activity within groups. Inexperienced investors may increase the network's deal flow, and the group's professional investors provide managerial expertise. Survey evidence from the INVEST evaluation supports this explanation. More than 90% of inexperienced investors report investing with more experienced investors (Gottschalk et al., 2016).

To see whether syndication is, in fact, an explanation for our findings, we return to the firm-level data. For the sample of firms that have received financing from at least one angel investor (Sample D), we analyze how many angel investors have invested in the company since the company was started.

**Table 3.9.: Syndication of angel investors**

*Sample D: Angel finance*

Panel A: Dependent variable: $\mathbb{1}$[# of angel investors>1]

| | Unbalanced | | Entropy balanced | | PS balanced | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Eligible × Post | 0.121* | 0.115* | 0.030 | 0.056 | 0.057 | 0.058 |
| | (0.065) | (0.068) | (0.085) | (0.081) | (0.082) | (0.076) |
| Post | 0.047 | -0.105 | 0.092 | -0.026 | 0.097* | -0.002 |
| | (0.045) | (0.124) | (0.075) | (0.213) | (0.055) | (0.167) |
| Eligible | | | | | 0.337*** | 0.438*** |
| | | | | | (0.068) | (0.120) |
| R2 | 0.08 | 0.09 | 0.11 | 0.14 | 0.10 | 0.12 |
| Firm obs. | 849 | 849 | 849 | 849 | 813 | 813 |

Panel B: Dependent variable: # of angel investors

| | Unbalanced | | Entropy balanced | | PS balanced | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Eligible × Post | 0.959*** | 0.921*** | 1.132 | 1.030* | 1.056* | 0.979** |
| | (0.325) | (0.299) | (0.783) | (0.587) | (0.543) | (0.460) |
| Post | -0.013 | -0.985** | -0.356 | -1.410* | -0.108 | -0.973** |
| | (0.196) | (0.384) | (0.738) | (0.834) | (0.439) | (0.433) |
| Eligible | | | | | 1.275*** | 0.615*** |
| | | | | | (0.439) | (0.185) |
| R2 | 0.08 | 0.10 | 0.09 | 0.13 | 0.08 | 0.09 |
| Firm obs. | 849 | 849 | 849 | 849 | 813 | 813 |
| **Fixed effects:** | | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | | Yes | | Yes | | Yes |

**Note**: Table 3.9 shows the average effect of the angel investor grant on the syndication, i.e., whether startups received financing from more than one investors (Panel A), or the number of angel investors from which startups raise venture capital (Panel B). Sample D contains startups that raised venture capital from angel investors but not venture capital funds. *Eligible* startups operate in one of the industries that qualify for the grant, listed in Table B.4. *Post* is the observation period after 2013 when the angel investor grant was introduced. Coefficients are estimated using ordinary least squares. Columns (1) and (2) do not balance the covariate distribution and use unit weights for the calculation of Equation (3.2). Columns (3) and (4) use Entropy Balancing to balance the covariate distribution. Columns (5) and (6) use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The *balancing covariates* include Team, Female, Academic, Opportunity, Industry exp., Founding exp., Successful exit, Patent at start, Public subsidy, Size at start, Startup age, LLC/Inc., and Region. See Table B.11 for the balancing results.
Standard errors clustered at the industry level in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.9 shows the effect of the policy on the likelihood to syndicate. The coefficients in Column (1) of Panel A indicate a weakly significant positive effect on the propensity to syndicate in the eligible group; however, when balancing covariates, the effect becomes insignificant. However, the average syndicate size - meaning the number of angels investing per company -

increased by about one investor and remains significant after balancing, as shown in Columns (4) to (6) in Panel B. Syndication between investors could explain why we do not find negative effects on managerial support, albeit subsidies to angel investors trigger significant entry from inexperienced individuals into angel investing. When new investors join forces with experienced investors, startups can access larger amounts of capital. At the same time, startups profit from experienced investors' managerial expertise.

If syndication is the main driver of our results, we would expect that financing amounts have increased because firms can raise money from more individuals, but not necessarily because they can raise higher amounts from each individual. We, therefore, return to estimate the effect of the subsidy on financing volumes. This time we account for the number of investors that have provided financing. The results are shown in Table B.12 in the appendix. When accounting for the number of investors, the effect drops in size by about one-third and becomes insignificant. We, therefore, conclude that an increase in syndicate sizes strongly drives the effect of investor subsidies on financing volumes.

### 3.5.6. Robustness test: Technological shocks and pre-treatment trends

Given that companies' eligibility is based on industry affiliation, we might be concerned that our results are driven by technological shocks specific to these industries. Suppose the policy maker was able to identify these shocks. In that case, it could be the case that our results are merely driven by new technological opportunities rather than the effect of the subsidy itself. This is especially problematic for our analysis of the financing volumes, as investment-specific technology shocks drive up risk premia of companies with growth opportunities (Kogan and Papanikolaou, 2014). This may lead to much higher valuations and, therefore, more capital inflow into these companies. Related to this is the observation that technological shocks have decreased the cost of starting a business (Ewens, Nanda, et al., 2018). In the end, this may limit the validity of our results for financing volumes. To alleviate concerns that our results are driven by factors other than the policy, we test for pre-treatment trends in the financing variables.

We run additional tests on a restricted sample of startups in eligible industries (Sample E). In this sample, the control group is a set of firms that receive financing from venture capital funds (VCFs) that were not subject to the policy. The idea here is that firms within eligible industries should be equally affected by technological shocks. If we find no significant pre-treatment trend, we can be certain that our results are driven by the program rather than technological shocks to specific industries. To test for pre-treatment trends, we augment the Startup Panel with data from the ZEW/ Microsoft High-tech Startup Survey. This survey was conducted in 2007 and is a precursor to the IAB/ZEW Startup Panel. It contains many of the items that were later included in the Startup Panel and the special survey on venture capital. The crucial difference is that the sample in the High-Tech Startup Survey contains only companies from the high-tech sectors (see Tables B.2 and B.3 in the appendix). This is not an issue for our robustness tests, but it explains why we cannot test for pre-treatment trends with the entire sample of companies.

Figure B.1 in the appendix shows the distributions of financing volumes in 2006, 2012 and 2018 for financing from angel investors and VCFs. The distribution of volumes in 2006 and 2012 is relatively stable for both types of financing. While this is also true for VCF financing volumes comparing the years 2012 and 2018, there is a clear shift to the right for financing volumes by angel investors. These results are also supported in regressions. Table B.14 shows the results for our robustness tests for technology shocks and pre-treatment trends. Columns (1), (3), and (5) indicate that financing from angel investors has increased relative to VCFs. The results remain qualitatively and quantitatively the same across different balancing procedures. Columns (2), (4), and (6) give the results of our test for pre-treatment trends. The coefficient on Angel$\times$Pre is insignificant for financing volumes provided by angel investors before the introduction of the policy. When entropy balancing the results, the coefficient drops substantially and approaches an economically insignificant size. From these results, we would reject the existence of a pre-treatment trend.

We also conduct robustness tests at the extensive margin. To do so, we compare the change in the likelihood of receiving financing from Angel, VCF, or Angel & VCF between treatment and control groups in seemingly unrelated linear regressions (SUR). Again we only include firms in eligible industries. Table B.15 shows that statistically and economically significant effects can only be found for Angel and Angel & VCF-financed firms. At the same time, the coefficient for VCF is both statistically and economically insignificant. These coefficients are also significantly different from each other, as indicated by the $\chi^2$-test in the lower part of Table B.14. Conversely, the test for pre-treatment trends rejects that the prevalence of any financing types (Angel, VCF, or Angel & VCF) was significantly different in the period before 2007 compared to the period before 2012. We also find that these results hold when accounting for the fact that the baseline probability of receiving either VCF or Angel & VCF-financing is smaller (see Table B.16). We, therefore, conclude that our main results are indeed driven by the subsidy program and not by technological shocks that the funding agency was able to anticipate.

## 3.6. Conclusion

In this study, we investigated the effect of investor subsidies on financial and managerial support from angel investors. Angel investor subsidies have been introduced in various countries to stimulate the early-stage capital market for venture capital financing, which is regarded as a catalyst for innovation and high-growth entrepreneurship. We investigate the case of Germany, where we have detailed firm-level information on the financial and managerial support activities of angel investors in startup companies before and after introducing a major subsidy program for angel investors.

Using a Difference-in-Differences framework, we estimate the effect of the introduction of the policy on i) the likelihood of receiving VC from angel investors, ii) the amount of VC raised from angel investors, and iii) managerial support activities. We find that angel investor subsidies raise the likelihood of raising VC from angels by about 37% and funding amounts by about 63%. In contrast, we do not find strong support for adverse effects on managerial support. The results for financing amounts are robust to alternative explanations that see technological shocks as a possible cause of the results.

We further investigate the mechanisms underlying these results and find that the increase in angel financing is driven mainly by new investors entering the market. We see an increase in syndication size, suggesting that new investors syndicate their investments more often with existing investors. This could also explain why we find little evidence for the conjectured negative effect of the policy on managerial outcomes, which we would expect from a theoretical standpoint.

Overall, our results suggest that angel investor subsidies are an effective policy tool to stimulate early-stage capital markets for innovative startups. While our data is limited to the case of Germany, the underlying mechanisms that drive our results should not be unique to the German market for angel financing. Nevertheless, we suggest further research in other countries and regions.

# 4. Outside Equity and Startup Innovation: Evidence from the German INVEST Program

## 4.1. Introduction

Startup companies are viewed as an essential driver of innovation in knowledge-based economies. In part, this is owed to the fact that some of the most groundbreaking innovations over the past decades came from young, relatively unknown firms instead of large established companies. Investments in research and development (R&D) constitute a central element in creating these innovations. Various studies provide evidence that these entrepreneurial companies are subject to financing constraints (Czarnitzki and Hottenrott, 2009; Kerr and Nanda, 2009). Therefore, the comparatively high cost of capital for R&D poses a fundamental problem for innovation activities in entrepreneurial firms (Hall and Lerner, 2010).

Equity financing (or venture capital) has gained considerable interest from academics and policymakers as a market-based solution to finance innovation in entrepreneurial firms. As informed *inside investors* venture capitalists are viewed to overcome financing constraints (Admati and Pfleiderer, 1994; Myers, 2000). Firms that receive venture capital (VC) develop more radical innovations, as indicated by larger knowledge spillovers (Schnitzer and Watzinger, 2020). Equity capital is therefore seen as an important financing source for technological change (Florida and Kenney, 1988).

Prima facie, there is an apparent link between equity financing and investments into R&D related activities. It is therefore often assumed that "the bulk of venture financing supports innovative activities" and only "some of the venture financing goes to low-technology concerns or is devoted to marketing activities" (Kortum and Lerner, 2000, p.677). However, data on R&D investments in non-publicly traded firms are rarely reported, so there is little empirical

* This Chapter is based on joint work with Johannes Bersch

evidence regarding the direct link between equity financing on R&D investments in privately held entrepreneurial ventures. At the same time, firms that raise money from venture capitalists often rely on public funds to realize their ideas in the first place (Berger and Hottenrott, 2021; Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Söderblom et al., 2015; Zhao and Ziedonis, 2020). It is not clear whether financing from venture capitalists adds to firms' R&D investments. In other words, it is still an open question whether outside equity allows startups to increase their R&D activity or whether VCs are especially good at selecting and supporting firms already investing heavily in R&D.

Existing research on the relationship between equity financing and innovation has focused on patents as a proxy for innovation (Bernstein, Giroud, et al., 2016; Caselli, Gatti, et al., 2009; Engel and Keilbach, 2007; Hirukawa and Ueda, 2011; Kortum and Lerner, 2000; Lahr and Mina, 2016; Peneder, 2010; Popov and Roosenboom, 2012). However, patents only measure innovation outputs and may be an imperfect indicator of innovation inputs. Patents are often filed strategically, and certain technologies are not patented at all. This paper explicitly distinguishes between innovation inputs - as measured by startups' R&D - and innovation outputs - as measured by the introduction of market novelties. The data for this comes from a large-scale panel survey of startups in Germany from 2007 to 2018.

An empirical assessment of the causal link between equity financing and innovation is complicated because financing decisions are endogenous to technological opportunities. More technological opportunities may affect both the level of innovation and the propensity to finance with outside equity. To account for the endogenous nature of equity financing decisions, we use the introduction of a major subsidy program for private investors (angel investors) in Germany. The program reimburses individuals who directly invest a substantial part of their investment in startup companies. This results in exogenous variation in the cost of outside equity financing for eligible firms over time. Assuming that the policymaker was not able to predict the arrival of new technological opportunities allows us to identify the effect of equity capital on firms' innovation inputs and outputs.

Our results indicate that financing from outside equity investors is positively related to startups' innovation inputs and outputs. However, when accounting for the endogenous nature of financing decisions in our instrumental variable regressions, we find that the causal relation only holds for innovation outputs. For the group of firms that raised outside equity as a result of the policy, the likelihood of introducing a global market novelty increases by 83 percentage points. However, there is no effect on any of the R&D inputs that we consider. These results suggest that firms primarily use outside equity financing to commercialize their ideas rather than to increase their R&D efforts in the first place.

The paper is organized as follows. Section 4.2 provides an overview of the existing literature on equity financing and innovation. We then present a simple theoretical framework to derive testable hypotheses in our setting. Section 4.4 describes our empirical approach and how the subsidy program for angel investors helps us with identification. Data sources and our sample are described in Section 4.5. In Section 4.6 we give an overview of our results. We discuss these results and conclude in Section 4.7.

## 4.2. Literature

Entrepreneurial firms, i.e., privately held young and innovative companies, are considered a key element in discovering and exploiting new ideas (Acs, Braunerhjelm, et al., 2008). These companies have a relative advantage in seizing growth opportunities in highly innovative industries (Acs and Audretsch, 1987). They are also seen as important drivers of innovation and growth in the larger economy (Acs and Audretsch, 1988; Becker et al., 2022). However, financing innovation proves challenging for these companies, given the high degree of uncertainty resulting from their innovative business models. Outside equity has several advantages compared to other financing modes in this context. Equity provides investors with more information and monitoring rights (Admati and Pfleiderer, 1994; Gompers, 1996; Myers, 2000). Likewise, it is argued that venture capitalists' "networks and the information flow at their disposal enable them to reduce many of the risks associated with new enterprise formation and thus to overcome many of the barriers that hold back innovation" (Florida and Kenney, 1988, p.119). Also, the fact that equity gives investors the right to participate in future profits allows firms to finance projects with potentially high but uncertain returns (Ueda, 2004; Winton and Yerramilli, 2008).

The literature studying the link between outside equity financing and innovation has mostly focused on innovation outputs (measured by patents and patent citations). It provides mixed evidence on the effect of venture capital on innovation. The seminal paper on the empirical relation between venture capital and innovation is Kortum and Lerner (2000). They use the 1979 clarification of the prudent man rule in the U.S. as an instrument for venture capital financing. Their results indicate that venture capital in the U.S. significantly increased patenting activity and accounted for 8% of industrial innovations from 1983-1992. Using a similar methodology, more recent estimates by Popov and Roosenboom (2012) for 1992-2005 confirm these findings, but only for countries with a developed VC industry.

Looking at patenting activity at the industry level has one crucial shortcoming. In their model, Kortum and Lerner (2000) assume that the propensity to patent is exogenous to venture capital financing. However, firms may decide to increase patenting of *existing* technologies to attract investors. For example, Hoenig and Henkel (2015) shows that patents play an important role for investors as a property right over the companies' technology. This logic implies that the increase in patenting activity associated with venture capital investments is not necessarily a result of increased innovation. Instead, it might be the case that venture capital investors increase the willingness of firms to file patents on existing technologies to increase their chances of obtaining financing from them. Several authors have questioned the causal link between venture capital and innovation activity in Europe (Caselli, Gatti, et al., 2009; Engel and Keilbach, 2007; Lahr and Mina, 2016; Peneder, 2010) and the U.S. (Hirukawa and Ueda, 2011). Looking at variation in patenting activity within firms over time, these authors find that the first receipt of venture capital is followed by a decline in patenting activity.

The decline in patenting activity is viewed as an indication that venture capitalists are less involved at the outset of the innovation process, i.e., when innovations are *created*, but rather at the back end, when innovation outcomes are *commercialized*. This has been documented as another role that venture capitalists play in entrepreneurial firms. For example, Hellmann and Puri (2000) find that venture capital financing is associated with significant reductions in time to market, and Bertoni, Colombo, and Grilli (2011) find a significant increase in revenue growth. Conversely, reducing patenting activity once an investor has joined the firm could also be for strategic reasons. Startups use patents as a signal to attract investors (Conti, Thursby, and Thursby, 2013; Conti, Thursby, and Rothaermel, 2013; Haeussler et al., 2014), but the value of patents as a signal diminishes once an investor is aboard (Hoenen et al., 2014). Because patents disclose information not only to investors but also to incumbents and competitors, firms incur disclosure costs when filing a patent (Heger and Zaby, 2013). To effectively protect their intellectual property (IP), companies need the financial strength to litigate it in court. The disclosure cost should be higher for firms without deep-pocket investors. Firms may therefore continue to engage in innovation activities but decide not to disclose their IP once they have attracted an investor. From there, patenting activity may be reduced, but innovation activity may continue. This may be particularly true for firms without deep-pocket investors, who cannot effectively protect firms' IP.

This reasoning suggests that it may not be equity financing alone but the level of equity capital that is relevant for sustained innovation efforts. Overall the number of deep-pockets investors seems to be limited (Lerner and Nanda, 2020). Most venture capital investments may not be sufficient in size to solve the fundamental appropriability problem, leading to underinvestment in R&D (Arrow, 1972). In line with this argument is the well-established link between the receipt of public startup subsidies and the likelihood of raising follow-on financing from venture capitalists (Berger and Hottenrott, 2021; Conti, 2018; Cumming, 2007; Feldman and Kelley, 2006; Giraudo et al., 2019; Hottenrott and Richstein, 2020; Howell, 2017; Islam et al., 2018; Lerner, 2000; Söderblom et al., 2015; Zhao and Ziedonis, 2020). These studies suggest that startups use public funds such as startup subsidies, R&D grants, or public venture capital to finance R&D instead of relying on outside equity in the first place. So far, it is unclear whether equity financing from venture capitalists is adding to firms' R&D investments or whether firms mainly require venture capital to commercialize their innovations.

We contribute to the existing literature in two ways. First, we measure innovation inputs and innovation outputs separately. This allows us to circumvent the limitations of measuring innovation by patents that we outlined above. Second, we propose the introduction of a subsidy program for private investors as an exogenous cost shifter of outside equity. This provides us with a framework to identify the causal effect of outside equity on innovation and differs from previous studies that have looked at correlations (Achleitner et al., 2011).

The paper is structured as follows: Section 4.3 introduces the theoretical model by Kortum and Lerner, 2000 to build some intuition for the underlying mechanisms. In Section 4.4 we present our empirical approach and identification strategy. A description of the data is provided in Section 4.5, followed by the results of our empirical analysis in Section 4.6. Section 4.7 discusses the results and concludes.

## 4.3. Equity financing and innovation

To build some intuition for the mechanisms underlying our analysis, we closely build on the partial equilibrium model by Kortum and Lerner (2000) to relate innovation and venture financing. We adapt their model where necessary to fit it to our context and setting. Consider a firm $i$ pursuing an innovation project in period $t$ that can fund this project through multiple sources. Either through equity capital $E_{it}$ from VCs (including both private investors and VC firms) or other innovation financing sources $G_{it}$ such as public startup subsidies, R&D grants, governmental VC, and internal funds. The relation between innovation and financing is given by the innovation production function

$$R_{it} = (G_{it} + bE_{it})^{\alpha} v_{it} = Y_{it}^{\alpha} v_{it}. \tag{4.1}$$

Innovation efforts $R_{it}$ are a function of total venture financing $Y_{it}$ and new technological opportunities $v_{it}$.[1] $Y_{it}$ consists of external equity $E_{it}$ and other innovation financing $G_{it}$. The parameter $\alpha \in (0,1)$ represents how efficiently financial resources can be transformed into innovation efforts. In the case where $R_{it}$ represents R&D expenditures, this implies that only parts of the financing raised will effectively go into R&D, while other funds will be used for marketing or other purposes.

[1] At this point our model deviates from Kortum and Lerner (2000) in an important aspect. The authors assume that the propensity to patent an innovation is governed by a disturbance term $\varepsilon_{it}$, which is unrelated to financing decisions. When firms file patents strategically to attract investors, this assumption may be violated. Instead, our data allow us to observe innovation activity directly through R&D inputs and market novelties.

The value each unit of R&D will produce in expectation is given by $\Pi_{it}$. It is assumed that firms take this value as given. The marginal cost of financing depends on the type of funds used. It is assumed that the marginal cost of equity financing is given by $\kappa_t f_E(E_{it}\mu_{it}/Y_{it})$, where $f_E$ is increasing in $E_{it}\mu_{it}/Y_{it}$, and the marginal cost of other funds is given by $f_G(E_{it}\mu_{it}/Y_{it})$, where $f_G$ is decreasing in $E_{it}\mu_{it}/Y_{it}$. In our setting, $\mu_{it}$ is a parameter representing the time to market of a specific technology. We assume that more developed technologies, i.e., those with a lower time to market, are more attractive to investors. The term $\kappa_t$ represents investors' cost of funds.[2] Kortum and Lerner (2000) use the introduction of the 1979 clarification of the prudent man rule as an exogenous shock to the cost of funds. By analogy, we use the introduction of the INVEST program as a cost shifter for equity financing.

The model provides a series of equilibrium conditions from the above assumptions. In equilibrium, firms set the marginal value of investment opportunities to the marginal cost of financing, which leads to the first-order conditions of the firm's optimization problem

$$\Pi_{it}\frac{\partial R_{it}}{\partial E_{it}} = \alpha\Pi_{it} b Y_{it}^{\alpha-1}\nu_{it} = \kappa_t f_E\left(\frac{E_{it}\mu_{it}}{Y_{it}}\right), \tag{4.2}$$

$$\Pi_{it}\frac{\partial R_{it}}{\partial G_{it}} = \alpha\Pi_{it} Y_{it}^{\alpha-1}\nu_{it} = f_G\left(\frac{E_{it}\mu_{it}}{Y_{it}}\right). \tag{4.3}$$

Equation (4.2) requires that the firm sets the level of equity financing such that the marginal benefit of innovation efforts equals the marginal cost of equity financing. Likewise, Equation (4.3) states that the optimal level of $G_{it}$ is where the marginal innovation benefit from other funds equals the marginal cost of other funds.

The first order conditions can be rearranged to express financing as a function of the underlying profit and cost shifter

$$Y_{it} = \left[\frac{\alpha\Pi_{it}\nu_{it}}{h_1(\kappa_t)}\right]^{1/(1-\alpha)} \tag{4.4}$$

$$\frac{E_{it}}{G_{it}} = \left[\frac{h_2(\kappa_t)}{\mu_{it} - b h_2(\kappa_t)}\right], \tag{4.5}$$

where $\partial h_1/\partial\kappa_t > 0$ and $\partial h_2/\partial\kappa_t < 0$. Equations (4.4) and (4.5) allow us to look at comparative statics and understand how financing decisions depend on the underlying structural parameters.

First, note that total innovation financing $Y_{it}$ is reduced when the cost of outside equity $\kappa_t$ falls. Conversely, in case new technological opportunities emerge (positive shock in $\nu_{it}$), the value of

[2] In the case of private investors, this can be thought of as the opportunity cost of investing in a risk-adjusted equivalent.

R&D increases (increase in $\Pi_{it}$) or funds can be more efficiently turned into innovation efforts (higher $\alpha$), then firms will increase innovation financing. Now consider the relation of external equity to other financing sources of innovation. Increases in the time to market $\mu_{it}$ will reduce equity financing relative to other funds for innovation. Also, a reduction in the cost of outside equity $\kappa_t$ reduces external equity financing relative to other funds for innovation. However, note that this does not imply that $E$ is reduced as a result of a cost shock. Instead, firms will adjust by increasing the level of other sources of innovation financing $G$ to balance the marginal benefits of innovation with its costs.

Kortum and Lerner (2000) argue that the endogeneity problem in the relationship between innovation activities and financing decisions results from the emergence of new technological opportunities. New technological opportunities may arise from prior academic research that an individual has engaged in or from reductions in the cost of applying novel technologies. Technological opportunities are known to firms and investors but unobservable to the econometrician. Likewise Kortum and Lerner (2000) argue that the parameter $\mu_{it}$ is correlated with technological opportunities $v_{it}$. In our case, $\mu_{it}$ captures the expected time to market and therefore implies that technological opportunities $v_{it}$ that startups pursue are likely to be correlated with time to market.

If $v_{it}$ was uncorrelated with financing choices, then regressing innovation inputs or innovation outputs on financing choices would yield unbiased estimates. However, some important aspects of $v_{it}$ will not be fully captured by our set of control variables. This implies that $Y_{it}$ and hence $G$ and $E/G$ are likely to remain correlated with the error term. In the next section, we explain how we use the introduction of the INVEST program to identify the effect of equity financing on innovation. Following the notion of Kortum and Lerner (2000), we argue that the INVEST program lowered the cost of funds for private investors $\kappa_t$. Using variation in eligibility to the program over time gives us exogenous variation in startups' cost of equity.

# 4.4. Empirical approach

## 4.4.1. Econometric model

Kortum and Lerner (2000) use a log-linearized version of a Cobb-Douglas patent production function, where they scale the industry level of venture capital by the level of corporate R&D to estimate their model. Since we do not have full information on the level of alternative innovation funding sources (which would correspond to corporate R&D in their setting), we take a slightly different approach. We use a reduced-form approach to investigate the impact of equity financing on innovation. The structural equation that relates financing to investment decisions is similar to the one proposed in the model by Himmelberg and Petersen (1994). They study the relation between internal finance and R&D in publicly traded high-technology firms. In contrast, we are interested in studying the relation between external finance and innovation in privately held entrepreneurial firms. Instead of looking at cash flow sensitivity like Himmelberg and Petersen (1994), we consider outside equity as an explanatory variable for innovation activity. The following equation gives the relation of interest

$$R_{it} = \alpha_0 + \alpha_1 G_{it} + \delta_1 E_{it} + \gamma_i + \tau_t + \beta_1 X_{it} + u_{it}, \tag{4.6}$$

where the outcome $R_{it}$ represents either *innovation inputs* measured by R&D activity, R&D expenditures or R&D employment, or *innovation outputs* measured by the introduction of global, domestic or regional market novelties. $G'_{it}$ is a vector of variables for alternative innovation financing sources. $E_{it}$ is our main variable of interest and represents outside equity. It is either a dummy variable equal to one when a firm uses external equity or a continuous variable giving the level of external equity that a firm uses in period $t$ (see Section C.5.1 in the appendix for details). The variables $\gamma_i$ and $\tau_t$ are group and time indicators. The last two terms can be thought of as capturing technological opportunities. The vector of firm controls $X'_{it}$ captures observed factors associated with technological opportunities, while unobserved factors go into the error term $u_{it}$.

To estimate our coefficient of interest $\delta_1$ consistently using ordinary least squares (OLS), the unobserved components $u_{it}$ in equation 4.6 must be unrelated to equity financing $E_{it}$. As described in the previous section, this condition is likely violated. Unobserved technological opportunities are likely to be correlated with outside equity financing. Naturally, such technological opportunities are also related to innovation. In that case, we would overestimate the effect of outside equity on innovation as we partly attribute an increase in innovation to equity financing when it actually comes from an increase in technological opportunities. To identify the effect of changes in equity financing in isolation, we need an instrumental variable (IV) that is unrelated to technological opportunities. In the next Section 4.4.2, we outline our IV estimation procedure. In particular, we propose the introduction of the INVEST program as an exogenous cost shifter for outside equity: firms in eligible industries should find it easier to receive outside equity after the introduction of the policy.

### 4.4.2. Identification

In May 2013, the German Federal Government introduced the program "INVEST - Zuschuss für Wagniskapital.” The program intends to stimulate direct equity investments by private investors in young and innovative companies by motivating existing investors to make additional investments and attracting new people with entrepreneurial (or managerial) backgrounds to become investors.

For eligible investments, investors receive a tax-free grant amounting to 20% of the investment amount. Since 2017, investors can also apply for an exit grant which is essentially a partial tax exemption on capital gains from the investment. As such, the program constitutes a reduction in equity investment costs for eligible investments.

To be eligible for the program, investments must be risk-bearing; that is, firms need to sell equity to investors, and in addition, firms need to be "innovative". A major objective of the program was to keep approval times fast and administrative cost low. Both the application process and eligibility criteria are kept simple. To this end, the funding agency provides a list of industries that the policy maker considers innovative. These eligible industries are defined by a list of NACE industry codes.[3]

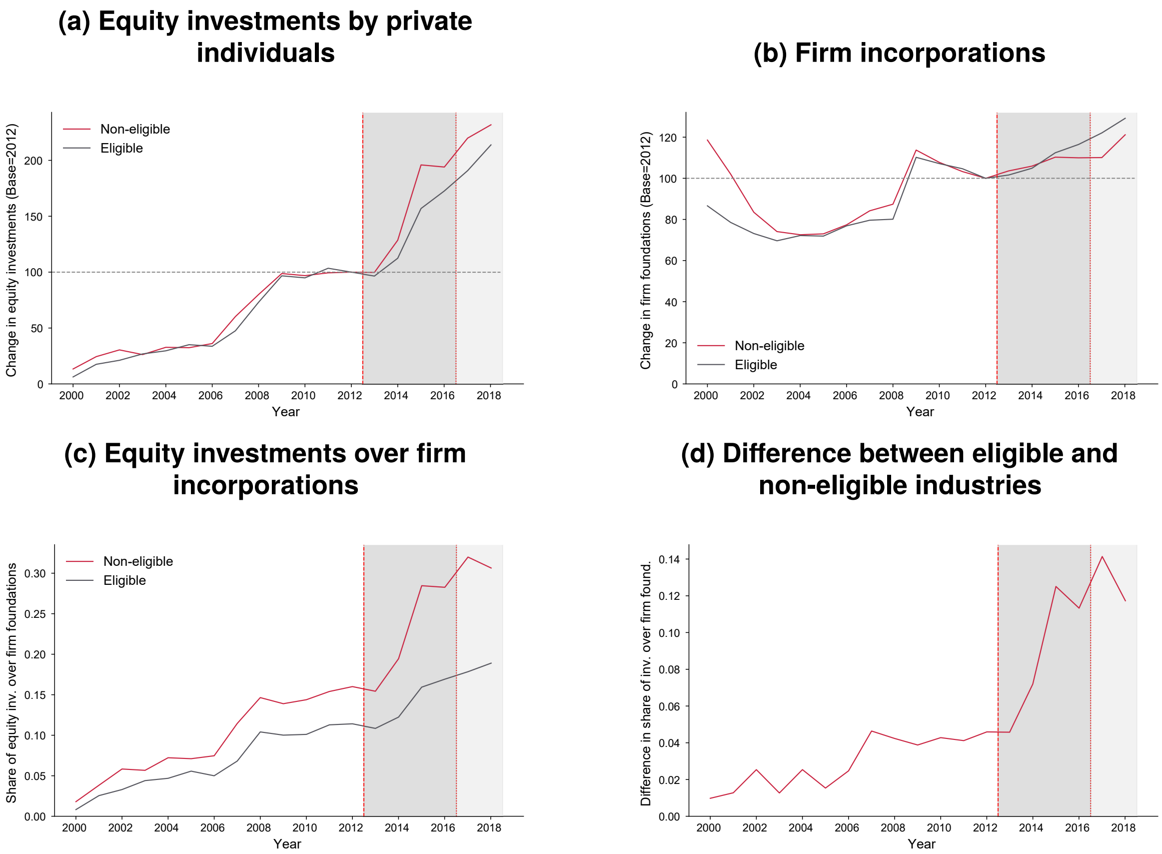
For an IV to be valid, it needs to be both relevant, i.e. (highly) correlated with the endogenous regressor, and exogenous, i.e., unrelated to the outcome of interest. In the following, we argue that the introduction of the INVEST program satisfies both of these criteria. Our main argument is that firms in eligible industries experience a lower cost of outside equity, irrespective of their actual R&D performance. Since the program has been introduced, firms in eligible industries should find it easier to access outside equity and experience an increased supply of outside equity. Assuming that policymakers could not predict the arrival of new technological opportunities, our approach allows us to identify the effect of external equity on innovation for the group of firms financed with equity as a result of the policy.

First, focus on relevance. For the policy to be relevant, it should affect firms' propensity to finance with outside equity. In other words, after introducing the policy, firms in eligible industries should be more likely to finance with external equity. Consider Figure 4.1 for preliminary evidence on this point.

Panel (a) in Figure 4.1 depicts the change in investments from private investors in young corporations relative to the base year 2012. After introducing the policy, these investments increased more strongly in eligible industries. Panel (b) shows that the larger increase relative to non-eligible industries is not driven by more firm incorporations in eligible industries. Panels (c) and (d) further illustrates this point. In Panel (c), the number of investments in young incorporations is set relative to the number of firm incorporations in a given year. Firms in eligible industries were more likely to receive investments from private investors. Panel (d) further illustrates this point, showing that the difference between the two groups over time (i.e., the Difference-in-Differences) increased sharply after the policy was introduced. This is consistent with earlier results from Berger and Gottschalk (2021). We provide statistical evidence on this relation in Section 4.6.2. In sum, the introduction of the INVEST program seems relevant for financing decisions, and as such, it satisfies the first requirement for a valid IV candidate.

[3]Note that there are other eligibility criteria that are less relevant for our approach. For a full description of the program see Section C.1 in the appendix.

**Figure 4.1.: Change in investments and incorporations over time relative to the year 2012**



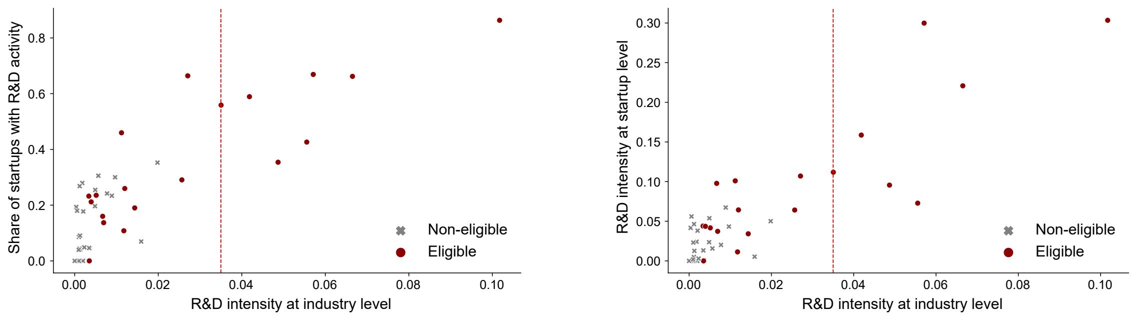

**Note:** Figure 4.1 shows changes over time relative to the base year 2012, the year prior to the introduction of the program. The gray shaded area indicates the period that the program has been active. The light-shaded area indicates the period since the revised version of the program was enacted. Panel (a) shows the change in the number of investments by individuals (natural persons) in those companies. Panel (b) shows the change in the number of incorporations (containing only the legal forms GmbH, AG, UG, and Limited). Panel (c) depicts the number of equity investments in young firms over the number of yearly incorporations. At the time of the investment, companies must not be older than ten years, and only corporations (GmbH, AG, UG, and Limited) are considered. Panel (d) shows the difference between the two lines. All numbers are calculated using the Mannheim Enterprise Panel.

Next, we consider exogeneity. To be exogenous, the program itself should not be related to firms' innovation activity over time. An essential aspect of the program is that it does not mandate how investors or companies should spend the grant. The use of funds from the grant is entirely up to the investor and is not attached to any specific purpose. This differs from most R&D support programs by public funding agencies that provide direct funding for specific R&D projects (Hussinger, 2008). Importantly, it implies that increases in outside equity as a result of the policy do not automatically result in increased R&D expenditures.

As Figure 4.2 shows, eligibility for the program is highly correlated with R&D intensity at the sector level. This is not a problem per se, as long as there is variation within industries. Evidently the distribution of R&D intensities within sectors - and thus technological opportunities - are fairly dispersed (Hughes, 1988) (see also Figure 4.3 in Section 4.5.3 on this point). As the program is based on *average* industry performance measures, there is variation in *realized* innovation performance at the firm level. This variation goes in both directions. Within eligible

**Figure 4.2.: Share of equity-financed startups by eligibility**

**(a) Share of R&D conducting firms** **(b) R&D intensity of startups in sample**




**Note:** Figure 4.2 shows the share of startups conducting R&D plotted against the R&D intensity at the industry level plotted against. The share of startups conducting R&D was calculated using population sampling weights from our sample. Sampling weights are available for firms not older than four years. The R&D intensity at the industry level is taken from administrative statistics. Industries are aggregated at NACE 2 level. Industries with NACE codes 13, 25, and 32 were not considered because eligible and non-eligible industries are mixed. Industries with NACE codes 12 and 19 were not considered because there were few firms in the sample. NACE 72 (Scientific research and development) was also not considered for better readability of the figure. For NACE codes 41-43, 45, 47, 55-56, 68, 77, 85, 90-93, and 95-96 R&D intensities at the industry level are unavailable.

industries, some firms do not pursue R&D projects, and likewise, firms in non-eligible industries may engage in innovation activities.[4] It is the variation over time that we care about.

To be plausibly exogenous, the policy maker should not have anticipated the arrival of technological opportunities and selected industries accordingly. Considering that this was likely not the case, consider Figure 4.1. If it were true that the policy maker could anticipate the arrival of new technological opportunities, we would expect a more substantial increase in funding activity in eligible sectors compared to non-eligible sectors. Looking at Panel (a), this is unlikely to be the case. The founding activity of corporations increased more in non-eligible sectors relative to eligible industries following the introduction of the policy. Based on these arguments, it is plausible to consider the program's introduction as exogenous from firms' innovation decisions and should satisfy the second condition to be a valid instrument.

In summary, the introduction of the INVEST program should satisfy the requirements for a good IV. The following section describes how we estimate our model with the IV approach.

[4] In fact, the rather strict focus on industry affiliation was sometimes criticized by founders and investors as one of the shortcomings of the program design, especially from those that operated in industries that the government did not consider innovative. This point is supported by anecdotal evidence from talks to investors and startup founders during a program evaluation. The founder of Lyzca - a company engaging in innovative food products - said, "*We had significant R&D expenditures, yet our company did not qualify for the INVEST program as a technology firm because we operate in a non-eligible business sector. However, I think digitization and technologies such as machine learning impact all sectors of the economy and therefore open up innovation potential in all sectors. As policymakers cannot predict in which sector the next great innovations will appear, the classification of innovative sectors can be quite arbitrary.*"

### 4.4.3. Wald Difference-in-Differences estimator

The instrument for our variable of interest $E_{it}$ is a dummy variable $D_{it}$ switching to one when a firm operates in an eligible industry ($\gamma_i = 1$) and observed in $t \geq 2013$, i.e. periods in which the program is active. We estimate Equation (4.6) by two-stage least-squares (2SLS) using as first stage the following equation

$$E_{it} = \alpha_0 + \delta_2 D_{it} + \gamma_i + \tau_t + \beta_2 X_{it} + v_{it}. \tag{4.7}$$

Since we expect a subsidy on outside equity to increase the supply of equity capital, we expect that the coefficient of interest $\delta_2$ is larger than zero. In other words, under our null hypothesis we test $H_0 : \delta_2 = 0$. The coefficient $\delta_2$ gives an estimate of how a reduction in the cost of outside equity (i.e., the introduction of the program) changes the propensity of entrepreneurial firms to switch to equity financing. This estimation approach is also known as the Wald-Difference-in-Differences estimator (for brevity, WDID). For the case where $E_{it}$ is a binary indicator, the estimator can be written as

$$\delta_1^{WDID} = \frac{\mathbb{E}[R(1)|D=1] - \mathbb{E}[R(0)|D=1] - \mathbb{E}[R(1)|D=0] - \mathbb{E}[R(0)|D=0]}{\mathbb{E}[E(1)|D=1] - \mathbb{E}[E(0)|D=1] - \mathbb{E}[E(1)|D=0] - \mathbb{E}[E(0)|D=0]}, \tag{4.8}$$

where $R(1)$ gives the potential innovation effort of a firm that receives equity financing and $R(0)$ of a firm that does not, $E(1)$ gives the propensity of a firm to finance with equity in an eligible industry, and $E(0)$ in a non-eligible sector.

Previous studies have applied this estimation approach in different contexts.[5] Equation (4.8) is equivalent to a 2SLS estimator, with a Difference-in-Differences estimator in the first stage regression. Using the first stage prediction $\hat{E_{it}}$, we use a 2SLS estimator to estimate how innovation activity responds to changes in the supply of outside equity. Given that eligibility is based on industry affiliation, and the sampling procedure of the data we use is stratified by industries, we cluster our standard errors at the industry level, as suggested by Abadie et al. (2017).

Under our identifying assumptions, the WDID gives the *local average treatment effect* (LATE) for individuals that decide to finance with equity as a result of the policy. To verify that equity financing increased as a result of the policy and constitutes an exogenous supply shifter, we provide results for parallel trends in the pre-treatment periods. Under parallel trends, there should be no difference before the policy intervention (Lechner, 2011). We will present the test for pre-treatment trends when discussing the first stage results in Section 4.6.

[5]For a well-known application of the method in the context of a school construction program in Indonesia, see Duflo (2001). For more examples, see Chaisemartin and D'HaultfŒuille (2017).

# 4.5. Data.

## 4.5.1. Data sources and sample

Our empirical analysis is based on data from the IAB/ ZEW Startup Panel (SUP).[6] The SUP is an unbalanced panel of young German firms, covering high-tech and non-high-tech industries (see Table C.8 in the appendix for details). We use the first twelve waves of the SUP comprising the founding cohorts from 2005 to 2018. For our main analysis, we use the following information from the SUP: (1) startups' industry classification, (2) startups' innovation inputs, (3) startups' innovation outcomes, and (4) startups' financing decisions. We also use the information on founding team characteristics and startups' incorporation year from the SUP. In addition, we use the information on startups' location, legal form, and economic activity from the Mannheim Enterprise Panel (MEP). The MEP is a large-scale firm database containing the universe of German firms and the sampling basis for the SUP. For our analysis, we only keep firms that are either limited liability companies or incorporations.[7] We make this restriction because companies that receive venture capital most commonly choose one of these legal forms. In addition, the program guidelines stipulate that companies must choose one of these legal forms to be eligible. We also discard observations that have missing values in one of the variables used in our analysis. Our final sample contains 10,580 firms and 21.094 firm-year observations.

## 4.5.2. Variable definitions

Our explanatory variable of interest is measured in two ways. First, by an indicator variable *Equity (Y/N)* showing whether a company used external equity in the reference year. Until 2014 the survey did not distinguish between different sources of venture capital. Therefore we treat outside equity as a generic financing type. Second, we construct a variable *Equity*, which gives the level of external equity capital employed in the reference year. In the estimations, we use $\ln(1+Equity)$ to measure the level of outside equity. For details on how this variable is constructed see Section C.5.1 in the appendix.

Innovation inputs are measured by three different variables taken from the survey. First, an indicator for whether or not a firm engages in *R&D activity* in year $t$, second a continuous variable for *R&D expenditures*, indicating how much a firm spends on R&D in a given year, and third a count variable for *R&D employees* giving the number of employees working at least 50% of their time on R&D related tasks. Innovation outputs are measured by a series of binary variables, indicating whether a firm has introduced a *global*, *domestic* or *regional* market novelty

[6]For details on the IAB/ZEW Startup Panel, see Fryges, Gottschalk, and Kohn (2009).
[7]To be specific, we keep firms that chose the legal form *GmbH, UG, AG* or *Limited*.

in the reference year. For the full list of variables employed in the analysis and their definitions, see Table C.9 in the appendix.

To identify eligible firms, we use the information on industry classification. We consider startups as *Eligible* if they operate in an industry that is part of the list of "innovative" industries provided by the funding agency. The appendix contains the full list of eligible industries in Table C.2. Tables C.6 to C.8 in the appendix give an overview of the sample by eligibility.

**Table 4.1.: Summary statistics**

| | Firm-year obs. | Mean | SE | Min. | Max. |
|---|---|---|---|---|---|
| **Financing** | | | | | |
| Equity (Y/N) | 21,094 | 0.06 | 0.23 | 0 | 1 |
| Equity (in thsd. Euros) | 1,232 | 255.10 | 733.62 | 0 | 14,800 |
| Public subsidy | 21,094 | 0.18 | 0.38 | 0 | 1 |
| Public VC | 21,094 | 0.01 | 0.12 | 0 | 1 |
| Sales (Y/N) | 21,094 | 0.90 | 0.29 | 0 | 1 |
| Sales (in thsd. Euros) | 19,066 | 677.76 | 1617.98 | 0 | 45,000 |
| **Innovation inputs** | | | | | |
| R&D activity | 21,094 | 0.41 | 0.49 | 0 | 1 |
| R&D expenditures (in thsd. Euros) | 8,751 | 101.77 | 193.00 | 0 | 2,000 |
| R&D employment | 6,483 | 2.73 | 4.64 | 1 | 240 |
| **Innovation outputs** | | | | | |
| Global market novelty | 21,094 | 0.09 | 0.29 | 0 | 1 |
| Domestic market novelty | 21,094 | 0.09 | 0.29 | 0 | 1 |
| Regional market novelty | 21,094 | 0.03 | 0.17 | 0 | 1 |
| | Firm obs. | Mean | SE | Min. | Max. |
| **Firm characteristics at start** | | | | | |
| Team | 10,580 | 0.47 | 0.50 | 0 | 1 |
| Female | 10,580 | 0.06 | 0.24 | 0 | 1 |
| Academic | 10,580 | 0.66 | 0.47 | 0 | 1 |
| PhD | 10,580 | 0.10 | 0.30 | 0 | 1 |
| Industry exp. | 10,580 | 14.49 | 10.15 | 0 | 60 |
| Founding exp. | 10,580 | 0.57 | 0.49 | 0 | 1 |
| Exit exp. | 10,580 | 0.12 | 0.32 | 0 | 1 |
| Patent | 10,580 | 0.05 | 0.22 | 0 | 1 |
| Opportunity | 10,580 | 0.48 | 0.50 | 0 | 1 |
| Size | 10,580 | 3.04 | 5.67 | 1 | 285 |
| West | 10,580 | 0.83 | 0.38 | 0 | 1 |
| **Region** | | | | | |
| Berlin | 10,580 | 0.06 | 0.24 | 0 | 1 |
| East | 10,580 | 0.11 | 0.32 | 0 | 1 |
| Hightech manufacturing | 10,580 | 0.16 | 0.37 | 0 | 1 |
| Software and tech-services | 10,580 | 0.36 | 0.48 | 0 | 1 |
| Non-hightech | 10,580 | 0.48 | 0.50 | 0 | 1 |

**Note**: For a detailed description of the variables, see Table C.9 in the appendix.

Table 4.1 shows the summary statistics of the variables we employ in our analysis. About 6% of firm-year observations are financed with equity capital. On average, firms' outside equity capital amounts to 255 thousand Euros. However, the difference is considerable. Some firms employ less than one thousand Euros annually; others use more than 14.8 M. in a year. About 18% of firms receive public subsidies, and most firms (90%) generate revenues in the observed periods. We use revenues as a proxy for cash flows. On average, revenues amount to about 678 thousand Euros, again the standard deviation on sales is large. The maximum for annual revenues in our sample amounts to about 45 M. Euros, the minimum to less than a thousand Euros. Regarding innovation inputs, firms report to engage in R&D in about 41% of firm-year observations. On average, they spend about 102 thousand Euros on R&D. Firms that conduct in-house R&D employ, on average, 2.7 employees that devote more than half of their time on R&D related tasks. Regarding innovation outputs, firms introduce global or domestic market novelties in 9% of firm-year observations and regional market novelties in 3% of firm-year observations. This shows that firms in our sample focus on innovations with a high degree of novelty.

### 4.5.3. Descriptive results

Table 4.2 shows the number of observations, means, and differences in means for firm characteristics and alternative financing sources. The upper part of Table 4.2 summarizes all equity-financed firms in our sample differentiating founding cohorts before and after the policy has been introduced. Below, only equity-financed firms that were eligible for the program are considered. Looking at the upper part of Table 4.2 we see that firms of founding cohorts before introduction are relatively similar to those after, but with a few notable exceptions: When it comes to funding, substantially fewer firms were financed by public VC after the introduction of the investor subsidy program. This could be either because firms substitute public VC through (more) private equity financing sources or because the government has reduced the supply of public VC, shifting more resources towards private investors in those firms. Interestingly, firms that pertain to founding cohorts established before the investor subsidy program have generated more sales.

Regarding firm characteristics, about 8% fewer firms started as teams after the policy was introduced. The share of female founders has slightly increased by 2.7 percentage points (p.p.), as well as the share of founders with an academic background (+8.6 p.p.). While this difference may raise concerns about an increased quality of startups due to the policy, it may also reflect a more general trend in the population. According to OECD statistics, the share of Germany's population with academic degrees has been rising in the last decades. Not all of this increase will be attributable to increases in the population's ability. Conversely, founders of startups founded after the policy was introduced have about one year less industry experience. Initial firm size

**Table 4.2.: Comparison of founding cohorts relative to program introduction**

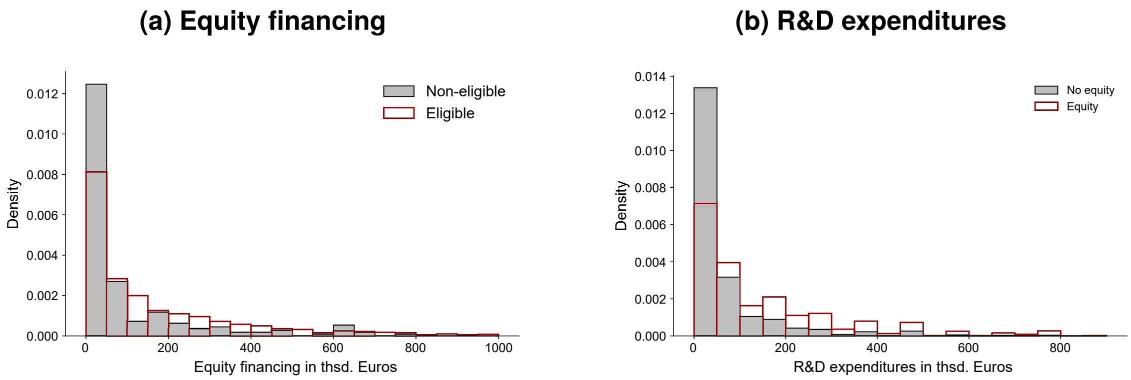
| | All equity-financed firms | | | | |
|---|---|---|---|---|---|
| | Before | | After | | |
| | Firm-year obs. | Mean | Firm-year obs. | Mean | Δ |
| Public subsidy | 435 | 0.37 | 797 | 0.37 | 0.003 |
| Public VC | 435 | 0.21 | 797 | 0.11 | −0.093*** |
| Sales (Y/N) | 435 | 0.81 | 797 | 0.77 | −0.039 |
| Sales (log) | 435 | 9.77 | 797 | 9.07 | −0.703** |
| | Firm obs. | Mean | Firm obs. | Mean | Δ |
| **Firm characteristics at start** | | | | | |
| Team | 529 | 0.67 | 529 | 0.59 | −0.076** |
| Female | 529 | 0.03 | 529 | 0.06 | 0.026** |
| Academic | 529 | 0.76 | 529 | 0.84 | 0.083*** |
| PhD | 529 | 0.21 | 529 | 0.22 | 0.011 |
| Industry exp. | 529 | 13.25 | 529 | 12.19 | −1.059* |
| Founding exp. | 529 | 0.64 | 529 | 0.64 | −0.002 |
| Exit exp. | 529 | 0.19 | 529 | 0.22 | 0.030 |
| Patent | 529 | 0.10 | 529 | 0.08 | −0.023 |
| Opportunity | 529 | 0.64 | 529 | 0.64 | 0.006 |
| Size | 529 | 3.66 | 529 | 3.04 | −0.621*** |
| | Eligible equity-financed firms | | | | |
| | Before | | After | | |
| | Firm-year obs. | Mean | Firm-year obs. | Mean | Δ |
| Public subsidy | 332 | 0.40 | 685 | 0.41 | 0.013 |
| Public VC | 332 | 0.23 | 685 | 0.13 | −0.103*** |
| Sales (Y/N) | 332 | 0.77 | 685 | 0.75 | −0.025 |
| Sales (log) | 332 | 9.35 | 685 | 8.80 | −0.545 |
| | Firm obs. | Mean | Firm obs. | Mean | Δ |
| **Firm characteristics at start** | | | | | |
| Team | 401 | 0.69 | 431 | 0.60 | −0.090*** |
| Female | 401 | 0.03 | 431 | 0.05 | 0.019 |
| Academic | 401 | 0.82 | 431 | 0.87 | 0.050** |
| PhD | 401 | 0.25 | 431 | 0.23 | −0.013 |
| Industry exp. | 401 | 13.02 | 431 | 12.24 | −0.786 |
| Founding exp. | 401 | 0.67 | 431 | 0.65 | −0.019 |
| Exit exp. | 401 | 0.21 | 431 | 0.23 | 0.018 |
| Patent | 401 | 0.12 | 431 | 0.08 | −0.043** |
| Opportunity | 401 | 0.68 | 431 | 0.65 | −0.033 |
| Size | 401 | 3.63 | 431 | 2.87 | −0.765*** |

**Note**: Table 4.2 compares the means in funding and startup characteristics between firms started before and after the introduction of the investor subsidy program. The lower panel contains only firms in eligible industries financed with outside equity for at least one year. Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

decreased slightly by 0.7 p.p. to about three full-time equivalents (FTEs). When looking at the location of business startups, there is a clear trend toward Berlin.

Compared to the upper part, the lower part of Table 4.2 shows a similar picture for eligible firms, with most differences being slightly smaller in magnitude and significance. Notable differences include that fewer eligible firms were founded in teams after the policy was introduced, and fewer firms have patents when they start a business. The size of these firms is slightly smaller.

**Figure 4.3.: Distribution of equity financing and R&D expenditures (in thsd. Euros)**



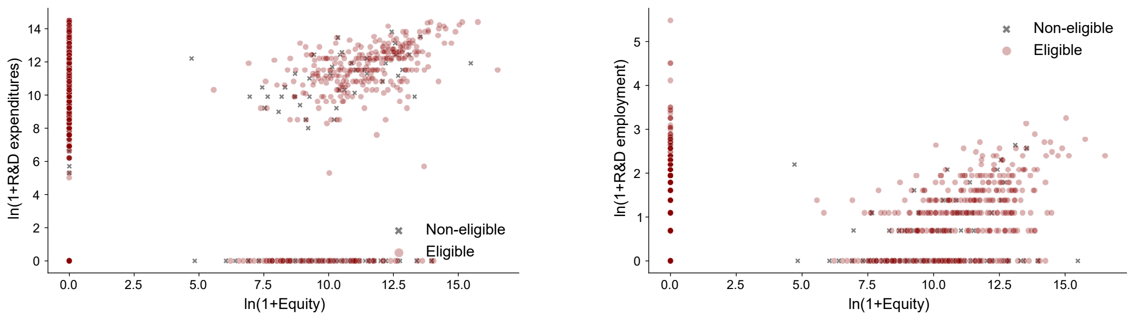

**Note:** Panel (a) depicts the distribution of the outside equity financing in eligible and non-eligible companies covering only those with positive outside equity financing. Panel (b) depicts the distribution of R&D expenditures for equity and non-equity-financed firms covering only those with positive R&D expenditures. For better visualization, the values are truncated at one million Euros in each case.

Figure 4.3 depicts the key variables of our analysis - the level of equity capital and R&D expenditures - in more detail. Panel (a) shows the distribution of equity financing amounts. We see that eligible firms receive higher financing amounts than non-eligible firms. Both distributions are highly skewed, with most firms using small amounts of outside equity capital. The median equity financing amount for non-eligible firms is 28 thousand Euros, and 96 thousand Euros for eligible firms. Looking at R&D expenditures in Panel (b), distributions are again highly skewed. Many firms invest small amounts, and only a few make large investments. Non-equity-financed firms that conduct R&D tend to invest smaller amounts into R&D. Only one quarter have annual R&D expenditures exceeding 100 thousand Euros. But even for equity-financed firms, only half of the observations exceed this amount. What motivates this research is understanding whether these observed differences are a consequence of outside equity financing.

Figure 4.4 suggests a positive relation between outside equity and R&D efforts. Yet it is unclear whether this is caused by outside equity. In the next section, we take a closer look at these relations to understand the causal links at work.

**Figure 4.4.: Relation between equity financing and innovation inputs**

**(a) R&D expenditures** **(b) R&D employment**




**Note:** Figure 4.4 shows scatter plots of firms' R&D-Expenditures (a) and R&D-Employment (b) against Equity Financing (in logs). Furthermore, eligible and non-eligible firms, according to the program definition, are distinguished.

# 4.6. Results

## 4.6.1. Reduced form regressions

### OLS - Innovation inputs

Table 4.3 shows the results of the reduced form estimations of Equation 4.6 using OLS. Panel A in Table 4.3 shows how equity financing is correlated with the likelihood of engaging in R&D activities. The coefficient for *Equity(Y/N)* in Column (1) tells us that financing with outside equity is associated with a 22.1 p.p. increase in the likelihood of conducting R&D. However, we see that this effect is strongly reduced to 12.6 p.p. once we account for firm characteristics that are both associated with conducting R&D and financing with outside equity. Turning to Panel B in Table 4.3, the coefficient *ln(1+Equity)* can be interpreted as an elasticity, as both the explanatory variable and the outcome are measured in natural logarithms. The coefficient in Column (1) tells us that a 1% increase in the level of outside equity finance is associated with a 0.3% increase in the level of R&D expenditures. Including control variables (Columns (2) - (4)) reduces the size of the coefficient, but it remains economically relevant and highly significant. The coefficient indicates that more equity financing does not seem to translate into higher R&D expenditures.

As an alternative measure for innovation inputs, we consider R&D employment. Conducting intramural R&D should be associated with more radical innovations. Again, the coefficient in Panel C of Table 4.3 can be interpreted as an elasticity, as the outcome gives the log number of R&D employees, and equity finance is again the natural logarithm. Therefore, the coefficient in Column (1) of Panel C tells us that doubling the level of outside equity financing (increasing the level of equity by 100%) is associated with a 4.7% increase in R&D employment. Taken together, these results suggest that increases in equity financing are related to sizeable increases

**Table 4.3.: OLS - Association between equity financing and innovation inputs**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A: 𝟙[R&D activity="Yes"] | | | |
| | (1) | (2) | (3) | (4) |
| Equity (Y/N) | 0.221*** | 0.218*** | 0.175*** | 0.127*** |
| | (0.021) | (0.020) | (0.014) | (0.012) |
| Constant | 0.392*** | 0.392*** | 0.410*** | 0.244*** |
| | (0.001) | (0.001) | (0.017) | (0.020) |
| R2 | 0.197 | 0.201 | 0.213 | 0.258 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| | Panel B: ln(1+R&D expenditures) | | | |
| | (1) | (2) | (3) | (4) |
| ln(1+Equity) | 0.305*** | 0.302*** | 0.258*** | 0.208*** |
| | (0.025) | (0.024) | (0.016) | (0.015) |
| Constant | 4.194*** | 4.195*** | 3.894*** | 1.921*** |
| | (0.015) | (0.015) | (0.221) | (0.286) |
| R2 | 0.219 | 0.223 | 0.239 | 0.288 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| | Panel C: ln(1+R&D employees) | | | |
| | (1) | (2) | (3) | (4) |
| ln(1+Equity) | 0.047*** | 0.047*** | 0.039*** | 0.034*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| Constant | 0.321*** | 0.321*** | 0.300*** | 0.105*** |
| | (0.002) | (0.002) | (0.024) | (0.038) |
| R2 | 0.195 | 0.198 | 0.227 | 0.270 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| **Fixed Effects:** | | | | |
| Year | Yes | Yes | Yes | Yes |
| Founding Cohort | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes |
| Region | | Yes | Yes | Yes |
| **Firm Controls:** | | | | |
| Time-varying | | | Yes | Yes |
| Time-fixed | | | | Yes |

**Note**: Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity. Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

in R&D expenditures and R&D employment. These results are consistent with the notion of Kortum and Lerner (2000) that venture capital investors finance startups' innovation activities.

## OLS - Innovation outputs

**Table 4.4.: OLS - Association between equity financing and innovation outputs**

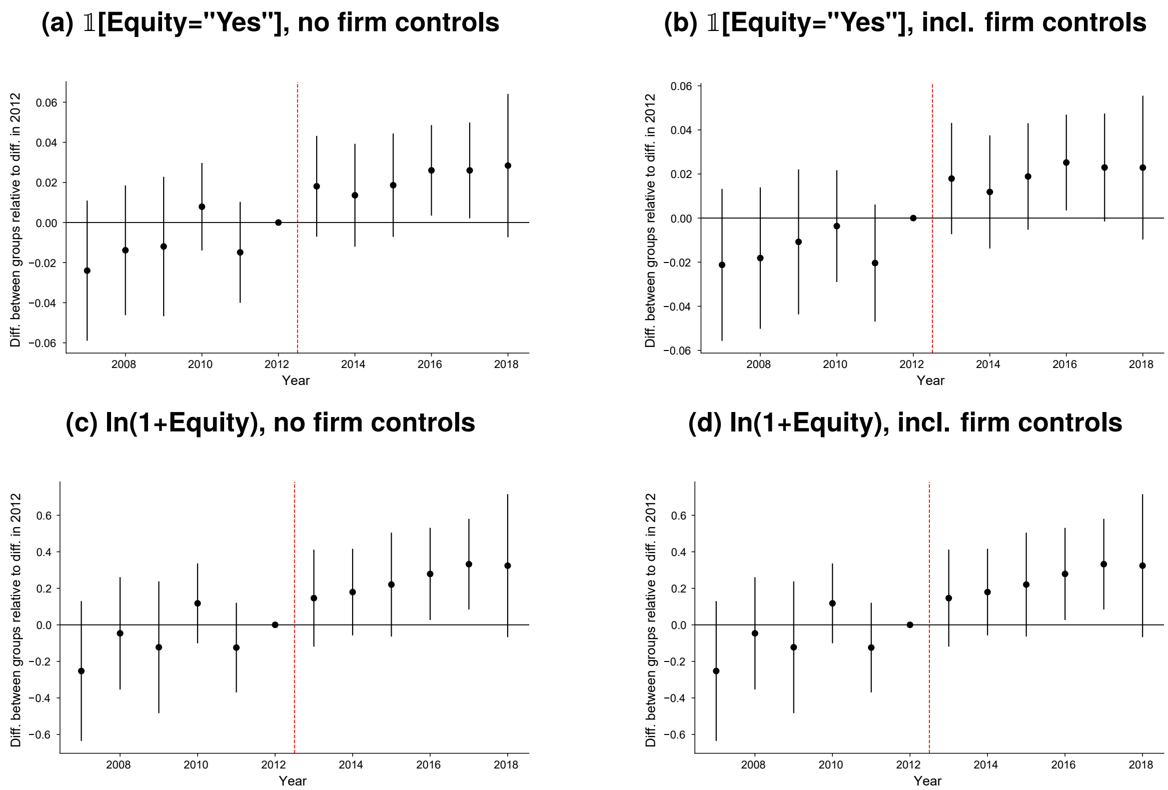
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Panel A: 𝟙[Global market novelty="Yes"]** | | | |
| Equity (Y/N) | 0.094*** | 0.092*** | 0.081*** | 0.065*** |
| | (0.013) | (0.013) | (0.012) | (0.014) |
| Constant | 0.089*** | 0.090*** | 0.030** | -0.038** |
| | (0.001) | (0.001) | (0.014) | (0.019) |
| R2 | 0.061 | 0.064 | 0.071 | 0.092 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| | **Panel B 𝟙[Domestic market novelty="Yes"]** | | | |
| | (1) | (2) | (3) | (4) |
| Equity (Y/N) | 0.056** | 0.056** | 0.057** | 0.046** |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| Constant | 0.088*** | 0.088*** | 0.043*** | -0.003 |
| | (0.001) | (0.001) | (0.006) | (0.015) |
| R2 | 0.023 | 0.024 | 0.027 | 0.035 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| | **Panel C: 𝟙[Regional market novelty="Yes"]** | | | |
| | (1) | (2) | (3) | (4) |
| Equity (Y/N) | -0.013*** | -0.013*** | -0.012*** | -0.013*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Constant | 0.032*** | 0.032*** | 0.024*** | 0.025*** |
| | (0.000) | (0.000) | (0.003) | (0.004) |
| R2 | 0.011 | 0.013 | 0.013 | 0.014 |
| Cluster | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| **Fixed Effects:** | | | | |
| Year | Yes | Yes | Yes | Yes |
| Founding Cohort | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes |
| Region | | Yes | Yes | Yes |
| **Firm Controls:** | | | | |
| Time-varying | | | Yes | Yes |
| Time-fixed | | | | Yes |

**Note**: Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity. Standard errors in parentheses clustered at the industry level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4.4 shows again OLS estimates for Equation 4.6, where now the outcomes are innovation outputs. Innovation outputs are measured by a binary indicator for whether the company has introduced a *global*, *domestic* or *regional* market novelty in period $t$. Panel A in Table 4.4 indicates that financing with outside equity is associated with a 9 (6) p.p. increase in the likelihood of introducing a global (domestic) market novelty. Again, the coefficient for equity financing becomes smaller when accounting for factors that correlate with the likelihood of using equity financing and the introduction of global or domestic market novelties. Conversely, financing with outside equity negatively correlates with introducing regional market novelties. This coefficient remains stable, even after including additional control variables, suggesting that firms seek venture capital when targeting large markets, independent of their characteristics. Overall, these results are consistent with Hellmann and Puri (2000), who show that innovator firms are more likely to receive equity financing than imitator firms.

## 4.6.2. Two-stage least squares regressions

**Figure 4.5.: Marginal change in equity financing between groups relative to the year 2012**




**Note:** Figure 4.5 shows the relative change in the difference in equity financing between eligible and non-eligible firms over time. The change is relative to the difference between the two groups in 2012. Dots indicate point estimates for the difference between groups relative to the base year 2012, and lines give the 95%-confidence bands. The red line indicates the start of the investor subsidy program in May 2013.

The discussion in Sections 4.3 and 4.4 illustrated that the coefficients in Section 4.6.1 cannot be interpreted as causal effects - leading from equity financing to innovation. To address endogeneity concerns, we instrument equity financing with the introduction of the INVEST program. Figure 4.5 provides evidence of the program's effectiveness in raising external equity financing. Panels (a) and (b) depict the relative change in the likelihood of using equity financing between eligible and non-eligible firms over time. Panels (c) and (d) depict the natural logarithm of the level of outside equity. Relative to the base year 2012 - before the subsidy program was introduced - there is a clear increase in the difference between the two groups. Also, there seem to be no significant changes before the policy. This is both true for the likelihood as well as the level of equity financing, as well as different model specifications. For eligible firms, the average likelihood of raising external equity capital has increased by 2.9 p.p., or - taking the constant term of 0.059 as baseline probability - by about 49% (see Table C.11, Panel A). Likewise, the level of outside equity financing increased by 30% (see Table C.11, Panel B). This is within the range that Berger and Gottschalk (2021) find using a similar approach. Overall, these results are consistent with the evidence provided in Section 4.4.2. It is also in line with research by González-Uribe and Paravisini (2019) for the U.K., Denes et al. (2020) for the U.S., and Biancalani et al. (2021) for Italy. All studies find significant increases in equity financing after the introduction of similar programs in these countries.

### 2SLS - Innovation inputs

Table 4.5 shows the results from the 2SLS estimation with innovation inputs as outcomes. Compared to the reduced form coefficients from the OLS estimates, these coefficients are smaller, and in the case of R&D activity and R&D expenditures even become negative when accounting for firm characteristics. The point estimate in Column (2) of Table 4.5 suggests that equity financing reduces the likelihood of engaging in R&D by about 1.4 p.p. Likewise, Column (4) suggests that increasing equity financing by 100% reduces R&D expenditures by about 8.7%. Finally, Column (6) suggests that doubling the level of outside equity financing increases the level of R&D employment by only 1.8%. Since all of these results are insignificant, we cannot reject the null hypothesis that on average outside equity does not change the level of innovation inputs in startup companies. It is important to note that weak instruments do not drive these results. All specifications surpass the critical value for the first stage F-statistic, even when taking the more robust criterion by Olea and Pflueger (2013), which is robust to heteroscedasticity, autocorrelation, and clustering.

**Table 4.5.: Two-Stage Least Squares - Effect of equity financing on innovation inputs**

| | R&D-Activity (Y/N) | | ln(1+R&D-Expenditures) | | ln(1+R&D-Employees) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.251 | -0.014 | | | | |
| | (0.384) | (0.408) | | | | |
| ln(1+Equity) | | | 0.211 | -0.087 | 0.052 | 0.018 |
| | | | (0.380) | (0.405) | (0.046) | (0.049) |
| **Fixed effects:** | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Region | Yes | Yes | Yes | Yes | Yes | Yes |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 18.8 | 16.6 | 18.8 | 16.6 |
| Robust F | 26.1 | 23.8 | 28.3 | 26.9 | 28.3 | 26.9 |
| Effective F | 25.4 | 24.6 | 26.4 | 27.0 | 26.4 | 27.0 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 | 21,094 | 21,094 |

**Note**: Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size. Standard errors in parentheses clustered at the industry level.
Significance levels: *** p$<$0.01, ** p$<$0.05, * p$<$0.1.

## 2SLS - Innovation outputs

Table 4.6 shows the 2SLS estimates for the effect of equity financing on innovation outputs. The results suggest that equity financing has a strong positive effect on introducing major innovations to the market (global market novelties). Equity financing increases the probability that an equity-financed company introduces a global market novelty by 87 p.p. (or 83 p.p. when other firm characteristics are considered). The estimated effect is considerably larger than the OLS estimates from the previous section suggest. Contrary to the results of the previous section, there appears to be no significant effect on the introduction of domestic or regional market novelties. In the case of domestic market novelties, however, the sign has changed, suggesting a negative albeit insignificant effect. This suggests that the correlations found by Hellmann and Puri (2000) are indeed driven by venture capital investors steering firms to commercialize more radical innovations. Again we provide test statistics for weak instruments and find that the effective F-statistic is large enough in all models to surpass the critical value. We conclude that our estimates are not subject to a weak-instrument problem.

**Table 4.6.: Two-Stage Least Squares - Effect of equity financing on innovation outputs**

| | 𝟙[X Market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Global | | Domestic | | Regional | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.873*** | 0.825*** | -0.382 | -0.443 | -0.073 | -0.082 |
| | (0.254) | (0.264) | (0.339) | (0.371) | (0.220) | (0.234) |
| **Fixed effects:** | | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Region | Yes | Yes | Yes | Yes | Yes | Yes |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 21.0 | 18.8 | 21.0 | 18.8 |
| Robust F | 26.1 | 23.8 | 26.1 | 23.8 | 26.1 | 23.8 |
| Effective F | 25.4 | 24.6 | 25.4 | 24.6 | 25.4 | 24.6 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 68 | 68 |
| Firm obs. | 10,580 | 10,580 | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm-year obs. | 21,094 | 21,094 | 21,094 | 21,094 | 21,094 | 21,094 |

**Note**: Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size. Standard errors in parentheses clustered at the industry level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

### 4.6.3. Robustness tests

We conduct several robustness tests on different samples (see Tables C.21 - C.23 in the appendix). For the first robustness test, we exclude the years 2017 and 2018. In these years, the program's revised guidelines applied, and we want to ensure that this does not drive our results. The results remain qualitatively the same. In the case of innovation inputs, i.e., R&D activity, R&D expenditures, and R&D employment, the coefficient becomes more negative but remains statistically insignificant. The same holds for domestic and regional market novelties, i.e., coefficients remain insignificantly different from zero. In the case of regional market novelties, the point estimate remains quantitatively stable. Importantly, the coefficient for global market novelties remains qualitatively stable and increases somewhat. However, it remains in the same effect range.

For the second robustness test, we exclude the retail sector and other consumer-oriented service sectors. These sectors were not part of the sampling procedure in 2013 and 2014. Since this coincides with the year that the policy was introduced, we want to make sure our results are not due to this sampling effect. Again, the results remain qualitatively the same for all outcomes considered. In sum, our results hold across different samples and do not seem to be driven by program changes or sampling choices.

Finally, we want to see whether we find similar effects using patenting as a measure for innovation output. Table C.27 in the appendix uses patent applications at the European Patent Office (EPO) in period $t$ as outcome. Our estimates suggest that doubling the level of equity financing leads to about 2.2 additional patent applications, which is significant at the 10% level.

## 4.7. Discussion and Conclusion

This study investigates the link between equity financing and innovation in entrepreneurial firms. Our approach differs from prior research in that we consider innovation inputs (R&D) and innovation outputs (market novelties) separately from each other in a quasi-experimental setting. We use the introduction of a major policy program for early-stage equity investors in Germany to instrument endogenous financing decisions related to innovation activity. Eligibility for the program results in exogenous variation in firms' cost of outside equity over time. Compared to patents, which are commonly used as a measure for innovation, our measures have the important advantage of being less susceptible to being confounded with firms' strategic decisions.

Our results indicate that outside equity is essential to bringing global innovations to the market. However, it seems less critical to finance innovation activities in startup firms. We find that for those firms that decide to finance with equity as a result of the program, equity financing increases the likelihood of introducing a global market novelty by 84%. Conversely, there is no economically or statistically significant effect on R&D activity, R&D expenditures, and R&D employment. The results provide evidence consistent with the view that venture capital investors are important to drive the commercialization of innovation results (Lahr and Mina, 2016; Samila and Sorenson, 2010).

What remains unclear still are the exact mechanisms that drive our findings. In particular, it remains unclear whether a large share of venture capitalists stay away from financing technology development per se or whether this is limited to certain types of investors, industries, or regions. For example, Dutta and Folta (2016) find that angel groups and VC funds contribute equally to innovation rates (i.e., the number of innovations produced). Still, the innovations financed by venture capital funds generate a significantly higher impact compared to angel groups. As the policy affected angel investors and not VC funds, our results may not translate to VC funds per se. Furthermore, angel investors could engage in technologies with comparatively low development costs to arrive at a minimum viable product or prototype (Ewens, Nanda, et al., 2018). For such technologies, it should be relatively easy to substitute between different funding sources, such as a founders' own funds, startup subsidies, and R&D grants to conduct technical experiments. Increasing the supply of capital may, therefore, not affect firms' innovation inputs but still affect innovation outputs. The results by Berger and Hottenrott (2021) somewhat support this, showing that, unlike independent and corporate venture capital funds, angel investors respond strongly to public startup subsidies. This could imply that angel investors may have a relative advantage in commercializing innovations that require lower amounts to be realized in the first place. Our setting and empirical research approach do not allow us to make such distinctions. Future research should therefore take a closer look at what mechanisms drive these findings.

The results in our paper have important implications for entrepreneurship policy. The main message of our findings is that equity investments in young firms do not increase investments in innovation activities per se. Stimulating investments from private individuals in startup companies through investor subsidies may, therefore, not be sufficient to stimulate the emergence of radical innovations. Rather direct subsidies to startups such as development grants may be required. Yet, investors seem to play an essential role in the commercialization of potentially radical innovations. Easing access to angel investors and venture capitalists may allow more firms that have already developed innovations to bring them to the market. Effective entrepreneurship policy should comprise a mix of policy instruments, allowing for the development and commercialization of radical innovations.

# 5. The Private Value of Entrepreneurial Control

## 5.1. Introduction

VC contracts commonly place strong control rights in the hand of VCs. Through various mechanisms ranging from board rights to CEO replacement clauses, control rights thus align the incentives of VCs and entrepreneurs (Ewens, Gorbenko, et al., 2021; Kaplan and Stromberg, 2003; Tykvová, 2007). Whereas control rights enable investment from the perspective of investors, they also present a puzzle, as freedom and independence are important returns to entrepreneurship (e.g. Moskowitz and Vissing-Jørgensen, 2002). Thus, entrepreneurs are faced with a dilemma, as growth through external equity might lead to a loss of control and, by extension, freedom (Cestone, 2013; Wasserman, 2016). In the extreme, control considerations might dissuade entrepreneurs from pursuing growth altogether. However, while it is well understood that entrepreneurs face a trade-off between control and growth, it is not known how strong this trade-off is.[1]

This study quantifies how much entrepreneurs value control rights in VC offers. We conduct a discrete choice experiment with entrepreneurs in Germany ($n = 317$) who made a sequence of choices between hypothetical investment offers. Each investment offer provides the same amount of capital but varies in the stake that the VC will take and the level of control rights that the VC will receive. By confronting entrepreneurs in a controlled setting, our study solves the issues of endogeneity and non-observance of failed negotiations that hinder estimating the causal impact of control rights from observational data (Da Rin, Hellmann, et al., 2013).[2]

[*] This Chapter is based on Berger, Doherr, et al. (2020, 2021)

[1] We are not the first to notice this. See, for instance, Hyytinen et al., 2013, p.57: *"Hardly anyone thinks that the returns to entrepreneurship would not be both monetary and non-monetary. There is less agreement on how large those returns are."*

[2] Discrete choice experiments are commonly used for eliciting preferences, that have previously been used to study which characteristics of startups are most important for VCs (e.g. Block, Fisch, et al., 2019; Drover et al., 2014; Franke et al., 2008; Hoenig and Henkel, 2015; Hsu et al., 2013; Theinert et al., 2017). A similar logic is applied

Our results indicate, first, that entrepreneurs highly value control. Compared to offers that only provide minimal monitoring rights to the VC, offers that include the intermediate level of control rights and a veto right have a 13% lower marginal probability of being selected. Offers with the highest level of control, providing a voting majority to the VC, have a 34% lower marginal probability of being selected. In terms of valuation, we show that entrepreneurs are willing to trade an additional 12% of their equity to avoid veto rights requirements and an additional 38% of equity to prevent a voting majority. We further show that willingness to pay for control is higher among entrepreneurs with VC experience compared to entrepreneurs that have no experience with external equity investors or only with business angels and that willingness to pay for control is comparable among firms with and without growth orientation.

Additionally, the offers in our study vary in the value-added activities that the VC provides. VCs are distinct from other investors in that they, through their business experience and extensive networks, add value to their investments beyond the equity they contribute (Sørensen, 2007). In that way, VCs contribute to maturing their ventures by developing strategies and financing plans, finding potential partners, recruiting managers, and mentoring founders (Gorman and Sahlman, 1989). VC affiliation also brings certification, aiding the legitimization of otherwise unestablished ventures (Hsu, 2004). Through these extra-financial activities, VCs contribute to innovation and growth (Kortum and Lerner, 2000). Our analysis contributes to understanding which contributions are valued most by entrepreneurs by having entrepreneurs choose between offers that include VC value added in terms of attracting finance, providing market access, support with R&D, and support with developing the firm's strategy. We find that entrepreneurs value VC value-added activities, but to different degrees: willingness to pay for the possibility of support with strategy, product development, and finance is estimated at 4-5% of equity, but support with market access is estimated at 12%.

To the best of our knowledge, our study is the first to quantify entrepreneurs' control preferences in a venture capital setting. The high private value of control has the important implication that, even though control rights are essential for efficient contract design in venture capital investment (Aghion and Bolton, 1992), they also represent an important share of the non-monetary returns to entrepreneurship. That means that the prospect of losing control might be especially costly for entrepreneurs, and it might form a barrier for them to seeking out venture finance. For VCs, our results indicate that reducing control right requirements could allow them to invest at a significant discount. For policymakers, our results imply that measures aiming to foster entrepreneurship by increasing the supply of financial capital in the market for startups might be more effective when they are provided with less stringent control requirements.

The remainder of this article is structured as follows. Section 5.2 discusses the role of control rights in venture capital investment and develops the trade-offs entrepreneurs face. Section

in the experimental approach of Bernstein, Korteweg, et al. (2017).

5.3 discusses the empirical setting of a discrete choice experiment. Section 5.4 describes the measures and data. Section 5.6 describes the results of the analysis, and Section 5.7 concludes.

# 5.2. Conceptual background

## 5.2.1. Entrepreneurs' preferences for control and independence

It is commonly argued that entrepreneurs draw a large share of the value of their activities from non-pecuniary benefits of entrepreneurship, including, but not limited to, flexibility, independence, and the intrinsic reward of being an entrepreneur. In particular, the higher job satisfaction entrepreneurs enjoy (Andersson, 2008; Blanchflower, 2000; Blanchflower and Oswald, 1998; Kawaguchi, 2008) seems to be mainly driven by a higher degree of independence (Benz and Frey, 2004; Hundley, 2001). Independence is an essential driver of the decision to become self-employed (Taylor, 1996, 2004), more important than wealth attainment (Amit, MacCrimmon, et al., 2001).

The literature studying the returns to entrepreneurship considers control and independence as compensations for the often low financial returns to entrepreneurship. Hamilton (2000) estimates that entrepreneurs earn 35% less than they would make as paid employees and concludes that large non-pecuniary benefits, such as being an own boss, compensate for this gap. Moskowitz and Vissing-Jørgensen (2002) likewise argue that independence might compensate for the higher risk of entrepreneurship. Hyytinen et al. (2013) document a negative return to entrepreneurship. Entrepreneurs work longer hours and have more responsibilities than employees but enjoy more varied and independent working conditions. Jones and Pratap (2020) show that the non-pecuniary return to entrepreneurship is large enough to offset a 42% drop in consumption.

Control considerations are also argued to affect entrepreneurs' financing decisions (Cestone, 2013; Sapienza et al., 2003). Several empirical studies corroborate this. Participants in a discrete choice experiment at a German technical university consider investment offers less attractive when they entail more control or monitoring (Theinert et al., 2017). Half of the business owners in the United Kingdom consider maintaining control over the company the main business goal and would therefore not consider issuing external equity (Poutziouris, 2002). In Sweden, small business owners do not believe that the growth potential brought by external equity finance compensates for the potential loss of control (Cressy and Olofsson, 1997), even though the aversion to ceding control is smaller among firms in stronger need of financing (Berggren et al., 2000). In Italy, family firms, hypothesized to highly value control, are more likely to refuse VC offers (Croce et al., 2018). Evidence from equity sale decisions also shows that firms with a greater potential loss of control have smaller equity increases and rely more on debt. This, in turn, results in lower company growth (Müller and Zimmermann, 2008). In a more general setting of equity transactions – not necessarily related to entrepreneurship – Dyck and Zingales (2004) quantify the value of control through the premium attached to the sale of a controlling block. The average value of control is estimated at 14% of the equity value of the firm.

If the prospect of losing control leads entrepreneurs to reject external capital, it can jeopardize growth. Beyond the impact of the choice not to expand the venture, the venture does not profit from the positive impact of venture capital support (Kortum and Lerner, 2000; Sørensen, 2007, e.g.). Several studies have documented that CEO replacement leads to higher growth in startups (Conti and Graham, 2020; Wasserman, 2016). Croce et al. (2018) estimate that the refusal to accept venture capital funding leads to average lost yearly sales growth of 18%.

### 5.2.2. VC value-adding activities

VC investment differs from other forms of investments in that VCs are high-skill investors who add value beyond financial resources through deep involvement in their investments. To do that, VCs draw on their own business experience and extensive networks, which can compensate for lacking experience and networks in the founder team (Gorman and Sahlman, 1989). Their value-added activities generally relate to developing the firm's strategy and professionalizing the venture, including setting organizational structures, financial planning, networking, and hiring (Kaplan and Strömberg, 2004). VCs also add value by certifying and legitimizing their investments, which is especially important for startups without a strong reputation (Hsu, 2004). The value-adding activities of VCs are considered to be more distinctive for them than their financial contributions (Quas et al., 2020), and VC involvement has been shown to contribute to innovation and economic growth (Gompers, 1999; Gompers and Lerner, 2001, 2003; Kortum and Lerner, 2000; Lerner, 2002). Control is also relevant for VC value-adding activities, as control rights circumvent a double moral hazard problem where VCs hedge their effort against the possibility that the entrepreneur does not act in alignment with the VCs interests. At the same time, the entrepreneur hedges himself against the possibility that the VC will not invest extra-financial resources (Chan et al., 1990).

In concordance with the literature on VC value-added, entrepreneurs are willing to pay a premium for VCs with a stronger reputation (Hsu, 2004). They are more inclined to cede control when they believe that investors can add value to the firm (Bettignies and Brander, 2007; Cressy and Olofsson, 1997). In this study, we further contribute to the literature by estimating the value premium attached to VC support with different activities. In doing so, we establish how much VC support is valued and which support activities are valued most.

### 5.2.3. A toy model

To illustrate the relationship we aim to capture, we consider the following simple model. We assume that entrepreneurs draw utility from two components. The first is the monetary value of their company, $V$, which consists of all of the company's future discounted profits. The company's value can be increased through VC value-added activities, which are captured in the vector $a$. The monetary value of the firm is transferable to others and, therefore, can be split among several parties, of which the entrepreneur retains an equity stake $s$. The other component of utility is the entrepreneur's private enjoyment of control $b$. Private benefits are non-transferable and depend on the contractually specified control rights in the company $c$. For the sake of simplicity, assume that $c$ is a binary variable so that entrepreneurs either receive control benefits or not. Therefore $c = 1$ means that the entrepreneur remains in control of the company (e.g., through a voting majority on the board), and $c = 0$ means that the entrepreneur needs to hand control rights to an investor. Entrepreneur's utility is therefore given by

$$U(s,c) = sV(a) + b(c). \tag{5.1}$$

To finance her company's future development, the entrepreneur can choose between investment offers, represented as bundles of equity stakes, value-adding activities, and control rights $\{s,a,c\}$. We first distinguish bundles with high-powered equity claims, that is, with strong control rights for the investor, and bundles with low-powered claims, where the entrepreneur maintains control and keeps value-adding activities constant across offers. The utility gained for the entrepreneur from a high-powered claim is then expressed as $U_H(s,a,c=0)$, and a low-powered claim is expressed as $U_L(s,a,c=1)$. The entrepreneur will then prefer to give up control whenever the following condition holds:

$$U_L(s,a,c=1) \leq U_H(s,a,c=0) \tag{5.2}$$

$$s_L V(a) + b \leq s_H V(a)$$

$$b \leq \Delta s V(a). \tag{5.3}$$

In other words, the equity stake that the entrepreneur receives in a deal with strong control rights for the investor, $s_H$, must be large enough to compensate the entrepreneur for the loss of control benefits. When Equation (5.3) holds with equality, $\Delta s$ is the additional equity the entrepreneur would be willing to give up to remain in control of her company. Note that this condition is more likely to be satisfied when the VC adds more value to the firm. This study aims to quantify $\Delta s$, i.e., to understand the trade-off between equity claims and control rights. Understanding how large this trade-off is might be a key to understanding why some venture capital deals fail to manifest.

# 5.3. Experimental design

## 5.3.1. General motivation

We use a discrete choice experiment (DCE) to measure entrepreneurs' preferences for control. The goal of a DCE is to measure the effect of one (or more) treatment variables on a response variable, where the response variable is a discrete indicator reflecting an individual's choice from a set of alternatives. Because DCEs are based on random utility theory, observed choices can be directly linked to a behavioral model, which allows for a statement about the effect of the treatment variable on an individual's utility (Louviere et al., 2010). Notably, the behavioral model allows the formulation of trade-offs between the different treatment variables. If one of the treatments is a price attribute, we can formulate individuals' willingness-to-pay (WTP) for non-price attributes (McFadden, 1974). In our DCE, we want to measure the effect of contractual and non-contractual features of investment offers on entrepreneurs' financing decisions. In particular, we are interested in measuring entrepreneurs' willingness to pay, in terms of equity, for investments that allow them to retain control over their ventures and investments that offer different VC value-added activities.

Two key features make DCEs, especially appealing to our research question. First, DCEs allow us to elicit information about preferences that would otherwise be difficult to observe or unobservable (Carson et al., 1994). Since control benefits are private to the entrepreneur, they cannot be directly observed. In principle, one could use actual contracts from venture capital deals to measure control benefits, comparing average contractual cash-flow rights for contracts with fewer and more contractual control rights. However, this approach poses several obstacles. First, actual contracts are rarely available and, when available, can be obtained only for a small fraction of venture deals, which may not be representative of all deals.[3] More importantly, using real-world contracts may lead to biased results since only realized contracts are observed. The bias stems from selection into contracts. If investors require high control rights, entrepreneurs with a high preference for control might be more likely to reject venture capital offers. Contract data would then over-represent entrepreneurs with relatively low preferences for control, implying that real-world contracts will downward bias the estimated private control benefits. A second reason DCEs appeal to our research question is that DCEs are formulated and designed as formal experiments. If properly implemented, this circumvents typical endogeneity issues in economics and finance (Roberts and Whited, 2013) and allows us to identify causal effects (Hainmueller, Hopkins, et al., 2014). At the same time, concerns may arise about the external validity of results from discrete choice experiments, i.e., whether the results from the experiment translate to real-world decision-making (Grégoire et al., 2019). In the next section,

[3]Examples of studies that make use of real-world contracts include Bienz and Walz (2010), Ewens, Gorbenko, et al. (2021), and Kaplan and Strömberg (2001).

we describe in detail how our design takes care of those concerns.

### 5.3.2. Experimental procedure

In our DCE, we asked entrepreneurs to imagine a situation in which they seek a substantial amount of funds to develop their company further and have decided to look for external investors.[4] Participants were then confronted with a series of hypothetical investment offers from generic investors and had to indicate which alternative they liked best. To make the entrepreneurs' decision independent of capital requirements, we indicated that all offers covered 100% of the required funds. Participants were asked to choose their most preferred among three proposed investment offers. Each investment offer is a compound of contractual covenants and investor characteristics. We refer to each variable of an offer as an attribute and the value of a particular attribute as an attribute level. Investment offers differ in attribute levels, but each presents the same attributes. Table 5.1 gives an overview of the attributes and levels employed.

One challenge in the design of DCEs is to establish external validity. To do so, it is important that choices are not too complex to parse while still providing a realistic choice situation (Batsell and Louviere, 1991; Carson et al., 1994). Typically, this requires reducing the number of attributes and carefully choosing relevant attributes for decision-making. To determine the set of relevant attributes, we first conducted an in-depth literature review, from which we generated a list of candidate attributes that we believed to be important to entrepreneurial financing decisions. We then presented this list of twelve candidate attributes to four experts in the field, including entrepreneurs and experienced venture capital investment professionals. After the expert interviews, we reduced the number of attributes to six, two representing cash-flow and control rights in the venture and four describing the general attributes of the investor. Specifically, we included the investor's required equity share, the investor's required control rights, and the investor's ability to support the entrepreneur with acquiring additional funds, market access, product development, and management strategy (see Table 5.1). In our model, entrepreneurs draw utility from two primary sources: future cash-flow rights in the company, which depend on the value of the company and the entrepreneur's equity stake, and non-financial benefits, which we assume to be greater when the entrepreneur has a higher degree of control over the company. The company's value is unobserved in our data. However, as all investments were stated to be the

[4] We slightly varied the text depending on the development stage of the venture to make the situation closer to the companies' actual situation. To this end, we first assessed the companies' current development stage, having either not yet introduced a product to the market (seed), having developed a product but not yet generating sales (startup), or having introduced a product to the market and generating significant sales (growth). Companies in the seed phase were asked to imagine a situation where they needed funds to develop their product further or introduce it to the market. Those in the startup stage were asked to imagine a situation where they require the funds to introduce the product to the market, and those in the growth phase were asked to imagine a situation in which they want to expand their business.

same size, the company's value should be individual-specific and not differ between choices for the same respondent. Variation in entrepreneurs' utility is driven by the investor's equity stake, control rights, and non-financial support activities, which all differ across investment offers.

It is essential that respondents can cognitively separate attributes (Hensher et al., 2005). This is not straightforward for control and cash-flow rights, as ownership shares provide both kinds of rights. To account for this, we designed our experiment such that control rights and cash-flow rights can be separated in a convenient way that is also well understood by entrepreneurs, relying on the German legal context to do so.[5] We distinguish three levels of control, which are reflected in German shareholder rights. We indicate the presence of each control covenant in the VC offer with a simple yes or no indicator. In Germany, shareholders have a right to information about company affairs and inspection of the company's books and records. We view this as the most basic level of control, which is present independent of ownership share, and include it as the base level of control in our experiment. The intermediate level of control is based on a qualified majority of votes: Shareholders that own more than 25% of outstanding shares receive an automatic veto right. We include a veto right as the intermediate level of control in our experiment. Lastly, shareholders with more than 50% of their outstanding shares possess a voting majority and can control company decisions. We include this as the strongest level of control in the experiment. While these levels of control should be cognitively separable for respondents, they are still linked to ownership shares. We make sure that respondents view control and ownership shares as separate attributes by restricting the range of equity shares required by the VC between 5% and 25%. This way, the VC would never receive control beyond the right to monitor based on their ownership share alone. Thus, for the experiment context, the level of offered equity should capture cash-flow rights, and control rights are captured through the presence or absence of contract covenants.

We created choice sets from the attributes and levels in the following way. The full factorial design of our experimental setup has $5 \times 3 \times 2^4 = 240$ different combinations. Therefore, using the full factorial design, where respondents need to evaluate all combinations, is not practical. Walker et al. (2017) argue that when uncertainty about the size of the parameters to be estimated is high, a random design is as efficient as other fractional factorial designs while being more easily implemented. As we did not have prior information about the expected effect sizes, we employed a fractional factorial design that randomly selected the respondent's ten choice tasks.

Our final experiment was set up as an online survey tool that we distributed to respondents in a

[5] In Germany, the rules for limited liability companies (Gesellschaft mit beschränkter Haftung, short GmbH) are laid down in §51 GmbHG, and for corporations (Aktiengesellschaften, short AG) in §131 AktG. Rules concerning the veto rights and voting majorities are laid down in §59 GmbHG for GmbHs, and in §179, Paragraph 2 AktG for AGs. Both require a qualified majority of 75% of votes to make changes to the shareholders' agreement. Likewise, §60 GmbHG and §262 Paragraph 1 No. 2 AktG require a two-thirds majority for the liquidation of a company. Respondents were not required to be aware of these institutional features to make informed decisions in the experiment.

personalized email. The data collection process, including the sampling procedure, is described in Section 5.4.

**Table 5.1.: Attributes and levels**

| Attribute | Survey text | Levels |
|---|---|---|
| Equity share | "The investor(s) require(s) a share of ... in your company." | 5%/ 10%/ 15%/ 20%/ 25% |
| Control rights | "Beyond the compulsory control- and voting rights, the investor(s) require(s) ... ." | No further control rights / A veto right / A voting majority |
| Finance support | "The investor(s) offer(s) support in acquiring more financial capital." | Yes / No |
| Market access | ’The investor(s) offer(s) support in marketing your product/ your service." | Yes / No |
| R&D support | "The investor(s) offer(s) support in (further) developing your product/ your service." | Yes / No |
| Strategic support | "The investor(s) offer(s) support in strategic management for your company." | Yes / No |

**Note**: To further clarify the meaning of each attribute to respondents, we provided respondents with further information in roll-over buttons. The following descriptions were provided. *Equity share*: "A higher valuation of your company by the investor is equivalent to a lower equity share the investor gets. The assumption is that all three investment offers have the same amount." *Control rights*: "Compulsory control rights comprise, i.a., access to a company’s books and correspondence, as well as the right to information about all legal matters." *Finance Support*: "This may be through the investor(s) themselves, their network of investors, or through support in searching for new investors." *Market access*: "This may contain contact to potential customers here or abroad, or opening up new distribution channels." *R&D support*: "This may be through searching for and hiring experts, searching for cooperation partners, and adopting new production technologies." *Strategic support*: "E.g., through support in positioning the company, and defining long-term goals of the company, including support in employee management."

## 5.4. Data

### 5.4.1. Population and sample

Our sampling frame is the population of German startup founders. We obtain our data through an online experiment that we ran as part of the twelfth wave of the IAB/ZEW Startup Panel Survey in 2019. The IAB/ZEW Startup Panel is a joint project of the Institute for Employment Research (IAB), the Centre for European Economic Research (ZEW), and Creditreform (Germany’s largest credit rating agency). The panel is a stratified random sample of legally independent new ventures drawn from the Mannheim Enterprise Panel, which essentially represents the population of all firms in Germany and contains basic startup information. To be included in the sample, firms cannot be older than three years. The survey excludes subsidiaries or ventures that resulted from merger activities.[6] After initial participation, startups are followed for up to seven successive years. The information on venture capital investment rounds is obtained from transaction data compiled by ZEW on a yearly basis, containing records from Bureau van Dijk's Zephyr database and the transaction data from Majunke Consulting.

The startup panel data collection proceeds through computer-assisted telephone interviews (CATI) with the founder-managers of the companies. For the online DCE, we further selected companies typically associated with venture capital investment. Founders were asked to participate in the online DCE when their company fulfilled any of the following criteria: 1) it has received venture capital or was in contact with an investor; 2) it conducts R&D, or 3) its main objective is to grow. This sampling approach allows us to construct results that are representative of German startup founders that are either seeking venture capital or potential targets of venture capital investors. The appendix shows the sampling scheme in Figure D.1. The gross random sample of the Startup Panel 2019 consists of 24,500 firms that are representative of the population of German startups.[7] Of all the firms, 7,793 completed the CATI. The target group fulfilling at least one of the four criteria amounts to 3,376 startups. We sent the founder-managers of these startups an email containing a link to the DCE and a personalized access key, allowing us to link responses to the information in the IAB/ZEW Startup Panel. To increase the response rate, we sent four reminders to all founder managers who indicated an interest in the online DCE during the CATI. The timing of the reminders and the distribution of responses over time are depicted in Figure D.2 in the appendix. As a result, 411 entrepreneurs participated in the online DCE. Of these, 94 did not complete the experiment. Our final sample consists of 317 founder managers who completed the online DCE. This amounts to a net response rate of 9.6%.

### 5.4.2. Description of sample

Table 5.2 describes the sample of relevant firms and the respondents. 30% of respondents in the completed sample received an investment from a VC Investor. For 7% of the completed sample, this was a VC fund, and 28% of completed respondents received investment by an angel investor. 29% was in contact with a potential investor. 60% of respondents conducted R&D activities in 2018, and 44% had as the main company objective to grow. There are no significant differences in these variables between respondents who completed the survey and

[6] see Bersch et al. (2014) for more information

[7] For the Startup Panel 2019, two additional samples for the states of Baden-Württemberg and Northrhine Westfalia were drawn.

those who did not. Compared to non-respondents, companies with experience with external equity investors seem to be slightly overrepresented in the sample, and companies with growth as the main objective seem to have a lower propensity to respond.

Table 5.2 also describes the more general characteristics of the founders and ventures. The average founder that completed the experiment is 46 years old and is somewhat older than non-responding founders. 18% of completed participants are female, representing the broader population of founders. The sample is slightly overrepresented in terms of founders with prior founding experience and in terms of industry experience. Considering firm characteristics, the firms of completed participants are slightly older but representative in terms of sales and the number of employees. The sample is slightly overrepresented in high-tech service firms and underrepresented in B2B services. In terms of the development stage, around 11% of the respondents are in the seed stage of their development, i.e., they have not yet introduced their product to the market, 33% of respondents are in the startup stage, having just introduced their first product to the market, and around 56% already have significant sales and are to expand their business.

# 5.5. Empirical analysis

## 5.5.1. Estimation

The data generated in our DCE allows us to analyze the role of private control benefits and non-financial support activities in entrepreneurs' financing decisions. In discrete choice models, individuals face a series of choice situations consisting of a set of mutually exclusive choice alternatives. The statistical models used to analyze discrete choice data are (multinominal) logistic regressions. McFadden (1973) was the first to link these statistical models to a corresponding economic theory, random utility theory (RUT). In RUT, utility is expressed by two components: a structural component $V(x) = \beta\mathbf{x} - \omega p$ that is observable in the data, and a non-observable random component $\varepsilon$ about which a set of assumptions must be made. The structural component consists of the utilities derived from the attributes of the choice alternative, $\beta\mathbf{x}$, and the loss in utility due to the price of that alternative, $\omega p$. An alternative is chosen if, and only if, its total utility – the sum of the structural and the random components – is at least as large as all the utilities from other alternatives in the choice set.

In our experiment, respondents had to choose one out of $J = 3$ investment offers from different generic investors in $M = 10$ choice tasks. In our model, entrepreneurs draw utility from two main sources: future cash-flow rights in the company, which depend on company value and the entrepreneur's equity stake, and non-financial benefits, which depend on the level of control in the

**Table 5.2.: Description of sample and respondents**

| | Respondents | | | | | | Non-respondents | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Completed | | Not completed | | | | | | | |
| | N | Mean | N | Mean | Diff. | t | N | Mean | Diff. | t |
| **Selection criteria** | | | | | | | | | | |
| VC investor | 316 | 0.30 | 94 | 0.26 | 0.05 | (0.93) | 2929 | 0.21 | 0.10*** | (3.57) |
| VC fund | 317 | 0.07 | 94 | 0.02 | 0.04* | (2.20) | 2930 | 0.04 | 0.03* | (2.14) |
| Angel | 316 | 0.28 | 94 | 0.24 | 0.03 | (0.60) | 2959 | 0.20 | 0.08** | (3.00) |
| VC contact | 317 | 0.29 | 94 | 0.27 | 0.02 | (0.46) | 2965 | 0.32 | -0.03 | (-1.25) |
| R&D in 2018 | 317 | 0.59 | 94 | 0.61 | -0.01 | (-0.23) | 2963 | 0.55 | 0.05 | (1.56) |
| Growth objective | 307 | 0.44 | 88 | 0.44 | -0.00 | (-0.00) | 1490 | 0.56 | -0.12*** | (-3.90) |
| **Founding team** | | | | | | | | | | |
| Founder age | 315 | 46.16 | 94 | 42.43 | 3.73** | (3.03) | 2937 | 42.89 | 3.27*** | (5.17) |
| Female founder | 317 | 0.18 | 94 | 0.13 | 0.05 | (1.20) | 2965 | 0.16 | 0.02 | (0.93) |
| Founding exp. | 317 | 0.57 | 94 | 0.56 | 0.01 | (0.18) | 2963 | 0.51 | 0.06* | (2.10) |
| Industry exp. (in yrs.) | 316 | 17.72 | 93 | 18.28 | -0.55 | (-0.43) | 2958 | 15.35 | 2.38*** | (3.73) |
| **Firm** | | | | | | | | | | |
| Firm age | 317 | 2.56 | 94 | 2.62 | -0.05 | (-0.26) | 2946 | 1.87 | 0.70*** | (7.03) |
| Sales (in thsd. Euros) | 309 | 420.52 | 91 | 526.84 | -106.31 | (-1.40) | 2770 | 392.84 | 27.69 | (0.70) |
| Employees (F.T.E.) | 316 | 6.16 | 94 | 6.79 | -0.63 | (-0.62) | 2621 | 5.58 | 0.58 | (1.03) |
| Patent | 317 | 0.13 | 94 | 0.07 | 0.06 | (1.75) | 1487 | 0.09 | 0.05* | (2.31) |
| **Industry** | | | | | | | | | | |
| Hightech manufacturing | 317 | 0.15 | 94 | 0.13 | 0.03 | (0.67) | 2946 | 0.12 | 0.03 | (1.62) |
| Hightech services/ softw. | 317 | 0.41 | 94 | 0.41 | -0.01 | (-0.14) | 2946 | 0.33 | 0.08** | (2.64) |
| Non-hightech manufact. | 317 | 0.09 | 94 | 0.02 | 0.07** | (3.06) | 2946 | 0.12 | -0.03 | (-1.85) |
| B2B services | 317 | 0.12 | 94 | 0.19 | -0.07 | (-1.68) | 2946 | 0.17 | -0.05** | (-2.60) |
| B2C services | 317 | 0.16 | 94 | 0.20 | -0.04 | (-0.96) | 2946 | 0.20 | -0.04 | (-1.94) |
| Construction | 317 | 0.08 | 94 | 0.04 | 0.03 | (1.29) | 2946 | 0.06 | 0.01 | (0.85) |
| **Phase** | | | | | | | | | | |
| Seed | 317 | 0.11 | 94 | 0.09 | 0.03 | (0.75) | | | | |
| Startup | 317 | 0.33 | 94 | 0.26 | 0.08 | (1.45) | | | | |
| Growth | 317 | 0.56 | 94 | 0.66 | -0.10 | (-1.79) | | | | |
| Number of obs. | 317 | | 94 | | 411 | | 2965 | | 3282 | |

**Note**: This table shows the distribution of the sample. T-test assumes unequal variances.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

company. Therefore the utility of respondent $i$ ($i = 1,...,N$) for investment offer $j$ ($j = 1,...,3$) in choice task $m$ ($m = 1,...,10$) is expressed by the following equation

$$U_{ijm} = \beta_i \mathbf{x}_{ijm} - \omega p_{ijm} + \varepsilon_{ijm}. \tag{5.4}$$

The first term in Equation (5.4) is the structural component of utility, where $\mathbf{x}_{ijm}$ is a vector containing the levels for each of the four non-financial support activities, and the required level of contractual control. The second structural utility component, $p_{ijm}$, represents the cash-flow rights that the investor receives. Note that in our setting, the cash-flow rights associated with an investment offer – i.e., the required equity stake in the firm for the investor – fully reflects its 'price' for the entrepreneur. $\beta_i$ and $\omega$ are a vector and a scalar of unknown preference coefficients that we aim to estimate. The final term, $\varepsilon_{ijm}$, is the random utility component, which is assumed to be independent and identically distributed (i.i.d.) with an extreme value type I distribution.[8] This distribution has the convenient property of providing a closed-form solution for the choice probabilities. However, it also leads to a rather restrictive substitution pattern between alternatives that essentially rules out that new alternatives may change the choice probability between two alternatives. This is known as the independence from irrelevant alternatives (IIA) property. Another implication of the IIA property is that the error terms are not allowed to be correlated across alternatives. Models that imply the IIA property are often seen as being too restrictive, which is why alternative models have been formulated that relax this assumption. A commonly used and convenient model is the random coefficient mixed logit model, or mixed logit model (Revelt and Train, 1998). The mixed logit model is highly flexible and can approximate any random utility model (McFadden and Train, 2000). Importantly, it is not plagued by the IIA property and allows for correlating random utility components across alternatives. This is achieved by introducing another term to the random utility component, which is the scalar product of the attribute vector $x_{ijm}$ and a vector $\Gamma\xi_i$, where $\xi_i$ is a vector of i.i.d. error terms, and $\Gamma$ is a scaling matrix. Including the additional term allows the interpretation of the model having *random coefficients*, which leads to individual-specific coefficients. The vector of coefficients in our model is therefore given by

$$\beta_i = \beta + \Gamma\xi_i. \tag{5.5}$$

When in Equation (5.5), $\Gamma$ is specified as a lower triangular Cholesky matrix, the random coefficients in the model are correlated. The elements are uncorrelated if $\Gamma$ is specified as a diagonal matrix. Given that $\xi$ is a random parameter, the unknown preference coefficients in the mixed logit model, $\beta_i$, follow a density function $f(\beta|\theta)$, where $\theta$ is a set of structural parameters consisting of a location and a scale parameter (Train, 2009). The vector $beta$ gives the location parameters, and the scale parameter is contained in $\Gamma$. The increased flexibility of the mixed logit comes at a cost. To estimate the model, we have to make assumptions about the distribution of $\xi_i$, which captures the distribution of $f$. In our application, we assume that control preferences and preferences for non-contractual support parameters are normally distributed, so that $\xi_i \sim N(0, 1)$.[9] Furthermore, the price coefficient is assumed to be fixed in mixed logit models (Hess and Train, 2017). In robustness checks, we show that taking the price coefficient to be fixed does not change our main results.[10]

To assess the relative importance of control preferences for entrepreneurs, we express private control benefits in terms of willingness to pay (WTP). This also allows us to compare our results to the estimates of previous studies that have investigated private control benefits in a different

[8] The extreme-value-type-1 distribution is also known as the *Gumbel*-distribution.

[9] We also ran estimations using a log-normal distribution. This did not change the results substantially.

[10] Revelt and Train (1998) advise against having all coefficients vary randomly. Their argument is based on Ruud (1996), who argues that if it is the case that all coefficients are allowed to vary, the random coefficients dominate the i.i.d. error term, which makes scaling of utility by the variance of the extreme value term unstable.

setting (Dyck and Zingales, 2004). We obtain individuals $i$'s willingness to pay for attribute $k$ by dividing the estimated coefficient associated with $k$ by the estimated cash-flow coefficient $\omega$, which gives us a measure of how much additional equity entrepreneurs are willing to give up to retain more control in their company.

$$wtp_i^k = -\frac{\beta_i^k}{\omega} \tag{5.6}$$

We estimate our models using the maximum simulated likelihood estimator for mixed logit models in panels proposed by Revelt and Train (1998).[11] This estimator states the conditional likelihood contribution for alternative $j$ by individual $i$ in choice situation $m$ by:

$$L_{ijm}(\beta_i) = \frac{\exp(\beta_i \mathbf{x}_{ijm} - \omega p_{ijm})}{\sum\limits_{j' \neq j} \exp(\beta_i \mathbf{x}_{ijm} - \omega p_{ijm})}. \tag{5.7}$$

The probability for a sequence of choices is then given by the product of the sequence of conditional likelihood contributions:

$$S_i(\beta_i) = \prod_{m=1}^{M=10} L_{ij(i,m),m}(\beta_i). \tag{5.8}$$

To get the unconditional choice probability for individual $i$ we multiply Equation (5.8) by the density $f(\beta|\theta)$ and integrate over $\beta$, resulting in:

$$P_i(\theta) = \int S_i(\beta_i) f(\beta|\theta) d\beta. \tag{5.9}$$

Equation (5.9) represents the likelihood to observe individual $i$ making a sequence of choices $S_i$ as a function of the vector of structural parameters $\theta$. Our goal is to find the values of $\theta$ that maximize the likelihood of observing the data we collected in the experiment. As there is no closed form expression for the likelihood function in Equation (5.9), we first need to simulate the likelihood and then iteratively search for the values of $\theta$ that constitute a maximum. As with standard maximum likelihood estimators, we maximize the log-likelihood, which does not change the result of the maximization operation but simplifies the numerical search. Denote the log-likelihood by:

$$LL(\theta) = \sum_{i=1}^{N} \ln P_i(\theta), \tag{5.10}$$

[11] Since Stata 16, the maximum simulated likelihood estimator for panel mixed logit models is implemented in the `cmxtmixlogit` command.

then the simulated log-likelihood is given by:

$$SLL(\theta) = \sum_{i=1}^{N} \ln \left( \frac{1}{R} \sum_{r=1}^{R} S_i(\beta^r) \right). \tag{5.11}$$

The simulated log-likelihood is obtained by randomly drawing a sequence of coefficient vectors $\beta^r$ from a joint normal distribution given the structural parameters $\theta$. We use $R = 1000$ replications to simulate the likelihood function. In robustness checks, we show that the number of replications has no material influence on our results.

## 5.6. Results

Table 5.3 presents our first set of main results. It lists the average marginal effects of the estimates from the mixed logit model (McFadden and Train, 2000) underlying Equation (5.4). The model is reported for the full sample (*Full*), as well as for subsamples that exclude respondents not interested in venture capital (*VC*), only startup stage firms (*Startup*), and only growth stage firms (*Growth*). All models allow coefficients to correlate as specified in Equation (5.5).[12] The results are highly similar across these samples, and we focus our discussion on the full sample. The reported average marginal effects represent the change in the probability of choosing the observed investment offer, given a change in the respective parameters. All estimated parameters are statistically significant at $p < 0.001$.

The estimated marginal effects for cash-flow and control rights are all negative, implying that if an investor requires higher control through veto rights or a voting majority or requires a higher equity share, the probability of the offer being chosen decreases. By far, the largest effect size is measured for the parameter of voting majority, which decreases the likelihood of an investment offer being chosen by 34% in the full sample. As expected, veto rights are regarded as less limiting by entrepreneurs and therefore have a smaller effect of 13% on the probability of the investment offer being chosen. A 10 percentage point increase in the required equity share decreases the probability that the offer is selected by 13%. Conversely, investment offers that include non-financial support activities are more likely to be chosen. Investors offering market access are 14% more likely to be selected. Investors that can provide support by attracting additional finance with R&D activities or with strategic decisions induce smaller increases in

[12] Table D.1 in Appendix presents the correlations of the random coefficients. Requiring veto rights is positively correlated with requiring a voting majority, as are offering support with market access and support with R&D, as well as offering support with R&D and support with strategy. Requiring a voting majority is also negatively correlated with offering support with market access, even though this correlation is only weakly significant in the full sample. See Table D.2 in the appendix for model variations in willingness-to-pay space where $\Gamma$ is specified as a diagonal matrix, forcing the coefficients to be uncorrelated. This does not significantly impact the results.

choice probabilities of 5-6%.

**Table 5.3.: Marginal effects of changes in attribute levels**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Full | VC | By phase: | |
| | | | Startup | Growth |
| Equity share | -0.01$^{***}$ | -0.01$^{***}$ | -0.01$^{***}$ | -0.01$^{***}$ |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Veto rights | -0.13$^{***}$ | -0.13$^{***}$ | -0.13$^{***}$ | -0.13$^{***}$ |
| | (0.01) | (0.02) | (0.02) | (0.01) |
| Voting majority | -0.34$^{***}$ | -0.34$^{***}$ | -0.32$^{***}$ | -0.36$^{***}$ |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| Finance support | 0.06$^{***}$ | 0.08$^{***}$ | 0.08$^{***}$ | 0.05$^{***}$ |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Market access | 0.14$^{***}$ | 0.16$^{***}$ | 0.14$^{***}$ | 0.14$^{***}$ |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| R&D support | 0.05$^{***}$ | 0.06$^{***}$ | 0.06$^{***}$ | 0.05$^{***}$ |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Strategic support | 0.05$^{***}$ | 0.05$^{**}$ | 0.04$^{**}$ | 0.05$^{***}$ |
| | (0.01) | (0.01) | (0.01) | (0.01) |
| Pseudo R2 | 0.101 | 0.108 | 0.109 | 0.100 |
| Number of respondents | 317 | 141 | 140 | 177 |
| Number of choices | 3170 | 1410 | 1400 | 1770 |

**Note**: This table shows the average marginal effects from the mixed logit estimations. The reported coefficients represent the average change in the probability that an alternative is chosen, given a change in the respective attribute. In Column (1), if the investment offer requires a veto right, the probability of choosing the same offer decreases by approx. 13% for the average entrepreneur. Model 1, Full, presents the results for all respondents who completed the survey. Model 2, VC, excludes respondents who have indicated that they are not interested in venture capital financing. Models 3 and 4 split the sample by the respondent firm's growth phase. Model 3 contains respondents in the startup phase that have not yet finished developing their product or have recently begun to market their product. Model 4 includes respondents in the growth phase whose products already generate significant sales.
The random coefficients of the underlying mixed logit model follow a fully correlated Gaussian distribution, except for the equity share coefficient, which is set to be fixed. For the simulation of the Gaussian, we used $R = 1000$ draws from a Hammersley point set. We used the Broyden-Fletcher-Goldfarb-Shanno algorithm to maximize the likelihood function, for which all models converged within a reasonable number of iterations. The matrix $\Gamma$ in Equation (5.5) is specified as a lower triangular Cholesky matrix, allowing the random coefficients in the model to be correlated. Standard errors for marginal effects have been calculated using the delta method. See Table D.2 in the appendix for model variations in willingness-to-pay space where $\Gamma$ is specified as a diagonal matrix, forcing the coefficients to be uncorrelated.
Standard errors in parentheses. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<$

The first set of results indicates that private control benefits matter to entrepreneurs: the inclusion of more stringent control measures in an investment offer strongly decreases the chance that it is the preferred option. This result is independent of interest in VC finance and the development stage of the venture. But how much do entrepreneurs value private control? Table 5.4 addresses this by reporting the average willingness to pay for specific attributes expressed in terms of equity shares. On average, and considering the full sample of respondents (Column (1)), entrepreneurs are willing to give up an additional 12% of their equity to prevent investors from having a veto right in their company and an additional 38% of equity shares to prevent them from having a voting majority. The estimated willingness to pay for retaining control is mostly similar across company development stages (Columns (3) and (4)). When excluding respondents not interested in venture capital funding, the estimated willingness to pay is higher, at 13% for veto rights and 42% for a voting majority. A plausible explanation for this difference is that respondents that consider venture capital funding have such considerations more readily in mind than those that do not consider such funding mechanisms. To put these valuations into perspective, we compare these estimates to the more general results by Dyck and Zingales (2004), who found an average value of control of 1% of a firm's equity value in the United States, and 10% in Germany based on the market premiums attached to controlling block sales of large publicly traded companies.[13] Taking the estimates by Dyck and Zingales (2004) for Germany as a benchmark, private control benefits seem to be more than three times as large among young private companies and in the setting of VC, reflecting that independence is a critical non-monetary return to entrepreneurship.

Entrepreneurs are also willing to give up additional equity for VC value-added activities. For example, for investors that provide entrepreneurs with access to new markets, entrepreneurs are willing to give up an additional 12% of equity. Access to follow-on financing (finance), technical experts and cooperation partners (R&D), and strategic support are valued at around 4 to 5% of equity. This again suggests that entrepreneurs are especially interested in investors who offer market opportunities. Respondents who might be more interested in venture capital financing (Column (2)) show a higher willingness to pay for support with finance and market access than others, at 8% and 15%. We compare these results to the estimates by Hsu (2004), who look at investment offers for startups of the *MIT E-Lab Program*. He finds that highly-reputable venture capital investors acquire startup equity at a discount of 10 to 14%.[14] If we sum together the willingness to pay for each additional support activity from an investor who provides all considered support activities, they could, on average, acquire equity at a 25% discount in the full sample. However, if we assume that even highly reputable venture capital investors, who manage to select their ventures well, still require some additional level of control and factor in the lower willingness to pay for offers, including veto rights, we arrive at a similar result, a discount of approximately 13%.

### 5.6.1. Robustness tests and further analysis

The main results assume a fixed price coefficient. However, this approach may be misleading if large unobservable differences remain in individuals' valuations of offers (Meijer and Rouwendal,

[13] The authors note that these differences become smaller once firm and buyer characteristics are controlled for.

[14] Hsu (2004) utilizes several measures to capture reputation, including the venture capital's prior experience in the industry and the entrepreneur's perceptions of the venture capital's ranking and network.

**Table 5.4.: Willingness to pay for attributes**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Full | VC | By phase: | |
| | | | Startup | Growth |
| Veto rights | -11.57*** | -12.72*** | -11.98*** | -11.18*** |
| | (0.13) | (0.19) | (0.21) | (0.17) |
| Voting majority | -37.85*** | -41.99*** | -35.07*** | -39.32*** |
| | (0.32) | (0.46) | (0.46) | (0.42) |
| Finance support | 5.01*** | 7.58*** | 6.05*** | 4.16*** |
| | (0.09) | (0.15) | (0.15) | (0.12) |
| Market access | 11.48*** | 15.37*** | 11.29*** | 11.64*** |
| | (0.12) | (0.19) | (0.17) | (0.17) |
| R&D support | 4.52*** | 5.82*** | 5.18*** | 3.99*** |
| | (0.09) | (0.14) | (0.15) | (0.11) |
| Strategic support | 3.83*** | 4.62*** | 3.73*** | 3.94*** |
| | (0.09) | (0.15) | (0.15) | (0.12) |
| Pseudo R2 | 0.101 | 0.108 | 0.109 | 0.100 |
| Number of respondents | 317 | 141 | 140 | 177 |
| Number of choices | 3170 | 1410 | 1400 | 1770 |

**Note**: This table shows the average willingness to pay estimated from the mixed logit models. The willingness to pay is calculated according to Equation (5.6), dividing the estimated attribute parameters by the equity share parameter. In Column (1), the average willingness to pay to retain veto rights amounts to an equity share of 11% for the average entrepreneur. Model 1, Full, presents the results for all respondents who completed the survey. Model 2, VC, excludes respondents who have indicated that they are not interested in venture capital financing. Models 3 and 4 split the sample by the respondent firm's growth phase. Model 3 contains respondents in the startup phase that have not yet finished developing their product or have recently begun to market their product. Model 4 includes respondents in the growth phase whose products already generate significant sales.
The random coefficients of the underlying mixed logit model follow a fully correlated Gaussian distribution, except for the equity share coefficient, which is set to be fixed. For the simulation of the Gaussian, we used $R = 1000$ draws from a Hammersley point set. We used the Broyden-Fletcher-Goldfarb-Shanno algorithm to maximize the likelihood function, for which all models converged within a reasonable number of iterations. The matrix $\Gamma$ in Equation (5.5) is specified as a lower triangular Cholesky matrix, allowing the random coefficients in the model to be correlated. Standard errors for marginal effects have been calculated using the delta method.
Standard errors in parentheses. Significance levels: *** p$<$0.001, ** p$<$0.01, * p$<$0.05.

2006). It may be more reasonable to model the price coefficient as a random parameter, allowing individuals to have different tastes with respect to the price attribute. However, as Hole and Kolstad (2011) shows, simply modeling the price coefficient as a random parameter may lead to unreasonably large estimates of willingness to pay because the distribution of willingness to pay may not be well defined.[15] They recommend estimating willingness to pay directly - as suggested by Train and Weeks (2005) - and comparing the results to those estimated in preference space. To see how sensitive our results are to the model specification, we estimate willingness to pay as described in Train and Weeks (2005). We also provide model specifications for different numbers of simulations and estimate each model with and without correlated preferences. Table

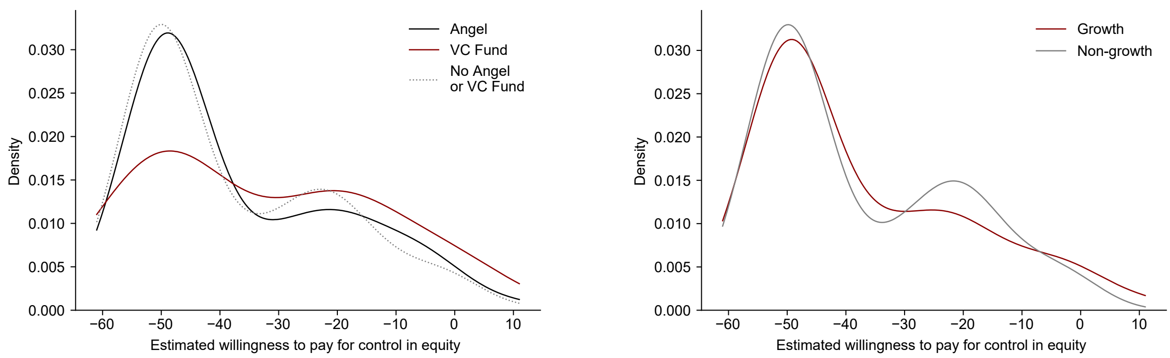
[15]Essentially, when the price coefficient is close to zero, estimates of willingness-to-pay result in ill-defined distributions.

D.2 in the appendix shows that all model variations yield very similar coefficient estimates and do not have a meaningful impact on interpreting the results.

Figure 5.1 further illustrates the validity and importance of our findings. The figures plot the distribution of the estimated equity share, in equity, that entrepreneurs are willing to pay for a VC investment that includes a voting majority for the VC. In line with the previous analysis, the estimated willingness to pay is negative. Panel (a) provides a small test of our findings' validity: if the estimated preferences are meaningful, they should correlate with observed behavior. Hence, we plot the estimated willingness to pay for entrepreneurs that did not receive external equity, for those that received angel investment, and for those that received VCF investment.[16] For those without prior investment experience with VCs, the willingness to pay peaks around -50, indicating that they would need to retain 50% more of equity to accept a VC offer that includes a voting majority of the VC. In contrast, for those that previously accepted VC funding, the peak at -50 is much smaller, and the willingness to pay is generally higher. While we cannot disentangle to what extent these effects are driven by pure preferences and to what extent they result from pure experience, these differences indicate that our estimated preferences relate to observed behavior.

**Figure 5.1.: Distribution of willingness to pay for control**

**(a) By investor type** **(b) By growth orientation**




**Note:** This figure shows the distribution of the estimated equity share that an entrepreneur is willing to give up for a VC offer that delivers a voting majority to the VC, which is strongly negative for the vast majority of entrepreneurs. Panel (a) compares entrepreneurs that received investment from different equity investors, as indicated in the Startup Panel Survey. Entrepreneurs that did not receive investment and those that received angel investment show a similar willingness to trade off equity for control, with a large peak around -50 indicating that they would be unwilling to yield control within the experiment's parameters. However, entrepreneurs that received investment by a VC show a more dispersed and generally higher willingness to pay. Thus, the estimated willingness to pay for control matches observed behavior. Panel (b) shows that control preferences are largely unrelated to the growth orientation of the firm, as measured through the firms' stated objective in the survey. Hence, both types of firms might self-select out of VC funding because of control considerations. Technical notes: Kernel densities are estimated using a Gaussian kernel. The bandwidth is calculated using Scott's Rule, i.e., $n(-1/(d+4))$, where $n$ is the number of data points and $d$ is the dimension of the data. For the weighted kernel density estimates, the effective number of data points $n_{eff} = \sum_i (w_i)^2 / \sum_i (w_i^2)$ is used, where $w_i$ is the weight of data point $i$. Kernel densities are clipped at the minimum and maximum of the sample (min=-61, max=11).

[16] Information on prior investments was recorded in the Startup Panel as yes/no indicators, considering the full-time period between the founding of the venture and the moment of the interview. While the ideal test would be to trace only the future investment behavior of experiment participants, the incidence of VC funding is too low to conduct such an analysis.

It is tempting to assume that growth-oriented entrepreneurs are more willing to trade away control, as entrepreneurs with high growth ambitions might be more willing to suffer a loss of control in return for the financial, reputational, and other resources that VC investment provides. If that were the case, our results would be less pressing, as the prevalence of control rights in VC funding would then only lead to stronger selection on growth orientation. However, Panel (b) of Figure 5.1 shows that this is not the case: entrepreneurs who describe growth as the firm's primary objective show a similar willingness to pay for control as entrepreneurs that do not consider growth the primary goal.[17] Thus, the degree up to which a founder is willing to pay for VC investment by giving up control does not directly relate to the growth orientation of their firm, and the control cost inherent to VC contracts selects out growth-oriented as well as non-growth-oriented entrepreneurs.

## 5.7. Conclusion

This study answers a core question in entrepreneurial finance: How much do entrepreneurs value being in control of their ventures? This question is important, as transfer of control is key to solving agency issues in early-stage equity finance (Aghion and Bolton, 1992). If entrepreneurs value control rights very highly, entrepreneurs might reject growth opportunities because they are costly in terms of control rights (Cestone, 2013; Wasserman, 2016).

We contribute to the literature by conducting a discrete choice experiment, where entrepreneurs in Germany are tasked with deciding between investment offers that offer varying levels of cash-flow rights, control rights, and VC value-added activities. In this framework, we can estimate entrepreneurs' valuations of control and VC value-added activities, avoiding issues of self-selection and endogeneity inherent to other approaches such as those based on VC contracts (Bienz and Walz, 2010; Ewens, Gorbenko, et al., 2021; Kaplan and Stromberg, 2003). Further, we can express these valuations in a meaningful way, namely the share of cash-flow rights that an entrepreneur is willing to give up to retain a specific control right. Our results show that entrepreneurs greatly value control. On average, they are willing to give up 12% more in cash-flow rights to avoid giving an investor a veto right and to trade 38% of cash-flow rights to avoid giving up a voting majority. Further analysis shows that the willingness to pay for control is higher among entrepreneurs experienced with VC investing. The willingness to pay for control is similar among firms with and without strong growth orientation. In addition, entrepreneurs are willing to give up additional cash-flow rights in return for VC value-added activities for further business development. Support with developing customer or distribution networks is valued especially highly, at 12% of equity, whereas support with finance, R&D, and strategy are valued less, at 4-5% of equity.

[17] Growth orientation was measured in the Startup Panel survey

Our study is the first to provide estimates of the value of control that can be generalized to the broader population of entrepreneurs. In line with the idea that the allocation of control is an essential issue in the context of entrepreneurship, our estimates of the value of control among entrepreneurs in the entrepreneurship setting are three times larger than prior estimates in a more general setting (Dyck and Zingales, 2004). Our results also hint that control rights likely make up a large share of the non-monetary returns to entrepreneurship, as discussed in, e.g., Hyytinen et al. (2013) and Moskowitz and Vissing-Jørgensen (2002). For the understanding of VC value-added activities, our result implies that, from the entrepreneur's perspective, VCs add the most value from their networking capabilities (Hochberg et al., 2007; Tykvová, 2007), as access to the market is valued highest.

Our results have the important implication that the tools employed for overcoming agency issues in the market for early-stage equity finance are highly costly for entrepreneurs. Whereas overcoming such problems is of critical importance for investors who otherwise face uncertainties about the intentions of entrepreneurs and the prospects of their ventures (Aghion and Bolton, 1992), they might also form important barriers for entrepreneurs to seeking out external finance. Our findings also speak to trends observed in recent literature, where VCs are more often acting under less strong control regimes (Lerner and Nanda, 2020), and where business angel activity is increasingly important (Cumming and Zhang, 2018). For VCs, our work implies that investments could be made at a discount when less strict control rights are attached. In addition, awareness of the importance of entrepreneurs' control rights might help advance negotiations in a more general sense. One clear policy implication of our findings is that programs that seek to strengthen entrepreneurship by expanding the supply of financial capital (Hellmann and Thiele, 2019, e.g.) should pay attention to the mode of delivery, as capital that is provided in modes that involve strong control rights might select entrepreneurs with a weak preference for independence. To reach all (potential) entrepreneurs, capital and enjoyment of independence need to be decoupled. While our framework does not allow us to quantify how much growth is not realized because of control considerations, it is likely to be substantial.

Our work is not without limitations. In reality, control manifests through different channels. It is subject to many contingencies, such as the riskiness of the investment for the VC and the size of the information asymmetry between VC and entrepreneur (Cestone, 2013; Kaplan and Stromberg, 2003; Lerner, 1995). Although essential, we are incorporating these nuances in a discrete choice experiment that likely goes beyond what can be comprehensibly estimated. At the same time, control over a venture is not a state but a continuum (Kirilenko, 2001). While our study estimates the value of control at critical levels, we still only estimate valuations at discontinuous levels. Future work could investigate more fine-grained shifts in control. Moreover, it remains ill-understood what discount entrepreneurs assign to contingencies, such as performance-based control rights. Furthermore, future work could investigate the role of uncertainties on the side of entrepreneurs, such as uncertainties revolving around the delivery of VC value-added activities.

# 6. Conclusion

Innovation-driven entrepreneurship plays an essential role in economic growth. Economists and policymakers are therefore interested in understanding how innovation-driven entrepreneurship emerges and under what framework conditions and policies it thrives. The main focus of this thesis is on policies that aim to ease access to finance for young and innovative firms, which is an essential precondition for innovation-driven entrepreneurship. The four main chapters of this thesis provide new empirical evidence on the effective interplay of different types of entrepreneurship policies to foster the supply of venture capital (Chapters 2 and 3), its role in innovation (Chapter 4), and its limitations (Chapter 5).

## 6.1. Summary and implications of results

The first chapter of the main body (Chapter 2) looks at the well-established link between public subsidies and access to venture capital. Based on the notion that the value of subsidies differs between investors, this chapter contributes to the literature by explicitly distinguishing between different types of venture capital investors. The analysis confirms the positive link between subsidies and all types of venture capital (including angel investors, independent, corporate and governmental VC). Yet when accounting for selection into subsidies, the positive link only remains for governmental VC and angel investors, who are more likely to be constrained in their resources. Different types of venture capital investors are known to have different effects on the longer-run performance of startups; these results, therefore, have important implications for policymakers. Stand-alone investments from governmental VCs and angel investors have been shown to result in less radical innovations (Bertoni and Tykvová, 2015; Chemmanur et al., 2014; Dutta and Folta, 2016) and lower exit rates compared to independent or corporate VCs (Cumming, Grilli, et al., 2017; Cumming and Zhang, 2018). The effectiveness of startup subsidies in nurturing radical innovations and creating valuable companies, therefore, depends on the ability of these investors to attract follow-on investments from independent or corporate VCs. Likewise, subsidies for startups may promote a particular type of innovation that is less radical and require less funding to become marketable in the first place.

An obvious implication from the study in Chapter 2 is that obtaining follow-on financing by venture capitalists requires the existence of a (sufficiently large) market for external equity capital. In recent years, various countries have introduced subsidy programs for private investors through tax credits or grants to stimulate the creation or increase the size of early-stage equity markets. Chapter 3 considers the case of Germany and the INVEST grant to investigate the effect of subsidy programs for angel investors on firms' access to financial *and* managerial resources. The latter is important in light of concerns about angel investor subsidies lowering the level of managerial support, which is considered to be particularly important for the success of innovative startups. The Difference-in-Differences estimates provide a lower bound on the effects of investor subsidies. The results indicate positive effects of angel investor subsidies on startups' access to financing. Angel investor subsidies increase the likelihood of closing a deal with an angel investor by about one-third and financing amounts by about two-thirds. Conversely, there is no strong support for an adverse effect of subsidies on managerial support. The results further indicate that angel investor subsidies increase the size of investor syndicates. Taken together, this is consistent with the notion that new and potentially less qualified investors join forces with more experienced investors. This could explain why there is a large positive effect on financing but no strong support for the presumed negative impact on the level of managerial support. In summary, the analysis in Chapter 3 indicates that subsidies to angel investors are an effective policy instrument to stimulate the market for early-stage equity capital.

A primary motive for startup subsidies and policies to foster an active market for equity financing is to encourage (radical) innovations. Venture capital is considered to be an important driver of innovation. Yet, previous research provides conflicting results on the role that equity financing plays in the creation of innovation. The basic question underlying these studies is: does private venture capital *generate innovation*, or does it primarily *facilitate* their *commercialization*? Chapter 4 provides empirical evidence on the causal link between outside equity financing and its role in innovation, using the introduction of the INVEST program for private investors as a quasi-natural experiment. The instrumental variable results show that outside equity financing does not induce startups to invest more in R&D but almost doubles the likelihood of introducing global market novelties. These results highlight that equity financing plays an important role in commercializing innovations with a high degree of novelty. In addition, these results point towards a complementary role of direct subsidies for startups and subsidies for angel investors to promote innovation. While direct support for startups through startup and R&D grants may allow startups to experiment with new technologies to create new products and services, subsidies for angel investors allow more firms to commercialize these products and services in unproven markets.

Financing radical innovation is characterized by many unknowns, i.e., a high degree of *Knightian uncertainty*. An essential element of VCs' investment model is to reduce these risks by actively exerting influence on the companies they finance. This is achieved through various contractually defined control rights but also requires a high level of industry and market-specific knowledge. The final chapter of the main section (Chapter 5) examines the extent to which these control rights limit the broader use of venture capitalists' investment model to finance innovation and growth. The chapter is based on a discrete choice experiment conducted with founders as part of a large-scale survey of young companies in Germany. The results of the experiment show that founders attach an extraordinarily important role to control rights, which exceed the perceived benefits from investors' expertise. This is especially true when their firms have patents, higher sales, and have not received financing from VC funds. The results indicate that founders' control preferences are a barrier to financing for innovative and growth-oriented firms and limit the potential of venture capital financed innovation and growth in the economy.

## 6.2. Prospects for future research

Limited data and limited time mean that this thesis had to ignore some interesting and relevant questions. In addition, the research presented here raises several new questions that set the stage for future research.

One crucial aspect that has remained unanswered due to limited data is the exact mechanisms leading to the results in Chapter 2. In particular, it is unclear why angel investors and governmental VCs are more responsive to startup subsidies. For the case of angel investors, Chapter 2 proposes two explanations: limited financial resources of these investors and differences in ex-ante information acquisition. Limited financial resources may constrain angel investors' ability to diversify risk and therefore have them rely much stronger on startup subsidies to lower technology-related uncertainty. Likewise, it has been argued that the intensive due diligence and knowledge base of independent and corporate VCs reduces the potential information value of startup subsidies. To separate these effects from each other, additional information on startup subsidies would be helpful. Data on the amount of funding as well as the information value of subsidies, i.e., their potential to serve as a separating signal, would prove beneficial. Understanding the relative salience of the two has important implications for efficient policy design. For example, if limited financial resources hold investors back from investing in early-stage companies, startup subsidies can be considered an efficient policy instrument. If, on the other hand, it is the information value of subsidies that over-weighs, then potentially less costly signals such as promoting startup competitions or seals of excellence may prove equally effective. Investigating the underlying mechanisms further is a promising avenue for future research.

The third chapter has covered various aspects of angel investor subsidies' effects on startups' access to financial and managerial resources, including the mechanisms that govern these effects. Given the role that syndication seems to play in the effectiveness of subsidy programs, it would be essential to understand the part of existing investors and their level of organization. For example, angel investor subsidies may be particularly effective in regions or countries where angel investors are highly organized in formal networks or clubs. In highly organized markets, new investors should find it easier to join existing networks and syndicate their investments. Further investigating this aspect would require data on angel investor networks at the regional or national level. Related to this are the dynamic elements of angel investor subsidies concerning syndication, which I could not investigate further in this thesis. In the case of new investors that enter the market as a result of the subsidy, it would be relevant to understand whether these investors remain in the market or exit after their initial investment. Also, do new investors take a more passive role from the start (something that could not be shown with the disposable data)? And if they do, do they remain passive investors, or do they learn from more experienced investors and become more actively involved investors over time? In addition, we would like to learn more about the motivation of professional investors to syndicate with new investors. Do new investors increase the deal flow of existing investors, or do they merely facilitate leveraging higher financing amounts? A final aspect I could not analyze with the disposable data is the potentially different incentive effects across individual elements of angel investor subsidies. In the case of the INVEST program, investors receive both an investment subsidy and an exit grant, of which the latter is essentially a capital gains credit. Not only might the overall incentive effects of these components differ, but they might also be valued differently by different investors. For example, the incentive effect of *ex-ante* investment subsidies may be more important for new investors. In contrast, experienced investors may be more responsive to *ex-post* capital gains credits on exit proceeds. Further insights on these aspects of investor subsidies would allow for more informed and targeted policy designs.

The INVEST program specifically targeted private individuals investing directly in startup firms. The immediate supply shift that I use in Chapter 4 to identify the causal effect of outside equity is therefore limited to a specific group of investors. Previous research shows that angel investor groups have a positive impact on the performance of startup companies (Lerner, Schoar, et al., 2018), but also indicates that stand-alone investments from angel investor groups result in less radical innovations compared to venture capital funds (Dutta and Folta, 2016). Our results may, therefore, not translate to independent or corporate VCs. In other words: increasing the supply of financing from independent or corporate VC funds may not only foster the introduction of market novelties but also allow startups to increase investments in R&D. a critical question that arises in this context is whether expanding the supply of angel financing through both direct startup subsidies and subsidies to angel investors caters to a specific type of potentially less radical innovations. Following the notion of Nanda and Rhodes-Kropf (2017b), uncertainty about follow-on financing - which angel investors may not be able to provide - could leave the most radical innovations untapped by angel investors, as more radical innovations are likely to require large upfront investments in R&D. If the majority of additional angel investments do not expect to secure follow-on financing from larger investors - such as independent or corporate VCs - this may have repercussions on the type of innovations that entrepreneurs pursue. Investigating the link between the prospects to raise larger financing amounts and the type of innovations pursued by angel-financed startups is another promising avenue for future research.

In Chapter 5, we argued that entrepreneurs' control preferences pose a barrier to VC financing. Our argument is based on the notion that these control benefits result from an intrinsic valuation of control. While the model is based on an extensive literature review that provides support for our modeling assumptions, it may also be the case that entrepreneurs' control preferences are based on a strategic rationale: entrepreneurs may view that relinquishing control to investors (early on) limits their potential to maximize their profits. This will be the case if entrepreneurs believe that investors are not able (or willing) to maximize firm value. Such beliefs can be plausibly consistent in capital markets with a low average quality of investors. While the experiment partially captures investors' quality through their value-adding support activities, it may not fully capture entrepreneurs' concerns about investors' qualities. Understanding whether intrinsic or strategic considerations make entrepreneurs abstain from relinquishing control to investors in exchange for financing is another promising avenue for future research. The relative salience of these two considerations will result in different policy implications. In case strategic considerations prevail, it is not entrepreneurs' control intentions but more likely entrepreneurs' perception of investors' qualities that may limit the potential of venture capital financed innovation and growth.

# II

# Appendix

# A. Startup Subsidies and the Sources of Venture Capital

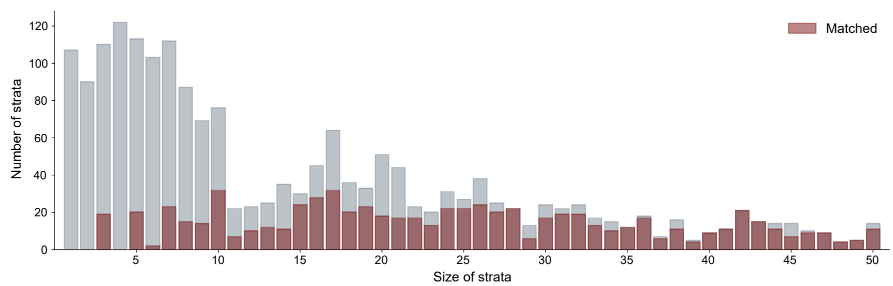
# A.1. Detailed description of matching algorithm

Our matching algorithm proceeds in the following way: First, we keep treated observations in the year that they have received their first subsidy, as well as the set of control observations that have been active in the same period. For those observations, we estimate the propensity score $p(x)$ for being treated, i.e. the treatment probability, using the full set of covariates $x$ displayed in the upper panel of Table 2.2.

Second, we define a set of strata $S = \{s_1, s_2, ..., s_M\}$ based on exact matching criteria. In particular, we require that firms in each stratum are from the same founding cohort, the same industry, are located in a similar region, have the same age when entering the survey and operate in the same year. Based on the number of categories within each variable in our data, this results in $\tilde{M} = 6,048$ distinct strata of which $M = 2,757$ have at least one observation in our sample.[1] Observations within each stratum $s_m$ can be divided into two groups: treated observations $i \in I$ and control observations $j \in J$.

To assign control observations to treated observations, we perform caliper matching on the estimated propensity score. That is we define observation $j$ within stratum $m$ to be a *counterfactual* for observation $i$ whenever $|\hat{p}_j^m - \hat{p}_i^m| \leq c$, where $\hat{p}$ are the estimated propensity scores and $c$ is the caliper width. The resulting set of matched strata $Z = \{z_1, z_2, ..., z_{\bar{M}}\}$ contains $\bar{M} = 1,533$ strata $z_m$ for which we identify at least one tuple $ij$ of caliper matches. Strata for which the sample contains more observation have a higher likelihood of having matching tuples. Strata that consist of only one observation cannot have a match by definition (see Figure A.1). Matched strata $z_m$ may contain multiple matches, whenever the number of treated observations within $z_m$ is larger than one.

**Figure A.1.: Number of strata by size of strata**




**Note:** Figure A.1 shows the number of strata by the size of strata, i.e. the number of observations within each stratum.

[1] The number of distinct strata can be calculated using the cross product. We have three regions, four industry groups, fourteen founding cohorts, three age groups and twelve observation periods, which gives $3 \times 4 \times 14 \times 3 \times 12 = 6,048$ strata. Given not every element of all potential quintuples is represented in our data, the number of strata in our sample is smaller.

Based on the set of matched strata $Z$, we calculate matching weights. Treated observations - i.e. firms that have received a subsidy in period $t$ - always receive a weight of one. For each treated observation $i$ that is matched, the weights of all counterfactuals must add up to one, i.e. $\sum_{j|ij\in z_m} w_j^{i,m} = 1$. Within each matched stratum $z_m$, control observation may be used multiple times as counterfactuals. To account for this, all matching weights of control observation $j$ are added up. If there are $N^{i,m}$ matches for observation $i$ in stratum $m$, then the matching weight for observation $j$ used in the estimation is given by

$$w_j^m = \sum_{i|ij\in z_m} 1/N^{i,m}.$$

Hence, the matching weight for observation $j$ in stratum $m$ is calculated by adding up all weights $1/N^{i,m}$ for all $i$ that are a match to control observation $j$.

The vector of calculated weights $w = (w_1^1, ..., w_J^{\bar{M}})'$ is the used in our main model specification in equation 2.1 as probability weight in parametric regressions.

# A.2. Additional Tables and Figures

**Table A.1.: Description of variables**

| Variable name | Variable description |
|---|---|
| Subsidy(T) | The startup has received a subsidy as a grant, loan or guarantee in any year. |
| VC(T) | The startup received at least one investment by any venture capital investor in any year. |
| GVC(T) | The startup received at least one investment by a governmental venture capital investor in any year. |
| IVC(T) | The startup received at least one investment by an independent venture capital investor in any year. |
| CVC(T) | The startup received at least one investment by a corporate venture capital investor in any year. |
| Angel(T) | The startup received at least one investment by an angel investor in any year. |
| Start-up age at VC (1) | Age of the startup at first VC financing round. |
| Start-up age | Age of the startup in years. |
| Founder age | Age of the founders at foundation, for teams it is the average founder age. |
| Team | The startup was founded by more than one person. |
| Academic | At least one founder has a university degree. |
| Female | At least one founder is female. |
| Industry experience | Years of industry experience at foundation. |
| Founding experience | At least one founder has previously founded a company. |
| Failure experience | At least one founder has failed before. |
| Opportunity-driven | The startup was founded to realize a concrete business idea. |
| R&D(T) | The startup has conducted research and/or development activity in any year. |
| Patent | The startup held a patent at foundation. |
| Founding year | The startup's year of foundation. |
| Industry | The main industry the startup operates in. |
| Region | The startup's business location (West Germany, East Germany, Berlin). |

**Note**: All of the variables used are binary variables. Except for Industry, Region and Founding year, which are categorical variables and Industry experience and Founder age which are measured in years.

**Table A.2.: Sector classification**

| IAB/ZEW classification | NACE rev. 1 |
|---|---|
| Hightech manufacturing | 20.13, 20.14, 20.16, 20.17, 20.2, 20.41, 20.51, 20.53, 20.59, 21.1, 21.2, 22.11, 22.19, 23.19, 24.46, 25.4, 26.11, 26.2 , 26.3 , 26.4 , 26.51, 26.6, 26.70, 27.1, 27.2, 27.4, 27.9, 28.1, 28.23, 28.24, 28.29, 28.3, 28.41, 28.49, 28.92, 28.93, 28.94, 28.95, 28.96, 28.99, 29.1, 29.3, 30.2, 30.3, 30.4, 32.5 |
| Hightech services & software | 61.1, 61.2, 61.3, 62, 63.1, 71.1, 71.2, 72.1 |
| Lowtech manufacturing | 10-33 (w/o hightech manufacturing) |
| B2B & knowledge-int. services | 49.2, 49.5, 50.2, 50.4, 51.2, 52, 53, 61.9, 63.9, 64, 69, 70.2, 72.2, 73.1, 73.2, 74.1, 74.3-74.9, 77.1, 77.3, 77.4, 78, 80-82 |
| B2C & retail | 45-47 (w/o 46.1), 49.1, 49.3, 49.4, 50.1, 50.3, 50.1, 50.3, 51.1, 55, 56, 58-60, 65-66, 68, 74.2, 77.2, 79, 85.5-85.6, 90-93, 95-96 |
| Construction | 41-43 |

**Note**: The classification of the sectors follows the definitions by the German Federal Statistical Office. The energy/mining sector (10-14, 40, 41), the transport sector (60-63), the postal system (64.1) and the banks and assurance sector 65-67) are not included in the sampling.

**Table A.3.: Distribution of sources of VC by data source**

| | Deals | | | | | |
|---|---|---|---|---|---|---|
| | Majunke | | Zephyr | | Disambiguated | |
| | N | % | N | % | N | % |
| Angel | 2,112 | 43 | 1,187 | 33 | 2,328 | 38 |
| IVC | 2,399 | 49 | 1,961 | 55 | 3,125 | 50 |
| GVC | 2,077 | 42 | 1,528 | 43 | 2,483 | 40 |
| CVC | 1,322 | 27 | 883 | 25 | 1,559 | 25 |
| Total | 4,891 | | 3,575 | | 6,200 | |

| | Firms | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Majunke | | Zephyr | | Disambiguated | | Full match | | Final sample | |
| | N | % | N | % | N | % | N | % | N | % |
| Angel | 1,543 | 49 | 891 | 38 | 1,693 | 44 | 152 | 46 | 125 | 48 |
| IVC | 1,545 | 50 | 1,318 | 56 | 1,976 | 52 | 150 | 45 | 117 | 45 |
| GVC | 1,467 | 47 | 1,138 | 48 | 1,733 | 45 | 224 | 68 | 178 | 68 |
| CVC | 941 | 30 | 654 | 28 | 1,092 | 28 | 77 | 23 | 62 | 24 |
| Total | 3,118 | | 2,351 | | 3,835 | | 331 | | 262 | |

**Note**: The upper part of the table shows the absolute (N) and relative (%) frequency of deals involving specific sources of venture capital in the different data bases. The column *Disambiguated* accounts for deals that may occur in both data bases, and represents the union of both databases discarding duplicate values. The lower panel accounts for firms receiving various funding rounds, looking at unique firm observations within each data base. *Full match* gives the intersection of the disambiguated transaction data and the IAB/ZEW Startup Panel, and *Final sample* is the sample used in the analysis. As firms may receive funding from various funding sources, the number of firms by financing source are larger than the total.

**Table A.4.: Share of VC sources within industries in database**

| | Angel | IVC | GVC | CVC |
|---|---|---|---|---|
| Hightech manufacturing | 0.35 | 0.49 | 0.66 | 0.23 |
| Hightech services & software | 0.46 | 0.51 | 0.50 | 0.28 |
| Lowtech manufacturing | 0.36 | 0.40 | 0.51 | 0.17 |
| B2B & knowledge-int. services | 0.43 | 0.54 | 0.34 | 0.32 |
| B2C & retail | 0.46 | 0.55 | 0.33 | 0.34 |
| Construction | 0.33 | 0.33 | 0.42 | 0.17 |
| N/A | 0.40 | 0.54 | 0.40 | 0.23 |
| Total | 0.44 | 0.52 | 0.45 | 0.28 |

**Note**: This table shows the relative frequency of firms in different industries, receiving specific sources of venture capital in the disambiguated data of Majunke and Zephyr. For example, 35% of firms in hightech manufacturing receive at least one round of financing from angel investors.

**Table A.5.: Industry distribution by data source**

| | Disambiguated | | Startup Panel (full) | | Startup Panel (sample) | |
|---|---|---|---|---|---|---|
| | N | % | N | % | N | % |
| Hightech manufacturing | 305 | 8 | 85 | 26 | 75 | 29 |
| Hightech services & software | 1,890 | 49 | 183 | 55 | 165 | 63 |
| Lowtech manufacturing | 168 | 4 | 11 | 3 | 9 | 3 |
| B2B & knowledge-int. services | 529 | 14 | 18 | 5 | 13 | 5 |
| B2C & retail | 703 | 18 | 14 | 4 | | |
| Construction | 12 | 0 | 1 | 0 | | |
| N/A | 228 | 6 | 19 | 6 | | |
| Total | 3,835 | | 331 | | 262 | |

**Note**: This table shows the absolute and relative frequency by industries in the different data sources. Disambiguated gives the union of the Majunke and Zephyr database, accounting for duplicate deals. Full gives the intersection of the disambiguated transaction data and the full IAB/ZEW Startup Panel, and sample is the sample we use in our analysis.

**Table A.6.: Correlation matrix of main variables**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) VC(T) | 1.00 | | | | | | | | | | | | | | |
| (2) GVC(T) | 0.82 | 1.00 | | | | | | | | | | | | | |
| (3) Angel(T) | 0.69 | 0.52 | 1.00 | | | | | | | | | | | | |
| (4) IVC(T) | 0.66 | 0.43 | 0.48 | 1.00 | | | | | | | | | | | |
| (5) CVC(T) | 0.48 | 0.37 | 0.44 | 0.32 | 1.00 | | | | | | | | | | |
| (6) Founder age | −0.09 | −0.07 | −0.07 | −0.06 | −0.06 | 1.00 | | | | | | | | | |
| (7) Team | 0.11 | 0.09 | 0.07 | 0.07 | 0.05 | −0.11 | 1.00 | | | | | | | | |
| (8) Founding experience | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.15 | 0.17 | 1.00 | | | | | | | |
| (9) Failure experience | −0.00 | 0.01 | 0.00 | −0.00 | 0.01 | 0.02 | 0.02 | 0.43 | 1.00 | | | | | | |
| (10) Industry experience | −0.09 | −0.07 | −0.07 | −0.06 | −0.06 | 0.54 | 0.02 | 0.10 | 0.03 | 1.00 | | | | | |
| (11) Opportunity-driven | 0.07 | 0.06 | 0.04 | 0.05 | 0.03 | 0.04 | 0.13 | 0.12 | −0.02 | −0.04 | 1.00 | | | | |
| (12) Academic | 0.10 | 0.09 | 0.07 | 0.07 | 0.04 | 0.05 | 0.22 | 0.04 | −0.02 | −0.06 | 0.10 | 1.00 | | | |
| (13) Female | −0.01 | −0.01 | 0.00 | −0.01 | −0.01 | 0.03 | 0.20 | −0.03 | −0.01 | −0.02 | 0.02 | 0.01 | 1.00 | | |
| (14) Patent | 0.02 | 0.03 | 0.01 | 0.00 | 0.01 | 0.11 | 0.01 | 0.06 | 0.02 | 0.04 | 0.08 | 0.05 | 0.01 | 1.00 | |
| (15) R&D(T) | 0.13 | 0.11 | 0.09 | 0.08 | 0.06 | −0.02 | 0.10 | 0.09 | 0.01 | −0.05 | 0.20 | 0.17 | −0.06 | 0.16 | 1.00 |
| Firm obs. | 9.743 | | | | | | | | | | | | | | |

**Table A.7.: Distribution of subsidies and VC by industry**

| | Subsidized | VC |
|---|---|---|
| Hightech manufacturing | 45.8 | 3.8 |
| Hightech services & software | 32.7 | 3.7 |
| Nontech manufacturing | 45.7 | 0.7 |
| B2B & knowledge-int. services | 23.8 | 0.6 |
| Total | 9743 | |

**Note**: The table shows the percentage of firms receiving a subsidy and some type of VC.

**Table A.8.: Results for unbalanced pooled models**

| | VC | GVC | Angel | IVC | CVC |
|---|---|---|---|---|---|
| Subsidy(t) | 0.0034*** | 0.0028*** | 0.0016*** | 0.0011*** | 0.0007** |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Startup age (log) | -0.0044*** | -0.0033*** | -0.0017*** | -0.0011*** | -0.0007*** |
| | (0.0004) | (0.0004) | (0.0003) | (0.0002) | (0.0002) |
| Founder age (log) | -0.0061*** | -0.0036*** | -0.0038*** | -0.0025*** | -0.0017*** |
| | (0.0012) | (0.0010) | (0.0009) | (0.0009) | (0.0005) |
| Team | 0.0039*** | 0.0029*** | 0.0013*** | 0.0016*** | 0.0008*** |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Academic | 0.0030*** | 0.0021*** | 0.0014*** | 0.0014*** | 0.0004* |
| | (0.0004) | (0.0003) | (0.0002) | (0.0002) | (0.0002) |
| Female | -0.0012 | -0.0011* | 0.0002 | -0.0006 | -0.0001 |
| | (0.0008) | (0.0006) | (0.0006) | (0.0005) | (0.0004) |
| Industry experience | -0.0001*** | -0.0001*** | -0.0001*** | -0.0000*** | -0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Founding experience | -0.0009 | -0.0009* | -0.0001 | 0.0005 | -0.0001 |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Failure experience | 0.0004 | 0.0010 | -0.0000 | -0.0002 | 0.0002 |
| | (0.0008) | (0.0007) | (0.0005) | (0.0006) | (0.0004) |
| Opportunity-driven | 0.0017*** | 0.0011** | 0.0005 | 0.0006 | 0.0003 |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| R&D | 0.0042*** | 0.0030*** | 0.0025*** | 0.0018*** | 0.0012*** |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Patent | 0.0004 | 0.0011 | 0.0002 | -0.0006 | 0.0001 |
| | (0.0014) | (0.0013) | (0.0009) | (0.0008) | (0.0006) |
| **Fixed effects:** | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes | Yes |
| Region | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.010 | 0.008 | 0.006 | 0.004 | 0.003 |
| Firm-year obs. | 55,051 | 55,330 | 55,659 | 55,589 | 55,837 |

**Note**: Year, industry and region fixed effects, and firm controls included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table A.9.: Results for balanced pooled models**

| | VC | GVC | Angel | IVC | CVC |
|---|---|---|---|---|---|
| Subsidy(t) | 0.0026*** | 0.0021*** | 0.0015*** | 0.0003 | 0.0007* |
| | (0.0008) | (0.0007) | (0.0005) | (0.0006) | (0.0004) |
| Startup age (log) | -0.0047*** | -0.0034*** | -0.0019*** | -0.0008 | -0.0008*** |
| | (0.0007) | (0.0006) | (0.0004) | (0.0005) | (0.0003) |
| Founder age (log) | -0.0072*** | -0.0051*** | -0.0047*** | -0.0033* | -0.0030*** |
| | (0.0021) | (0.0017) | (0.0013) | (0.0017) | (0.0011) |
| Team | 0.0023** | 0.0020*** | 0.0003 | 0.0009 | 0.0007* |
| | (0.0010) | (0.0008) | (0.0006) | (0.0007) | (0.0004) |
| Academic | 0.0033*** | 0.0021*** | 0.0013*** | 0.0016*** | 0.0008*** |
| | (0.0005) | (0.0005) | (0.0004) | (0.0005) | (0.0003) |
| Female | -0.0018 | -0.0011 | 0.0000 | -0.0016*** | -0.0008 |
| | (0.0011) | (0.0010) | (0.0008) | (0.0006) | (0.0005) |
| Industry experience | -0.0001** | -0.0001* | -0.0000 | -0.0000 | -0.0000** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Founding experience | -0.0013 | -0.0016** | -0.0009 | 0.0008 | -0.0000 |
| | (0.0010) | (0.0008) | (0.0006) | (0.0007) | (0.0005) |
| Failure experience | 0.0006 | 0.0008 | 0.0006 | 0.0007 | 0.0004 |
| | (0.0013) | (0.0011) | (0.0007) | (0.0014) | (0.0007) |
| Opportunity-driven | 0.0022** | 0.0021*** | 0.0006 | 0.0004 | 0.0003 |
| | (0.0008) | (0.0007) | (0.0005) | (0.0007) | (0.0004) |
| R&D | 0.0040*** | 0.0032*** | 0.0025*** | 0.0013** | 0.0005 |
| | (0.0007) | (0.0005) | (0.0005) | (0.0006) | (0.0004) |
| Patent | 0.0023 | 0.0028 | 0.0002 | 0.0004 | 0.0003 |
| | (0.0023) | (0.0022) | (0.0011) | (0.0017) | (0.0008) |
| **Fixed effects:** | | | | | |
| Year | Yes | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes | Yes |
| Region | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.009 | 0.008 | 0.005 | 0.004 | 0.003 |
| Firm-year obs. | 24,978 | 25,104 | 25,285 | 25,212 | 25,323 |

**Note**: Year, industry and region fixed effects, and firm controls included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table A.10.: Results for balanced within estimation models**

| | VC | GVC | Angel | IVC | CVC |
|---|---|---|---|---|---|
| Subsidy(t) | 0.0058** | 0.0044** | 0.0031* | 0.0013 | 0.0011 |
| | (0.0025) | (0.0021) | (0.0018) | (0.0017) | (0.0010) |
| Startup age (log) | 0.0092*** | 0.0070*** | 0.0051*** | 0.0035*** | 0.0030*** |
| | (0.0016) | (0.0013) | (0.0011) | (0.0011) | (0.0008) |
| R&D | 0.0014 | 0.0014 | -0.0019** | 0.0002 | -0.0018*** |
| | (0.0025) | (0.0023) | (0.0008) | (0.0013) | (0.0005) |
| **Fixed effects:** | | | | | |
| Firm | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.005 | 0.005 | 0.003 | 0.003 | 0.002 |
| Firm obs. | 3,953 | 3,955 | 3,963 | 3,961 | 3,961 |
| Firm-year obs. | 24,978 | 25,104 | 25,285 | 25,212 | 25,323 |

**Note**: Year and firm fixed effects included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table A.11.: Robustness test**

| | Timing assumption | | | | |
|---|---|---|---|---|---|
| | Panel A: POLS (unmatched)$^{+}$ | | | | |
| | VC | GVC | Angel | IVC | CVC |
| Subsidy(t) | 0.0021*** | 0.0018*** | 0.0009* | 0.0004 | 0.0006 |
| | (0.0008) | (0.0007) | (0.0005) | (0.0005) | (0.0004) |
| Constant | 0.0355*** | 0.0237*** | 0.0228*** | 0.0120* | 0.0068** |
| | (0.0090) | (0.0067) | (0.0070) | (0.0061) | (0.0029) |
| Firm-year obs. | 30,961 | 31,137 | 31,216 | 31,201 | 31,320 |
| | Panel B: POLS (matched)$^{+}$ | | | | |
| | VC | GVC | Angel | IVC | CVC |
| Subsidy(t) | 0.0029*** | 0.0025*** | 0.0013* | 0.0005 | 0.0008* |
| | (0.0009) | (0.0008) | (0.0007) | (0.0005) | (0.0004) |
| Constant | 0.0310*** | 0.0232*** | 0.0209*** | 0.0105 | 0.0065* |
| | (0.0107) | (0.0078) | (0.0079) | (0.0071) | (0.0038) |
| Firm-year obs. | 19,698 | 19,797 | 19,847 | 19,868 | 19,909 |

**Note**: $^{+}$ The sample includes only startups that enter the sample in their first year of operation. Year, industry and region fixed effects, and firm controls included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table A.12.: Results for unbalanced seemingly unrelated regression**

| | GVC | Angel | IVC | CVC |
|---|---|---|---|---|
| Subsidy(t) | 0.0030*** | 0.0017*** | 0.0011*** | 0.0007** |
| | (0.0006) | (0.0004) | (0.0004) | (0.0003) |
| Startup age (log) | −0.0032*** | −0.0018*** | −0.0011*** | −0.0007*** |
| | (0.0004) | (0.0003) | (0.0002) | (0.0002) |
| Founder age (log) | −0.0037*** | −0.0042*** | −0.0026*** | −0.0017*** |
| | (0.0012) | (0.0010) | (0.0009) | (0.0006) |
| Team | 0.0032*** | 0.0015*** | 0.0016*** | 0.0008*** |
| | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Academic | 0.0022*** | 0.0014*** | 0.0014*** | 0.0004** |
| | (0.0003) | (0.0003) | (0.0002) | (0.0002) |
| Female | −0.0009 | 0.0001 | −0.0006 | −0.0001 |
| | (0.0007) | (0.0006) | (0.0005) | (0.0004) |
| Industry experience | −0.0001*** | −0.0001*** | −0.0001*** | −0.0000*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Founding experience | −0.0011* | −0.0000 | 0.0005 | −0.0001 |
| | (0.0006) | (0.0005) | (0.0004) | (0.0003) |
| Failure experience | 0.0015* | 0.0000 | −0.0003 | 0.0002 |
| | (0.0008) | (0.0006) | (0.0006) | (0.0004) |
| Opportunity-driven | 0.0012** | 0.0005 | 0.0007* | 0.0003 |
| | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| R&D | 0.0033*** | 0.0027*** | 0.0018*** | 0.0012*** |
| | (0.0005) | (0.0004) | (0.0004) | (0.0003) |
| Patent | 0.0012 | 0.0001 | −0.0007 | 0.0001 |
| | (0.0014) | (0.0009) | (0.0008) | (0.0006) |
| Firm-year obs. | 55.977 | | | |

**Note**: Year, industry and region fixed effects, and firm controls included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table A.13.: Results for unbalanced seemingly unrelated regression**

| | GVC | Angel | IVC | CVC |
|---|---|---|---|---|
| Subsidy(t) | 0.0023*** | 0.0016*** | 0.0002 | 0.0007* |
| | (0.0008) | (0.0006) | (0.0006) | (0.0004) |
| Startup age (log) | −0.0034*** | −0.0018*** | −0.0008 | −0.0008** |
| | (0.0006) | (0.0004) | (0.0005) | (0.0003) |
| Founder age (log) | −0.0056*** | −0.0052*** | −0.0037** | −0.0032*** |
| | (0.0020) | (0.0015) | (0.0018) | (0.0011) |
| Team | 0.0023*** | 0.0004 | 0.0009 | 0.0008* |
| | (0.0008) | (0.0006) | (0.0007) | (0.0004) |
| Academic | 0.0022*** | 0.0013*** | 0.0016*** | 0.0009*** |
| | (0.0005) | (0.0004) | (0.0005) | (0.0003) |
| Female | −0.0012 | −0.0001 | −0.0017*** | −0.0008* |
| | (0.0011) | (0.0008) | (0.0006) | (0.0005) |
| Industry experience | −0.0001 | −0.0000 | −0.0000 | −0.0000** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Founding experience | −0.0017** | −0.0008 | 0.0009 | −0.0001 |
| | (0.0009) | (0.0007) | (0.0007) | (0.0005) |
| Failure experience | 0.0018 | 0.0007 | 0.0005 | 0.0005 |
| | (0.0013) | (0.0008) | (0.0014) | (0.0007) |
| Opportunity-driven | 0.0023*** | 0.0007 | 0.0005 | 0.0003 |
| | (0.0007) | (0.0006) | (0.0007) | (0.0004) |
| R&D | 0.0034*** | 0.0026*** | 0.0013** | 0.0005 |
| | (0.0006) | (0.0005) | (0.0006) | (0.0004) |
| Patent | 0.0034 | 0.0003 | 0.0005 | 0.0003 |
| | (0.0026) | (0.0013) | (0.0017) | (0.0008) |
| Firm-year obs. | 25.410 | | | |

**Note**: Year, industry and region fixed effects, and firm controls included. Observations are at the firm-year level. Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table A.14.: Correlations of seemingly unrelated regression results (after balancing)**

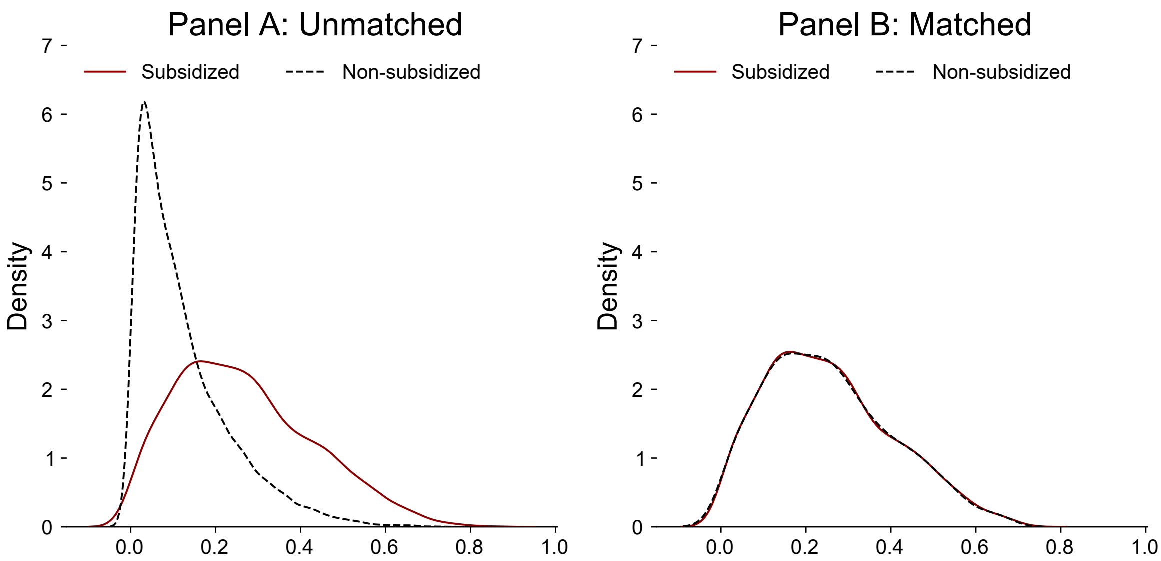
| | |
|---|---|
| GVC × Angel | 0.4737*** |
| | (00893) |
| GVC × IVC | 0.3129*** |
| | (00735) |
| GVC × CVC | 0.2171*** |
| | (00686) |
| Angel × IVC | 0.2727*** |
| | (00748) |
| Angel × CVC | 0.3953*** |
| | (00986) |
| IVC × CVC | 0.2330** |
| | (01060) |
| Firm-year obs. | 25410 |

**Note**: Coefficients presented with standard errors in parentheses, clustered at the firm level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table A.15.: Chi$^2$-tests for equality of subsidy coefficients**

| | Chi2 | df | p-value |
|---|---|---|---|
| GVC:Subsidy(t) vs. Angel:Subsidy(t) | 1.02 | 1 | 0.31 |
| GVC:Subsidy(t) vs. IVC:Subsidy(t) | 7.11 | 1 | 0.01 |
| GVC:Subsidy(t) vs. CVC:Subsidy(t) | 4.09 | 1 | 0.04 |
| | Chi2 | df | p |
| Angel:Subsidy(t) vs. IVC:Subsidy(t) | 3.78 | 1 | 0.05 |
| Angel:Subsidy(t) vs. CVC:Subsidy(t) | 2.83 | 1 | 0.09 |

**Figure A.2.: Estimated probability for subsidy receipt before and after matching observations**




**Note: Panel A** shows the kernel density estimates for the estimated probability of receiving a subsidy for the group of startups that have in fact received a subsidy (red line) and those that have not (black dashed line) before matching. **Panel B** shows the the same estimates weighted by the balancing weights obtained from the matching procedure. Kernel densities are estimated using a Gaussian kernel, the bandwidth is calculated using Scott's Rule, i.e $n(-1/(d+4))$, where $n$ is the number of data points, and $d$ the dimension of the data. For the weighted kernel density estimates, the effective number of data points $n_{eff} = \sum_i(w_i)^2/\sum_i(w_i^2)$ is used, where $w_i$ is the weight of data point $i$.

# B. Financing and Advising Early Stage Startups: The Effect of Angel Investor Subsidies

# B.1. Innovative industries

**Table B.1.: NACE codes of eligible industries**

| | |
|---|---|
| 13.96 | Manufacture of other technical and industrial textiles |
| 20 | Manufacture of chemicals and chemical products |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| 22 | Manufacture of rubber and plastic products |
| 23 | Manufacture of other non-metallic mineral products |
| 25.6 | Treatment and coating of metals; machining |
| 26 | Manufacture of computer, electronic and optical products |
| 27 | Manufacture of electrical equipment |
| 28 | Manufacture of machinery and equipment n.e.c. |
| 29 | Manufacture of motor vehicles, trailers, and semi-trailers |
| 30 | Building of ships and boats |
| 32.5 | Manufacture of medical and dental instruments and supplies |
| 33 | Repair and installation of machinery and equipment |
| 58 | Publishing activities |
| 59 | Motion picture, video, and television program production, sound recording, and music publishing activities |
| 60 | Programming and broadcasting activities |
| 61 | Telecommunications |
| 62 | Computer programming, consultancy, and related activities |
| 63 | Information service activities |
| 71 | Architectural and engineering activities; technical testing and analysis |
| 72 | Scientific research and development |
| 73 | Advertising and market research |
| 74 | Other professional, scientific, and technical activities |
| 90 | Creative, arts, and entertainment activities |

**Table B.2.: Sector classification**

| IAB/ZEW classification | NACE rev. 1 |
|---|---|
| Hightech manufacturing | 20.13, 20.14, 20.16, 20.17, 20.2, 20.41, 20.51, 20.53, 20.59, 21.1, 21.2, 22.11, 22.19, 23.19, 24.46, 25.4, 26.11, 26.2 , 26.3 , 26.4 , 26.51, 26.6, 26.70, 27.1, 27.2, 27.4, 27.9, 28.1, 28.23, 28.24, 28.29, 28.3, 28.41, 28.49, 28.92, 28.93, 28.94, 28.95, 28.96, 28.99, 29.1, 29.3, 30.2, 30.3, 30.4, 32.5 |
| Hightech services & software | 61.1, 61.2, 61.3, 62, 63.1, 71.1, 71.2, 72.1 |
| Non-hightech manufacturing | 10-33 (w/o hightech manufacturing) |
| B2B & knowledge-int. services | 49.2, 49.5, 50.2, 50.4, 51.2, 52, 53, 61.9, 63.9, 64, 69, 70.2, 72.2, 73.1, 73.2, 74.1, 74.3-74.9, 77.1, 77.3, 77.4, 78, 80-82 |
| B2C & retail | 45-47 (w/o 46.1), 49.1, 49.3, 49.4, 50.1, 50.3, 50.1, 50.3, 51.1, 55, 56, 58-60, 65-66, 68, 74.2, 77.2, 79, 85.5-85.6, 90-93, 95-96 |
| Construction | 41-43 |

**Note**: The classification of the sectors follows the definitions by the German Federal Statistical Office. The energy/mining sector (10-14, 40, 41), the transport sector (60-63), the postal system (64.1), and the banks and assurance sector 65-67) are not included in the sampling.

**Table B.3.: Overview on different samples used in the analysis**

| | Data | | | | | |
|---|---|---|---|---|---|---|
| | Startup Panel wave 12 | | Startup Panel wave 6 | | Hightech Startup Survey [a] | |
| Reference year | 2018 | | 2012 | | 2006 | |
| Founding cohorts | 2012 - 2018 | | 2005 - 2012 | | 1998 - 2007 | |
| Industries [b] | Hightech & Others | | Hightech & Others | | Hightech | |
| Controls | full | | full | | limited [c] | |
| Firm obs. (raw) | 7,137 | | 6,558 | | 3,017 | |
| Firm obs. (sample) | 6,766 | | 6,105 | | 2,916 | |
| | Questions on Angel and VCF Financing | | | | | |
| | Angel | VCF | Angel | VCF | Angel | VCF |
| Financing volume | ✔ | ✔ | ✔ | ✔ | ✔ | ✔ |
| Managerial support | ✔ | ✘ | ✔ | ✘ | ✔ | ✘ |
| Number of investors | ✔ | ✘ | ✔ | ✘ | ✔ | ✘ |
| Firm obs. (raw) | 639 | 124 | 453 | 121 | 262 | 72 |
| Firm obs. (sample) | 559 | 120 | 392 | 107 | 207 | 53 |

**Note**: [a] For more details on the Hightech Startup Survey, see Fryges, Gottschalk, Licht, et al. (2007). [b] For details on industries see Table B.2. [c] No information on founding motive, subsidies, founding, exit experience, or gender.

# B.2. Descriptives

**Table B.4.: Number of observations by industries and groups**

| NACE Rev. 2 | Angel & VCF | Angel | No deal | VCF | No VC | Total |
|---|---|---|---|---|---|---|
| Manufacturing | 26 | 261 | 372 | 39 | 2,306 | 3,004 |
| Construction | 1 | 29 | 48 | 3 | 1,053 | 1,134 |
| Wholesale and retail trade | 2 | 84 | 86 | 11 | 1,107 | 1,290 |
| Transporting and storage | 0 | 14 | 8 | 1 | 193 | 216 |
| Accommodation and food service activities | 0 | 35 | 20 | 3 | 263 | 321 |
| Information and communication | 44 | 188 | 452 | 36 | 1,519 | 2,239 |
| Financial and insurance activities | 0 | 12 | 19 | 0 | 177 | 208 |
| Real estate activities | 0 | 9 | 17 | 1 | 114 | 141 |
| Professional, scientific and technical | 21 | 144 | 304 | 28 | 2,385 | 2,882 |
| Administrative and support service activities | 2 | 30 | 44 | 5 | 599 | 680 |
| Education | 0 | 14 | 32 | 0 | 264 | 310 |
| Human health and social work activities | 0 | 0 | 1 | 0 | 7 | 8 |
| Arts, entertainment and recreation | 1 | 14 | 13 | 0 | 84 | 112 |
| Other services activities | 2 | 18 | 21 | 1 | 266 | 308 |
| Total | 99 | 852 | 1,437 | 128 | 10,337 | 12,853 |

**Table B.5.: Description of variables**

| Variable name | Type | Description |
|---|---|---|
| | | Financial outcomes |
| Angel (Y/N) | Binary | At least one financing round from a private investor. |
| VCF (Y/N) | Binary | At least one financing round from VC fund. |
| Total VC amount | Continuous | Total VC raised since foundation in thsd. Euros. |
| Angel amount | Continuous | Total capital raised from angel investors since foundation in thsd. Euros. |
| VCF amount | Continuous | Total capital raised from VC funds since foundation in thsd. Euros. |
| | | Managerial outcomes |
| Board | Ordinal | Ranking of angel engagement on board.[1] |
| Commercialization | Ordinal | Ranking of angels' support in commercialization-related tasks.[1] |
| Development | Ordinal | Ranking of angels' support in production-related tasks.[1] |
| Mentoring | Ordinal | Ranking of angels' engagement in mentoring.[1] |
| Network | Ordinal | Ranking of angels' network.[1] |
| | | Syndication |
| Syndication (Y/N) | Binary | More than one angel investor since foundation. |
| Syndicate size | Count | Number of angel investors since foundation. |
| | | Firm characteristics |
| Academic | Binary | At least one member of the founding team has an academic background. |
| Female | Binary | At least one female member in founding team. |
| Founding exp. | Binary | At least one founding team member had started a business before. |
| Industry | Categorical | Business sector of startup by two digit NACE rev. 2 code. |
| Industry exp. | Count | Years of industry experience of founding team. |
| LLC/ Inc. | Binary | Startup is limited liability or incorporated firm. |
| Opportunity | Binary | Startup was founded on a concrete business idea. |
| Patent at start | Binary | Business was started with at least one patent. |
| Public subsidy | Binary | Startup received a subsidy in year t. |
| Region | Categorical | Location of startup: East/ West/ Berlin. |
| Size | Continuous | Number of full-time equivalents employed at the company's start. |
| Startup age | Count | Age of the startup in the reference year. |
| Startup subsidy | Binary | Startup received subsidies in the first three years. |
| Successful exit | Binary | At least one founding team member has sold the previous company. |
| Team | Binary | Startup was founded by a team. |

**Note**: [1] Based on five-point Likert Scale, no engagement (1) – very active (5)

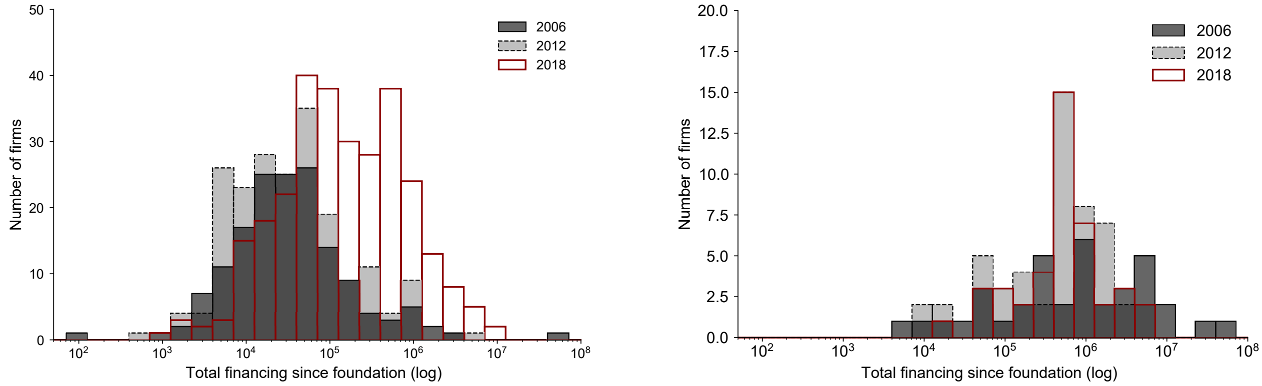
**Table B.6.: Correlation matrix of main variables for Sample D**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.00 | | | | | | | | | | | | | | | | | | | |
| (2) | 0.31 | 1.00 | | | | | | | | | | | | | | | | | | |
| | (0.00) | | | | | | | | | | | | | | | | | | | |
| (3) | 0.25 | 0.52 | 1.00 | | | | | | | | | | | | | | | | | |
| | (0.00) | (0.00) | | | | | | | | | | | | | | | | | | |
| (4) | 0.26 | 0.30 | 0.37 | 1.00 | | | | | | | | | | | | | | | | |
| | (0.00) | (0.00) | (0.00) | | | | | | | | | | | | | | | | | |
| (5) | 0.28 | 0.29 | 0.25 | 0.38 | 1.00 | | | | | | | | | | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | | | | | | | | | | |
| (6) | 0.27 | 0.20 | 0.10 | 0.04 | 0.10 | 1.00 | | | | | | | | | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.19) | (0.00) | | | | | | | | | | | | | | | |
| (7) | 0.09 | 0.15 | 0.13 | −0.00 | 0.07 | 0.32 | 1.00 | | | | | | | | | | | | | |
| | (0.01) | (0.00) | (0.00) | (0.98) | (0.04) | (0.00) | | | | | | | | | | | | | | |
| (8) | 0.21 | 0.16 | 0.10 | −0.04 | 0.08 | 0.30 | 0.57 | 1.00 | | | | | | | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.26) | (0.02) | (0.00) | (0.00) | | | | | | | | | | | | | |
| (9) | 0.12 | 0.15 | 0.09 | 0.00 | −0.00 | 0.23 | 0.08 | 0.11 | 1.00 | | | | | | | | | | | |
| | (0.00) | (0.00) | (0.01) | (0.93) | (0.95) | (0.00) | (0.02) | (0.00) | | | | | | | | | | | | |
| (10) | -0.08 | −0.02 | 0.03 | −0.00 | 0.05 | −0.11 | −0.07 | −0.05 | 0.02 | 1.00 | | | | | | | | | | |
| | (0.03) | (0.54) | (0.38) | (1.00) | (0.11) | (0.00) | (0.04) | (0.16) | (0.64) | | | | | | | | | | | |
| (11) | 0.13 | 0.05 | 0.04 | 0.00 | 0.02 | 0.17 | 0.05 | 0.10 | 0.22 | −0.01 | 1.00 | | | | | | | | | |
| | (0.00) | (0.18) | (0.29) | (0.92) | (0.48) | (0.00) | (0.14) | (0.00) | (0.00) | (0.74) | | | | | | | | | | |
| (12) | 0.14 | 0.12 | 0.06 | 0.06 | 0.03 | 0.24 | 0.09 | 0.09 | 0.21 | 0.13 | 0.26 | 1.00 | | | | | | | | |
| | (0.00) | (0.00) | (0.11) | (0.11) | (0.41) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | | | | | | | | | |
| (13) | 0.19 | 0.19 | 0.09 | 0.06 | 0.08 | 0.33 | 0.12 | 0.14 | 0.23 | −0.05 | 0.20 | 0.33 | 1.00 | | | | | | | |
| | (0.00) | (0.00) | (0.01) | (0.07) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.14) | (0.00) | (0.00) | | | | | | | | |
| (14) | -0.01 | −0.07 | −0.08 | −0.04 | −0.01 | 0.09 | −0.07 | −0.02 | −0.04 | −0.06 | 0.11 | 0.01 | −0.08 | 1.00 | | | | | | |
| | (0.70) | (0.05) | (0.02) | (0.20) | (0.80) | (0.01) | (0.03) | (0.62) | (0.30) | (0.06) | (0.00) | (0.71) | (0.02) | | | | | | | |
| (15) | 0.09 | 0.06 | 0.02 | −0.01 | 0.04 | 0.18 | 0.08 | 0.17 | 0.07 | −0.02 | 0.37 | 0.11 | 0.14 | 0.02 | 1.00 | | | | | |
| | (0.01) | (0.11) | (0.49) | (0.88) | (0.25) | (0.00) | (0.02) | (0.00) | (0.05) | (0.59) | (0.00) | (0.00) | (0.00) | (0.59) | | | | | | |
| (16) | 0.00 | −0.09 | −0.04 | −0.04 | 0.01 | −0.00 | −0.02 | −0.01 | 0.03 | 0.01 | −0.03 | 0.02 | −0.08 | 0.22 | −0.02 | 1.00 | | | | |
| | (0.96) | (0.01) | (0.26) | (0.27) | (0.69) | (0.98) | (0.53) | (0.83) | (0.39) | (0.69) | (0.42) | (0.49) | (0.02) | (0.00) | (0.54) | | | | | |
| (17) | 0.06 | 0.01 | 0.01 | 0.03 | 0.03 | 0.15 | 0.03 | 0.03 | 0.04 | 0.01 | 0.08 | 0.18 | 0.02 | 0.12 | −0.00 | 0.08 | 1.00 | | | |
| | (0.11) | (0.71) | (0.71) | (0.40) | (0.41) | (0.00) | (0.36) | (0.33) | (0.24) | (0.84) | (0.02) | (0.00) | (0.55) | (0.00) | (0.93) | (0.02) | | | | |
| (18) | 0.03 | −0.03 | 0.00 | 0.03 | 0.08 | 0.11 | 0.03 | 0.08 | 0.11 | −0.02 | 0.12 | 0.06 | 0.09 | 0.00 | 0.02 | 0.01 | 0.01 | 1.00 | | |
| | (0.32) | (0.37) | (0.98) | (0.33) | (0.02) | (0.00) | (0.31) | (0.02) | (0.00) | (0.56) | (0.00) | (0.09) | (0.01) | (0.92) | (0.54) | (0.76) | (0.76) | | | |
| (20) | 0.07 | 0.12 | 0.10 | −0.04 | 0.00 | 0.16 | 0.13 | 0.11 | 0.11 | −0.01 | 0.03 | 0.11 | 0.14 | −0.06 | −0.02 | −0.09 | 0.02 | 0.02 | 1.00 | |
| | (0.04) | (0.00) | (0.00) | (0.28) | (0.95) | (0.00) | (0.00) | (0.00) | (0.00) | (0.81) | (0.37) | (0.00) | (0.00) | (0.06) | (0.52) | (0.01) | (0.55) | (0.59) | | |
| (19) | 0.04 | 0.03 | 0.07 | −0.03 | −0.04 | 0.09 | 0.11 | 0.10 | 0.03 | −0.00 | −0.07 | 0.12 | 0.06 | −0.01 | 0.01 | 0.09 | 0.08 | −0.02 | 0.60 | 1.00 |
| | (0.25) | (0.39) | (0.04) | (0.43) | (0.29) | (0.01) | (0.00) | (0.00) | (0.45) | (0.93) | (0.05) | (0.00) | (0.07) | (0.68) | (0.71) | (0.01) | (0.02) | (0.59) | (0.00) | |
| Firm obs. | 852 | | | | | | | | | | | | | | | | | | | |

**Note**: (1) Board (2) Network (3) Mentoring (4) Commercial. (5) Development (6) Tot. VC amount. (log) (7) Syndication (8) Syndicate size (9) Opportunity (10) Female (11) Founding exp. (12) Team (13) Academic (14) Industry exp. (15) Success. exit (16) Startup age (17) Size at start (18) Patent (19) Startup subsidy (20) Subsidy.
P-values in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

### Figure B.1.: Distribution of financing volumes in eligible industries over time

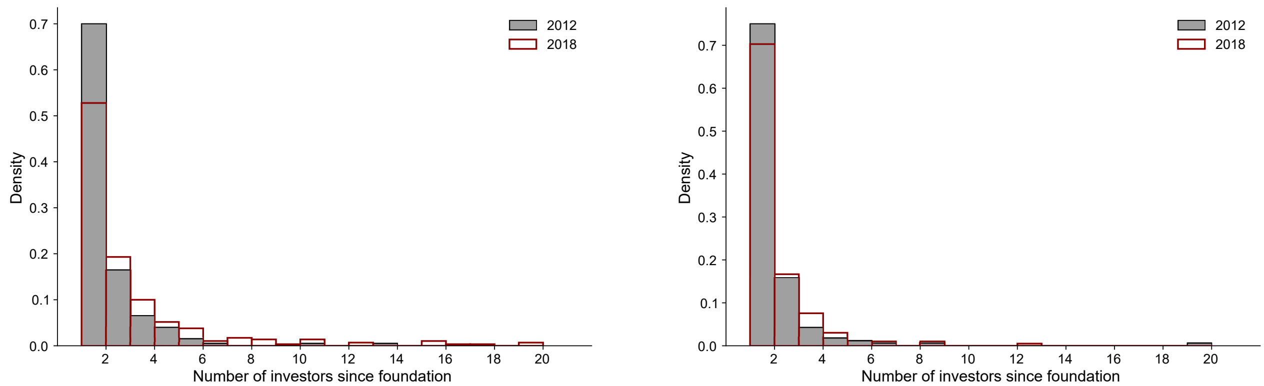
**(a) Angel investors** **(b) VC Funds**




**Note:** Figure B.1 shows the distribution of financing volumes for startups in eligible industries. Panel (a) compares the distribution of financing volumes by angel investors between 2006, 2012, and 2018. Panel (b) compares the distribution of financing volumes by venture capital funds between 2006, 2012, and 2018.

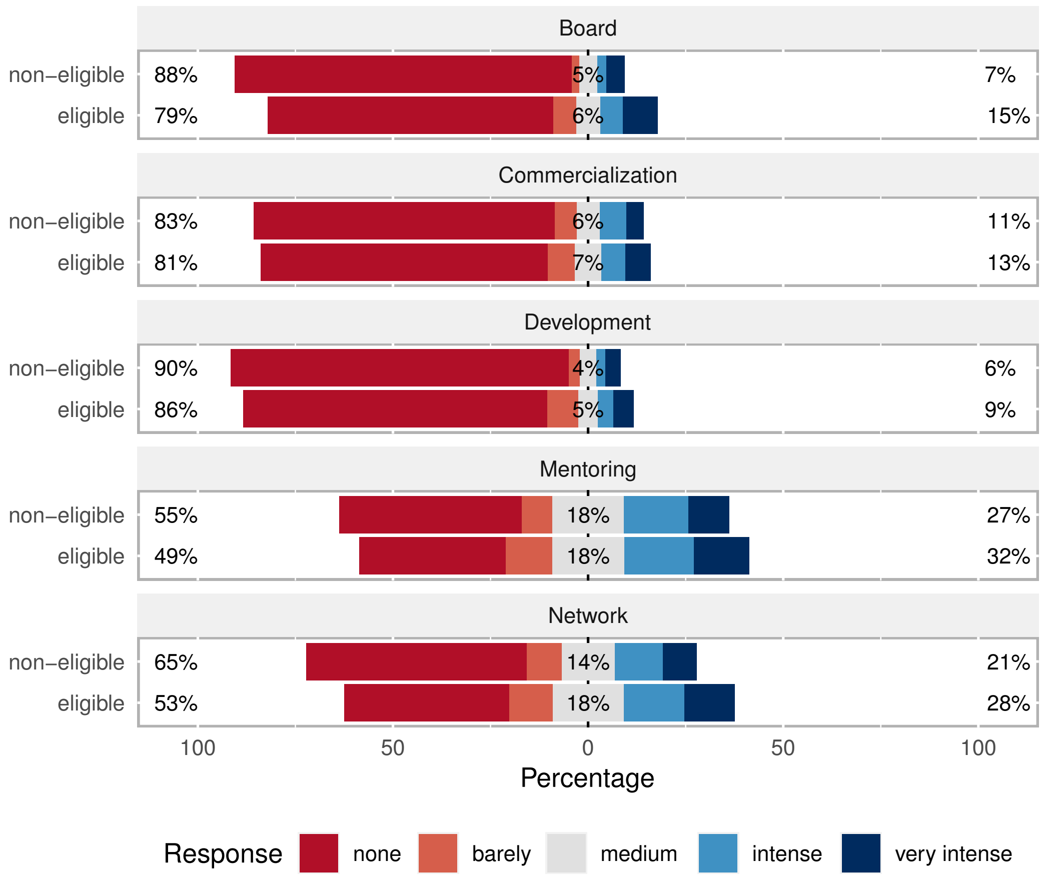
### Figure B.2.: Distribution of syndicate sizes

**(a) Eligible** **(b) Non-eligible**




**Note:** Table B.2 shows the distribution of syndicate sizes for angel financed firms. Panel (a) compares eligible firms' distributions between 2012 and 2018. Panel (b) compares the distributions between 2012 and 2018 for non-eligible firms.

**Figure B.3.: Likert scale ratings in eligible and non-eligible firms**



# B.3. Covariate balancing results

### Table B.7.: Balancing results Sample E: Angel or VCF financed, only eligible industries

| | Unbalanced | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 42 | | Control pre N= 52 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.40 | 0.49 | 0.64 | 0.48 | 0.71 | 0.46 |
| Academic | 0.81 | 0.39 | 0.65 | 0.48 | 0.88 | 0.33 | 0.83 | 0.38 |
| Industry exp. | 15.24 | 10.45 | 14.47 | 9.45 | 14.60 | 8.93 | 18.90 | 9.96 |
| Size at start | 2.65 | 1.85 | 2.60 | 2.65 | 2.65 | 1.65 | 3.27 | 3.28 |
| Startup age | 2.24 | 1.60 | 2.44 | 2.02 | 2.48 | 1.66 | 3.38 | 2.28 |
| LLC/ Inc. | 0.89 | 0.32 | 0.60 | 0.49 | 0.95 | 0.22 | 0.85 | 0.36 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.81 | 0.40 | 0.76 | 0.43 | 0.77 | 0.43 |
| East | 0.10 | 0.30 | 0.14 | 0.35 | 0.21 | 0.42 | 0.19 | 0.40 |
| Patent at start | 0.08 | 0.28 | 0.10 | 0.29 | 0.14 | 0.35 | 0.21 | 0.41 |
| Berlin | 0.10 | 0.31 | 0.05 | 0.22 | 0.02 | 0.15 | 0.04 | 0.19 |
| | Entropy balancing | | | | | | | |
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 37 | | Control pre N= 52 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.52 | 0.50 | 0.53 | 0.51 | 0.52 | 0.50 |
| Academic | 0.81 | 0.39 | 0.81 | 0.39 | 0.82 | 0.39 | 0.81 | 0.40 |
| Industry exp. | 15.24 | 10.45 | 15.24 | 9.64 | 15.41 | 8.87 | 15.24 | 9.87 |
| Size at start | 2.65 | 1.85 | 2.65 | 2.04 | 2.68 | 1.78 | 2.65 | 2.45 |
| Startup age | 2.24 | 1.60 | 2.24 | 1.93 | 2.27 | 1.47 | 2.24 | 2.03 |
| LLC/ Inc. | 0.89 | 0.32 | 0.89 | 0.32 | 0.90 | 0.31 | 0.89 | 0.32 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.80 | 0.40 | 0.82 | 0.39 | 0.80 | 0.40 |
| East | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 |
| Patent at start | 0.08 | 0.28 | 0.08 | 0.28 | 0.09 | 0.28 | 0.08 | 0.28 |
| Berlin | 0.10 | 0.31 | 0.10 | 0.31 | 0.09 | 0.28 | 0.10 | 0.31 |
| | Propensity score matching | | | | | | | |
| | Treated post N= 290 | | Treated pre N= 197 | | Control post N= 42 | | Control pre N= 48 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.40 | 0.49 | 0.58 | 0.50 | 0.45 | 0.50 |
| Academic | 0.81 | 0.39 | 0.66 | 0.47 | 0.87 | 0.34 | 0.71 | 0.46 |
| Industry exp. | 15.24 | 10.45 | 14.67 | 9.34 | 14.46 | 9.12 | 14.15 | 8.63 |
| Size at start | 2.65 | 1.85 | 2.63 | 2.71 | 2.58 | 1.63 | 2.47 | 2.75 |
| Startup age | 2.24 | 1.60 | 2.47 | 2.01 | 2.55 | 1.66 | 3.25 | 2.10 |
| LLC/ Inc. | 0.89 | 0.32 | 0.60 | 0.49 | 0.95 | 0.21 | 0.75 | 0.44 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.80 | 0.40 | 0.76 | 0.43 | 0.86 | 0.35 |
| East | 0.10 | 0.30 | 0.15 | 0.36 | 0.22 | 0.42 | 0.12 | 0.33 |
| Patent at start | 0.08 | 0.28 | 0.10 | 0.30 | 0.07 | 0.26 | 0.08 | 0.27 |
| Berlin | 0.10 | 0.31 | 0.05 | 0.22 | 0.02 | 0.13 | 0.01 | 0.12 |

**Note**: 'Unbalanced' shows the means and standard errors of the treatment group and control groups before balancing the covariates. 'Entropy Balanced' and 'Propensity Score Matching' show the means and standard errors after using the weights obtained from the respective balancing procedure described in Section 3.3.2. 'Treated Post' is the group of angel-financed firms in the post-policy period. 'Treated Pre' is the group of VCF financed firms in the period before the policy. 'Control Post' is the group of angel-financed firms in the post-policy period. 'Control Pre' is the group of VCF financed firms in the period before the policy.

## Table B.8.: Balancing results Sample A: All firms

| | Unbalanced | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Treated post N= 3,160 | | Treated pre N= 3,222 | | Control post N= 3,603 | | Control pre N= 2,868 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.39 | 0.49 | 0.37 | 0.48 | 0.25 | 0.43 | 0.25 | 0.43 |
| Female | 0.15 | 0.35 | 0.15 | 0.36 | 0.23 | 0.42 | 0.23 | 0.42 |
| Academic | 0.64 | 0.48 | 0.57 | 0.50 | 0.42 | 0.49 | 0.33 | 0.47 |
| Opportunity | 0.39 | 0.49 | 0.38 | 0.49 | 0.29 | 0.45 | 0.31 | 0.46 |
| Industry exp. | 17.21 | 10.38 | 17.51 | 9.95 | 15.94 | 10.64 | 16.89 | 9.98 |
| Founding exp. | 0.49 | 0.50 | 0.44 | 0.50 | 0.41 | 0.49 | 0.31 | 0.46 |
| Successful exit | 0.10 | 0.30 | 0.08 | 0.27 | 0.08 | 0.27 | 0.05 | 0.22 |
| Patent at start | 0.05 | 0.22 | 0.05 | 0.22 | 0.02 | 0.13 | 0.01 | 0.11 |
| Startup subsidy | 0.25 | 0.43 | 0.34 | 0.47 | 0.19 | 0.40 | 0.48 | 0.50 |
| Size at start | 2.26 | 1.93 | 2.44 | 2.79 | 2.30 | 2.60 | 2.73 | 5.99 |
| Startup age | 2.24 | 1.73 | 2.73 | 2.14 | 1.75 | 1.65 | 2.57 | 2.19 |
| **Region** | | | | | | | | |
| West | 0.82 | 0.39 | 0.81 | 0.40 | 0.86 | 0.35 | 0.82 | 0.38 |
| Berlin | 0.06 | 0.24 | 0.04 | 0.20 | 0.04 | 0.20 | 0.03 | 0.16 |
| East | 0.12 | 0.33 | 0.15 | 0.36 | 0.10 | 0.30 | 0.15 | 0.36 |
| | Entropy balancing | | | | | | | |
| | Treated post N= 3,160 | | Treated pre N= 3,222 | | Control post N= 3,603 | | Control pre N= 2,868 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.39 | 0.49 | 0.39 | 0.49 | 0.39 | 0.49 | 0.39 | 0.49 |
| Female | 0.15 | 0.35 | 0.15 | 0.35 | 0.15 | 0.35 | 0.15 | 0.35 |
| Academic | 0.64 | 0.48 | 0.64 | 0.48 | 0.64 | 0.48 | 0.64 | 0.48 |
| Opportunity | 0.39 | 0.49 | 0.39 | 0.49 | 0.39 | 0.49 | 0.39 | 0.49 |
| Industry exp. | 17.21 | 10.38 | 17.21 | 10.11 | 17.21 | 10.85 | 17.21 | 10.41 |
| Founding exp. | 0.49 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 |
| Successful exit | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 |
| Patent at start | 0.05 | 0.22 | 0.05 | 0.22 | 0.05 | 0.22 | 0.05 | 0.22 |
| Startup subsidy | 0.25 | 0.43 | 0.25 | 0.43 | 0.25 | 0.43 | 0.25 | 0.43 |
| Size at start | 2.26 | 1.93 | 2.27 | 2.10 | 2.27 | 2.05 | 2.27 | 1.91 |
| Startup age | 2.24 | 1.73 | 2.24 | 2.02 | 2.24 | 1.81 | 2.24 | 2.10 |
| **Region** | | | | | | | | |
| West | 0.82 | 0.39 | 0.82 | 0.39 | 0.82 | 0.39 | 0.82 | 0.39 |
| Berlin | 0.06 | 0.24 | 0.06 | 0.24 | 0.06 | 0.24 | 0.06 | 0.24 |
| East | 0.12 | 0.33 | 0.12 | 0.33 | 0.12 | 0.33 | 0.12 | 0.33 |
| | Propensity score matching | | | | | | | |
| | Treated post N= 3,160 | | Treated pre N= 3,195 | | Control post N= 3,602 | | Control pre N= 2,863 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.39 | 0.49 | 0.36 | 0.48 | 0.39 | 0.49 | 0.37 | 0.48 |
| Female | 0.15 | 0.35 | 0.15 | 0.36 | 0.15 | 0.36 | 0.15 | 0.36 |
| Academic | 0.64 | 0.48 | 0.56 | 0.50 | 0.63 | 0.48 | 0.56 | 0.50 |
| Opportunity | 0.39 | 0.49 | 0.38 | 0.48 | 0.38 | 0.49 | 0.38 | 0.49 |
| Industry exp. | 17.21 | 10.38 | 17.51 | 9.91 | 17.12 | 10.81 | 17.34 | 10.22 |
| Founding exp. | 0.49 | 0.50 | 0.43 | 0.50 | 0.49 | 0.50 | 0.43 | 0.50 |
| Successful exit | 0.10 | 0.30 | 0.07 | 0.26 | 0.10 | 0.31 | 0.07 | 0.26 |
| Patent at start | 0.05 | 0.22 | 0.05 | 0.21 | 0.05 | 0.21 | 0.04 | 0.20 |
| Startup subsidy | 0.25 | 0.43 | 0.33 | 0.47 | 0.23 | 0.42 | 0.31 | 0.46 |
| Size at start | 2.26 | 1.93 | 2.39 | 2.56 | 2.25 | 2.02 | 2.43 | 2.27 |
| Startup age | 2.24 | 1.73 | 2.73 | 2.14 | 2.27 | 1.82 | 2.72 | 2.24 |
| **Region** | | | | | | | | |
| West | 0.82 | 0.39 | 0.81 | 0.39 | 0.82 | 0.39 | 0.81 | 0.39 |
| Berlin | 0.06 | 0.24 | 0.04 | 0.19 | 0.06 | 0.24 | 0.03 | 0.18 |
| East | 0.12 | 0.33 | 0.15 | 0.36 | 0.12 | 0.33 | 0.15 | 0.36 |

**Note**: 'Unbalanced' shows the means and standard errors of the treatment group and control groups before balancing the covariates. 'Entropy Balanced' and 'Propensity Score Matching' show the means and standard errors after using the weights obtained from the respective balancing procedure described in Section 3.3.2. 'Treated Post' is the group of eligible firms in the post-policy period. 'Treated Pre' is the group of eligible firms in the period before the policy. 'Control Post' is the group of non-eligible firms in the post-policy period. 'Control Pre' is the group of non-eligible firms in the period before the policy.

## Table B.9.: Balancing results Sample B: Angel investor deal flow

| | Unbalanced | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Treated post N= 966 | | Treated pre N= 623 | | Control post N= 553 | | Control pre N= 309 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.51 | 0.50 | 0.36 | 0.48 | 0.33 | 0.47 |
| Female | 0.14 | 0.34 | 0.16 | 0.37 | 0.20 | 0.40 | 0.20 | 0.40 |
| Academic | 0.79 | 0.41 | 0.74 | 0.44 | 0.56 | 0.50 | 0.48 | 0.50 |
| Opportunity | 0.53 | 0.50 | 0.58 | 0.49 | 0.48 | 0.50 | 0.41 | 0.49 |
| Industry exp. | 15.29 | 10.10 | 15.08 | 9.87 | 14.32 | 10.64 | 15.43 | 9.62 |
| Founding exp. | 0.60 | 0.49 | 0.54 | 0.50 | 0.53 | 0.50 | 0.34 | 0.48 |
| Successful exit | 0.16 | 0.36 | 0.09 | 0.29 | 0.14 | 0.35 | 0.08 | 0.28 |
| Patent at start | 0.08 | 0.27 | 0.10 | 0.30 | 0.04 | 0.19 | 0.04 | 0.19 |
| Startup subsidy | 0.38 | 0.48 | 0.42 | 0.49 | 0.23 | 0.42 | 0.53 | 0.50 |
| Size at start | 2.70 | 2.30 | 2.61 | 2.42 | 2.39 | 2.25 | 3.33 | 6.38 |
| Startup age | 2.24 | 1.70 | 2.47 | 2.01 | 1.83 | 1.61 | 2.79 | 2.27 |
| **Region** | | | | | | | | |
| West | 0.79 | 0.41 | 0.78 | 0.42 | 0.86 | 0.35 | 0.86 | 0.34 |
| Berlin | 0.09 | 0.29 | 0.07 | 0.26 | 0.06 | 0.23 | 0.03 | 0.18 |
| East | 0.12 | 0.32 | 0.15 | 0.36 | 0.08 | 0.28 | 0.10 | 0.31 |
| | Entropy balancing | | | | | | | |
| | Treated post N= 966 | | Treated pre N= 623 | | Control post N= 553 | | Control pre N= 309 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 |
| Female | 0.14 | 0.34 | 0.14 | 0.34 | 0.14 | 0.34 | 0.14 | 0.34 |
| Academic | 0.79 | 0.41 | 0.79 | 0.41 | 0.78 | 0.41 | 0.79 | 0.41 |
| Opportunity | 0.53 | 0.50 | 0.53 | 0.50 | 0.53 | 0.50 | 0.53 | 0.50 |
| Industry exp. | 15.29 | 10.10 | 15.29 | 10.12 | 15.28 | 11.04 | 15.29 | 10.26 |
| Founding exp. | 0.60 | 0.49 | 0.60 | 0.49 | 0.59 | 0.49 | 0.60 | 0.49 |
| Successful exit | 0.16 | 0.36 | 0.16 | 0.36 | 0.16 | 0.36 | 0.16 | 0.36 |
| Patent at start | 0.08 | 0.27 | 0.08 | 0.27 | 0.08 | 0.27 | 0.08 | 0.27 |
| Startup subsidy | 0.38 | 0.48 | 0.38 | 0.49 | 0.38 | 0.48 | 0.38 | 0.49 |
| Size at start | 2.70 | 2.30 | 2.70 | 2.51 | 2.70 | 2.61 | 2.71 | 2.60 |
| Startup age | 2.24 | 1.70 | 2.24 | 1.95 | 2.24 | 1.73 | 2.24 | 2.15 |
| **Region** | | | | | | | | |
| West | 0.79 | 0.41 | 0.79 | 0.41 | 0.79 | 0.41 | 0.79 | 0.41 |
| Berlin | 0.09 | 0.29 | 0.09 | 0.29 | 0.09 | 0.29 | 0.09 | 0.29 |
| East | 0.12 | 0.32 | 0.12 | 0.32 | 0.12 | 0.32 | 0.12 | 0.32 |
| | Propensity score matching | | | | | | | |
| | Treated post N= 965 | | Treated pre N= 596 | | Control post N= 552 | | Control pre N= 303 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.53 | 0.50 | 0.49 | 0.50 | 0.52 | 0.50 | 0.51 | 0.50 |
| Female | 0.13 | 0.34 | 0.16 | 0.37 | 0.15 | 0.35 | 0.15 | 0.36 |
| Academic | 0.79 | 0.41 | 0.73 | 0.44 | 0.76 | 0.42 | 0.75 | 0.43 |
| Opportunity | 0.53 | 0.50 | 0.57 | 0.50 | 0.52 | 0.50 | 0.57 | 0.50 |
| Industry exp. | 15.29 | 10.11 | 15.02 | 9.86 | 14.95 | 10.80 | 15.20 | 10.01 |
| Founding exp. | 0.59 | 0.49 | 0.53 | 0.50 | 0.62 | 0.48 | 0.52 | 0.50 |
| Successful exit | 0.16 | 0.36 | 0.08 | 0.27 | 0.17 | 0.37 | 0.08 | 0.27 |
| Patent at start | 0.08 | 0.27 | 0.09 | 0.28 | 0.08 | 0.27 | 0.07 | 0.26 |
| Startup subsidy | 0.38 | 0.48 | 0.41 | 0.49 | 0.36 | 0.48 | 0.41 | 0.49 |
| Size at start | 2.71 | 2.30 | 2.58 | 2.44 | 2.64 | 2.43 | 2.56 | 2.10 |
| Startup age | 2.24 | 1.70 | 2.47 | 2.02 | 2.29 | 1.73 | 2.53 | 2.22 |
| **Region** | | | | | | | | |
| West | 0.79 | 0.41 | 0.78 | 0.41 | 0.77 | 0.42 | 0.82 | 0.39 |
| Berlin | 0.09 | 0.29 | 0.07 | 0.26 | 0.10 | 0.30 | 0.05 | 0.22 |
| East | 0.12 | 0.32 | 0.15 | 0.36 | 0.13 | 0.34 | 0.13 | 0.34 |

**Note**: 'Unbalanced' shows the means and standard errors of the treatment group and control groups before balancing the covariates. 'Entropy Balanced' and 'Propensity Score Matching' show the means and standard errors after using the weights obtained from the respective balancing procedure described in Section 3.3.2. 'Treated Post' is the group of eligible firms in the post-policy period. 'Treated Pre' is the group of eligible firms in the period before the policy. 'Control Post' is the group of non-eligible firms in the post-policy period. 'Control Pre' is the group of non-eligble firms in the period before the policy.

## Table B.10.: Balancing results Sample C: Angel or VCF financed

| | Unbalanced | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 247 | | Control pre N= 243 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.40 | 0.49 | 0.38 | 0.49 | 0.40 | 0.49 |
| Female | 0.16 | 0.37 | 0.18 | 0.39 | 0.19 | 0.40 | 0.23 | 0.42 |
| Academic | 0.81 | 0.39 | 0.65 | 0.48 | 0.55 | 0.50 | 0.52 | 0.50 |
| Opportunity | 0.55 | 0.50 | 0.52 | 0.50 | 0.51 | 0.50 | 0.46 | 0.50 |
| Industry exp. | 15.24 | 10.45 | 14.47 | 9.45 | 15.48 | 10.71 | 15.50 | 9.30 |
| Founding exp. | 0.58 | 0.50 | 0.48 | 0.50 | 0.51 | 0.50 | 0.37 | 0.48 |
| Successful exit | 0.18 | 0.39 | 0.05 | 0.22 | 0.11 | 0.31 | 0.11 | 0.31 |
| Patent at start | 0.08 | 0.28 | 0.10 | 0.29 | 0.06 | 0.25 | 0.06 | 0.24 |
| Public subsidy | 0.25 | 0.43 | 0.24 | 0.43 | 0.19 | 0.39 | 0.27 | 0.45 |
| Size at start | 2.65 | 1.85 | 2.60 | 2.65 | 2.73 | 2.70 | 3.63 | 6.94 |
| Startup age | 2.24 | 1.60 | 2.44 | 2.02 | 2.06 | 1.65 | 3.01 | 2.35 |
| LLC/ Inc. | 0.89 | 0.32 | 0.60 | 0.49 | 0.66 | 0.47 | 0.46 | 0.50 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.81 | 0.40 | 0.84 | 0.37 | 0.83 | 0.38 |
| East | 0.10 | 0.30 | 0.14 | 0.35 | 0.10 | 0.30 | 0.14 | 0.35 |
| Berlin | 0.10 | 0.31 | 0.05 | 0.22 | 0.06 | 0.23 | 0.03 | 0.18 |
| | Entropy balancing | | | | | | | |
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 247 | | Control pre N= 243 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 |
| Female | 0.16 | 0.37 | 0.16 | 0.37 | 0.16 | 0.37 | 0.16 | 0.37 |
| Academic | 0.81 | 0.39 | 0.81 | 0.39 | 0.81 | 0.39 | 0.81 | 0.39 |
| Opportunity | 0.55 | 0.50 | 0.55 | 0.50 | 0.55 | 0.50 | 0.55 | 0.50 |
| Industry exp. | 15.24 | 10.45 | 15.24 | 9.43 | 15.24 | 10.23 | 15.24 | 9.26 |
| Founding exp. | 0.58 | 0.50 | 0.58 | 0.50 | 0.58 | 0.50 | 0.58 | 0.50 |
| Successful exit | 0.18 | 0.39 | 0.18 | 0.39 | 0.18 | 0.39 | 0.18 | 0.39 |
| Patent at start | 0.08 | 0.28 | 0.08 | 0.28 | 0.08 | 0.28 | 0.08 | 0.28 |
| Public subsidy | 0.25 | 0.43 | 0.25 | 0.44 | 0.25 | 0.43 | 0.25 | 0.43 |
| Size at start | 2.65 | 1.85 | 2.65 | 2.16 | 2.65 | 2.17 | 2.65 | 2.15 |
| Startup age | 2.24 | 1.60 | 2.24 | 1.92 | 2.24 | 1.69 | 2.24 | 2.10 |
| LLC/ Inc. | 0.89 | 0.32 | 0.89 | 0.32 | 0.89 | 0.32 | 0.89 | 0.32 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.80 | 0.40 | 0.80 | 0.40 | 0.80 | 0.40 |
| East | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 |
| Berlin | 0.10 | 0.31 | 0.10 | 0.31 | 0.10 | 0.31 | 0.10 | 0.31 |
| | Propensity score matching | | | | | | | |
| | Treated post N= 290 | | Treated pre N= 199 | | Control post N= 243 | | Control pre N= 231 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.41 | 0.49 | 0.54 | 0.50 | 0.39 | 0.49 |
| Female | 0.16 | 0.37 | 0.18 | 0.39 | 0.17 | 0.38 | 0.18 | 0.39 |
| Academic | 0.81 | 0.39 | 0.65 | 0.48 | 0.82 | 0.39 | 0.64 | 0.48 |
| Opportunity | 0.55 | 0.50 | 0.52 | 0.50 | 0.55 | 0.50 | 0.51 | 0.50 |
| Industry exp. | 15.24 | 10.45 | 14.29 | 9.19 | 15.18 | 10.22 | 14.44 | 9.06 |
| Founding exp. | 0.58 | 0.50 | 0.48 | 0.50 | 0.58 | 0.49 | 0.47 | 0.50 |
| Successful exit | 0.18 | 0.39 | 0.05 | 0.22 | 0.15 | 0.36 | 0.05 | 0.21 |
| Patent at start | 0.08 | 0.28 | 0.09 | 0.29 | 0.09 | 0.28 | 0.08 | 0.27 |
| Public subsidy | 0.25 | 0.43 | 0.25 | 0.43 | 0.24 | 0.43 | 0.25 | 0.44 |
| Size at start | 2.65 | 1.85 | 2.48 | 2.09 | 2.58 | 2.00 | 2.48 | 2.02 |
| Startup age | 2.24 | 1.60 | 2.43 | 2.01 | 2.21 | 1.66 | 2.47 | 2.16 |
| LLC/ Inc. | 0.89 | 0.32 | 0.61 | 0.49 | 0.88 | 0.32 | 0.58 | 0.49 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.81 | 0.39 | 0.82 | 0.38 | 0.80 | 0.40 |
| East | 0.10 | 0.30 | 0.14 | 0.35 | 0.10 | 0.30 | 0.17 | 0.37 |
| Berlin | 0.10 | 0.31 | 0.05 | 0.22 | 0.08 | 0.27 | 0.03 | 0.17 |

**Note**: 'Unbalanced' shows the means and standard errors of the treatment group and control groups before balancing the covariates. 'Entropy Balanced' and 'Propensity Score Matching' show the means and standard errors after using the weights obtained from the respective balancing procedure described in Section 3.3.2. 'Treated Post' is the group of angel-financed and eligible firms in the post-policy period. 'Treated Pre' is the group of angel financed and eligible firms in the period before the policy. 'Control Post' is the group of non-eligible or VCF financed firms in the post-policy period. 'Control Pre' is the group of non-eligble firms or VCF financed firms in the period before the policy.

### Table B.11.: Balancing results Sample D: Angel financed

| | Unbalanced | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 198 | | Control pre N= 164 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.40 | 0.49 | 0.33 | 0.47 | 0.32 | 0.47 |
| Female | 0.16 | 0.37 | 0.18 | 0.39 | 0.20 | 0.40 | 0.24 | 0.43 |
| Academic | 0.81 | 0.39 | 0.65 | 0.48 | 0.48 | 0.50 | 0.44 | 0.50 |
| Opportunity | 0.55 | 0.50 | 0.52 | 0.50 | 0.47 | 0.50 | 0.37 | 0.48 |
| Industry exp. | 15.24 | 10.45 | 14.47 | 9.45 | 15.73 | 11.10 | 14.07 | 8.86 |
| Founding exp. | 0.58 | 0.50 | 0.48 | 0.50 | 0.50 | 0.50 | 0.32 | 0.47 |
| Successful exit | 0.18 | 0.39 | 0.05 | 0.22 | 0.12 | 0.32 | 0.09 | 0.28 |
| Patent at start | 0.08 | 0.28 | 0.10 | 0.29 | 0.05 | 0.22 | 0.02 | 0.13 |
| Public subsidy | 0.25 | 0.43 | 0.24 | 0.43 | 0.12 | 0.32 | 0.18 | 0.38 |
| Size at start | 2.65 | 1.85 | 2.60 | 2.65 | 2.70 | 2.75 | 3.87 | 8.19 |
| Startup age | 2.24 | 1.60 | 2.44 | 2.02 | 1.98 | 1.66 | 2.72 | 2.29 |
| LLC/ Inc. | 0.89 | 0.32 | 0.60 | 0.49 | 0.60 | 0.49 | 0.38 | 0.49 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.81 | 0.40 | 0.86 | 0.34 | 0.86 | 0.35 |
| East | 0.10 | 0.30 | 0.14 | 0.35 | 0.07 | 0.26 | 0.12 | 0.32 |
| Berlin | 0.10 | 0.31 | 0.05 | 0.22 | 0.07 | 0.25 | 0.02 | 0.15 |
| | Entropy balancing | | | | | | | |
| | Treated post N= 290 | | Treated pre N= 200 | | Control post N= 198 | | Control pre N= 164 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 | 0.52 | 0.50 |
| Female | 0.16 | 0.37 | 0.16 | 0.37 | 0.16 | 0.37 | 0.16 | 0.37 |
| Academic | 0.81 | 0.39 | 0.81 | 0.39 | 0.81 | 0.39 | 0.81 | 0.39 |
| Opportunity | 0.55 | 0.50 | 0.55 | 0.50 | 0.55 | 0.50 | 0.55 | 0.50 |
| Industry exp. | 15.24 | 10.45 | 15.24 | 9.43 | 15.24 | 10.70 | 15.24 | 9.06 |
| Founding exp. | 0.58 | 0.50 | 0.58 | 0.50 | 0.58 | 0.50 | 0.58 | 0.50 |
| Successful exit | 0.18 | 0.39 | 0.18 | 0.39 | 0.18 | 0.39 | 0.18 | 0.39 |
| Patent at start | 0.08 | 0.28 | 0.08 | 0.28 | 0.08 | 0.28 | 0.08 | 0.28 |
| Public subsidy | 0.25 | 0.43 | 0.25 | 0.44 | 0.25 | 0.44 | 0.25 | 0.44 |
| Size at start | 2.65 | 1.85 | 2.65 | 2.16 | 2.65 | 2.36 | 2.65 | 2.01 |
| Startup age | 2.24 | 1.60 | 2.24 | 1.92 | 2.24 | 1.76 | 2.24 | 2.13 |
| LLC/ Inc. | 0.89 | 0.32 | 0.89 | 0.32 | 0.89 | 0.32 | 0.89 | 0.32 |
| **Region** | | | | | | | | |
| West | 0.80 | 0.40 | 0.80 | 0.40 | 0.80 | 0.40 | 0.80 | 0.40 |
| East | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 | 0.10 | 0.30 |
| Berlin | 0.10 | 0.31 | 0.10 | 0.31 | 0.10 | 0.31 | 0.10 | 0.31 |
| | Propensity score matching | | | | | | | |
| | Treated post N= 274 | | Treated pre N= 190 | | Control post N= 190 | | Control pre N= 159 | |
| | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. | Mean | Std. Err. |
| Team | 0.52 | 0.50 | 0.39 | 0.49 | 0.52 | 0.50 | 0.37 | 0.48 |
| Female | 0.16 | 0.37 | 0.19 | 0.39 | 0.18 | 0.38 | 0.15 | 0.36 |
| Academic | 0.80 | 0.40 | 0.63 | 0.48 | 0.78 | 0.41 | 0.62 | 0.49 |
| Opportunity | 0.56 | 0.50 | 0.50 | 0.50 | 0.54 | 0.50 | 0.48 | 0.50 |
| Industry exp. | 15.05 | 10.43 | 14.11 | 9.29 | 14.60 | 10.31 | 14.98 | 9.35 |
| Founding exp. | 0.57 | 0.50 | 0.45 | 0.50 | 0.61 | 0.49 | 0.44 | 0.50 |
| Successful exit | 0.18 | 0.38 | 0.05 | 0.22 | 0.17 | 0.37 | 0.06 | 0.23 |
| Patent at start | 0.08 | 0.27 | 0.05 | 0.22 | 0.08 | 0.28 | 0.06 | 0.24 |
| Public subsidy | 0.21 | 0.41 | 0.23 | 0.42 | 0.20 | 0.40 | 0.20 | 0.40 |
| Size at start | 2.68 | 1.88 | 2.59 | 2.71 | 2.48 | 1.90 | 2.56 | 2.19 |
| Startup age | 2.18 | 1.60 | 2.42 | 2.01 | 2.15 | 1.69 | 2.66 | 2.22 |
| LLC/ Inc. | 0.88 | 0.33 | 0.59 | 0.49 | 0.87 | 0.33 | 0.58 | 0.50 |
| **Region** | | | | | | | | |
| West | 0.82 | 0.38 | 0.81 | 0.40 | 0.83 | 0.37 | 0.81 | 0.39 |
| East | 0.07 | 0.26 | 0.14 | 0.35 | 0.07 | 0.25 | 0.15 | 0.35 |
| Berlin | 0.11 | 0.31 | 0.05 | 0.22 | 0.10 | 0.30 | 0.04 | 0.20 |

**Note**: 'Unbalanced' shows the means and standard errors of the treatment group and control groups before balancing the covariates. 'Entropy Balanced' and 'Propensity Score Matching' show the means and standard errors after using the weights obtained from the respective balancing procedure described in Section 3.3.2. 'Treated Post' is the group of eligible firms in the post-policy period. 'Treated Pre' is the group of eligible firms in the period before the policy. 'Control Post' is the group of non-eligible firms in the post-policy period. 'Control Pre' is the group of non-eligble firms in the period before the policy.

# B.4. Results

## B.4.1. Angel financing

### Table B.12.: Financing amounts accounting for syndicate size

*Sample D: Angel financed*

| | Dependent variable: ln(angel amount) | | | |
|---|---|---|---|---|
| | Without syndicate size | | Accounting for syndicate size | |
| | (1) | (2) | (3) | (4) |
| Eligible × Post | 0.413** | 0.412** | 0.301 | 0.303 |
| | (0.182) | (0.193) | (0.189) | (0.201) |
| Syndicate size | | | 0.143*** | 0.143*** |
| | | | (0.030) | (0.029) |
| Post | 0.733*** | 0.607* | 0.733*** | 0.728* |
| | (0.134) | (0.361) | (0.140) | (0.392) |
| **Firm characteristics** | | | | |
| Team | 0.202 | 0.203 | 0.194 | 0.193 |
| | (0.129) | (0.129) | (0.132) | (0.133) |
| Opportunity | 0.320*** | 0.305*** | 0.290*** | 0.275** |
| | (0.090) | (0.097) | (0.096) | (0.104) |
| Academic | 0.533*** | 0.515*** | 0.527*** | 0.513*** |
| | (0.101) | (0.107) | (0.103) | (0.109) |
| Female | -0.246 | -0.250 | -0.219 | -0.222 |
| | (0.234) | (0.241) | (0.227) | (0.233) |
| Industry exp. | 0.011** | 0.012** | 0.012*** | 0.012*** |
| | (0.004) | (0.005) | (0.004) | (0.004) |
| Founding exp. | -0.193* | -0.177 | -0.180* | -0.166 |
| | (0.109) | (0.109) | (0.105) | (0.103) |
| Successful exit | 0.459*** | 0.402** | 0.323* | 0.273 |
| | (0.153) | (0.158) | (0.188) | (0.184) |
| Patent at start | 0.274 | 0.274 | 0.202 | 0.200 |
| | (0.209) | (0.207) | (0.203) | (0.198) |
| Public subsidy | 0.514*** | 0.523*** | 0.452*** | 0.464*** |
| | (0.132) | (0.122) | (0.132) | (0.122) |
| Size at start | 0.053** | 0.054** | 0.051** | 0.052** |
| | (0.026) | (0.025) | (0.024) | (0.023) |
| LLC/ Inc. | 0.623*** | 0.641*** | 0.603*** | 0.618*** |
| | (0.140) | (0.131) | (0.137) | (0.128) |
| Startup age | 0.017 | | 0.013 | |
| | (0.029) | | (0.026) | |
| **Region** | | | | |
| West | 0.278* | 0.295** | 0.277** | 0.294** |
| | (0.147) | (0.145) | (0.133) | (0.133) |
| Berlin | 0.258 | 0.267 | 0.238 | 0.251 |
| | (0.242) | (0.231) | (0.239) | (0.233) |
| **Fixed effects:** | | | | |
| Industry | Yes | Yes | Yes | Yes |
| Founding cohort | | Yes | | Yes |
| R2 | 0.37 | 0.38 | 0.40 | 0.41 |
| Firm obs. | 849 | 849 | 849 | 849 |

**Note**: Table B.12 shows the average effect of the angel investor grant on the amount (in logs) of venture capital raised from angel investors. Sample D contains startups that raised venture capital from angel investors but not venture capital funds. *Eligible* are startups that operate in one of the industries that qualify for the grant, listed in Table B.4. *Post* is the observation period after 2013 when the angel investor grant was introduced. Coefficients are estimated using ordinary least squares.
Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## B.4.2. Managerial support

**Table B.13.: Effect on managerial support activities (a)**

*Sample D: Angel financed*

| | Dependent variable: level of support for X | | | | |
|---|---|---|---|---|---|
| | Panel A: Unbalanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.231 | -0.040 | 0.077 | -0.173 | -0.079 |
| | (0.168) | (0.172) | (0.132) | (0.158) | (0.150) |
| Post | 0.029 | 0.096 | 0.254** | 0.235* | 0.268** |
| | (0.104) | (0.157) | (0.110) | (0.138) | (0.120) |
| R2 | 0.08 | 0.09 | 0.10 | 0.07 | 0.06 |
| Firm obs. | 849 | 849 | 849 | 849 | 849 |
| | Panel B: Entropy balanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.211 | -0.076 | -0.322** | -0.116 | -0.425** |
| | (0.298) | (0.232) | (0.155) | (0.230) | (0.197) |
| Post | -0.027 | 0.136 | 0.503*** | 0.166 | 0.590*** |
| | (0.243) | (0.199) | (0.125) | (0.202) | (0.169) |
| R2 | 0.13 | 0.19 | 0.15 | 0.07 | 0.10 |
| Firm obs. | 849 | 849 | 849 | 849 | 849 |
| | Panel C: Propensity score balanced | | | | |
| | Board | Mentoring | Network | Commercialization | Development |
| Eligible × Post | 0.224 | -0.135 | -0.126 | -0.114 | -0.246 |
| | (0.256) | (0.202) | (0.139) | (0.195) | (0.197) |
| Eligible | -0.159 | 0.445** | 1.287*** | 0.175 | 0.160*** |
| | (0.121) | (0.182) | (0.124) | (0.184) | (0.059) |
| Post | 0.038 | 0.204 | 0.457*** | 0.175 | 0.453*** |
| | (0.208) | (0.182) | (0.114) | (0.184) | (0.166) |
| R2 | 0.11 | 0.15 | 0.13 | 0.09 | 0.10 |
| Firm obs. | 813 | 813 | 813 | 813 | 813 |
| **Fixed effects:** | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | | | | | |

**Note**: Table B.13 shows the average effect of the angel investor grant on the level of managerial support from angel investors. Sample D contains startups that raised venture capital from angel investors but not venture capital funds. *Eligible* startups operate in one of the industries that qualify for the grant, listed in Table B.4. *Post* is the observation period after 2013 when the angel investor grant was introduced. Coefficients are estimated using ordinary least squares. Models in *Panel A* do not balance the covariate distribution and use unit weights for the calculation of Equation (3.2). Models in *Panel B* use Entropy Balancing to balance the covariate distribution. Models in *Panel C* use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The balancing covariates include Team, Female, Academic, Opportunity, Industry Exp., Founding Exp., Successful Exit, Patent at Start, Public Subsidy, Size at Start, Startup Age, LLC/Inc., and Region. See Table B.11 for the balancing results.
Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## B.4.3. Robustness tests

**Table B.14.: Technological shocks and pre-treatment trends on financing volumes**

*Sample E: Angel or VCF financed, only eligible industries*

| | Dependent variable: log(total VC amount) | | | | | |
|---|---|---|---|---|---|---|
| | Unbalanced | | Entropy balanced | | PS balanced | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Angel × Post | 1.281*** | | 0.992*** | | 0.987*** | |
| | (0.275) | | (0.275) | | (0.315) | |
| Post | -0.034 | | 0.740 | | 1.015 | |
| | (0.660) | | (0.891) | | (1.133) | |
| Angel × Pre | | 0.292 | | 0.068 | | 0.335 |
| | | (0.393) | | (0.487) | | (0.386) |
| Pre | | -0.861 | | -0.736 | | -0.606 |
| | | (0.593) | | (0.727) | | (0.501) |
| Angel | -2.392*** | -2.694*** | -1.969*** | -2.206*** | -2.037*** | -2.365*** |
| | (0.159) | (0.363) | (0.177) | (0.469) | (0.202) | (0.400) |
| **Fixed effects:** | | | | | | |
| Industry | Yes | Yes | Yes | Yes | Yes | Yes |
| Founding cohort | Yes | Yes | Yes | Yes | Yes | Yes |
| R2 | 0.32 | 0.40 | 0.39 | 0.53 | 0.37 | 0.45 |
| Firm obs. | 584 | 442 | 579 | 442 | 577 | 436 |

**Note**: Table B.14 shows the average effect of the angel investor grant on the amount (in logs) of venture capital raised from an angel investor. *Sample E* contains startups in eligible industries listed in Table B.4 that raised venture capital from angel investors or venture capital funds, but not both. *Angel* includes startups that raised venture capital from angel investors but not venture capital funds. *Post* is the observation period after 2013 when the angel investor grant was introduced. *Pre* is the observation period before 2006 that serves as a pre-treatment test. Coefficients are estimated using ordinary least squares. Columns (3) and (4) use Entropy Balancing to balance the covariate distribution for the calculation of the weights in Equation (3.2). Columns (5) and (6) use Propensity Score Matching to balance the covariate distribution, with the weights specified in Section 3.3.2. The balancing covariates include Team, Academic, Industry Exp., Patent at Start, Size at Start, Startup Age, LLC/Inc., and Region. See Table B.8 for the balancing results.
Standard errors clustered at the industry level in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## Table B.15.: Financing decision and pre-treatment trends using SUR model

| *Sample A+: Full, only eligible industries* | | | |
|---|---|---|---|
| | Angel | Angel & VCF | VCF |
| Post | 0.030*** | 0.012*** | -0.003 |
| | (0.008) | (0.003) | (0.002) |
| Pre | -0.001 | -0.003 | -0.001 |
| | (0.007) | (0.003) | (0.003) |
| Firm obs. | 8,885 | | |
| | $Chi^2$-test for comparison of means (Post) | | |
| | Chi2 | df | p-value |
| Angel vs. VCF | 14.94 | 1 | 0.00 |
| Angel vs. Angel & VCF | 7.59 | 1 | 0.01 |
| VCF vs. Angel & VCF | 14.35 | 1 | 0.00 |
| | $Chi^2$-test for comparison of means (Pre) | | |
| | Chi2 | df | p-value |
| Angel vs. VCF | 0.02 | 1 | 0.90 |
| Angel vs. Angel & VCF | 0.16 | 1 | 0.69 |
| VCF vs. Angel & VCF | 0.53 | 1 | 0.47 |

**Note**: Table B.15 shows the average effect of the angel investor subsidies on financing decisions. *Sample A+* contains all eligible startups in the startup panel, including those not in contact with angel investors, and all eligible startups from the Hightech Survey 2007. *Post* is the observation period after 2013 when the angel investor grant was introduced. *Pre* is the observation period before 2007 that serves as a pre-treatment test. Coefficients are estimated using seemingly unrelated linear regressions.
Standard errors clustered at the industry level in parentheses.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## Table B.16.: Transformed coefficients for SUR model

| *Sample A+: Full, only eligible industries* | | | |
|---|---|---|---|
| | Angel | Angel & VCF | VCF |
| Post | 0.478*** | 1.569*** | -0.176 |
| | (0.097) | (0.327) | (0.132) |
| Pre | -0.0088 | -0.3821 | -0.0841 |
| | (0.1115) | (0.3354) | (0.2098) |
| | $Chi^2$-test for comparison of means (Post) | | |
| | Chi2 | df | p-value |
| Angel vs. VCF | 17.24 | 1 | 0.00 |
| Angel vs. Angel & VCF | 10.43 | 1 | 0.00 |
| VCF vs. Angel & VCF | 19.64 | 1 | 0.00 |
| | $Chi^2$-test for comparison of means (Pre) | | |
| | Chi2 | df | p-value |
| Angel vs. VCF | 0.15 | 1 | 0.70 |
| Angel vs. Angel & VCF | 1.41 | 1 | 0.24 |
| VCF vs. Angel & VCF | 1.83 | 1 | 0.18 |

**Note**: Table B.16 shows the transformed coefficients, where the subsidy effect has been divided by the constant for each equation.
Standard errors in parentheses have been calculated using the Delta method.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

# C. Outside Equity and Startup Innovation: Evidence from the German INVEST Program

## C.1. The INVEST program for angel investments

In April 2013, the German federal government announced the "Directive for the Subsidization of Venture Capital by Private Investors for Young Innovative Companies", later renamed "INVEST - Zuschuss für Wagniskapital”. The policy came into effect in May 2013 and is administered by the Federal Office for Economic Affairs and Export Control (BAFA).[1] The program intends to stimulate direct equity investments by private investors in young and innovative companies by motivating existing investors to make additional investments and attracting new people with entrepreneurial (or managerial) bacbackgrounds to become investors.

Investors receive a tax-free grant amounting to 20% of the investment amount for investments between 10,000 and 500,000 Euros. Per year, investors can claim a maximum of 500,000 Euros of their venture capital investments for the subsidy.[2] Since 2017, investors can also apply for an exit grant which is essentially a partial tax exemption on capital gains from the investment. Investors and companies must apply jointly for the grant. Each company can claim up to 3 million Euros in venture capital per year for the subsidy, corresponding to a maximum subsidy amount of 600,000 Euros per company and year.[3]

A primary objective of the program is to keep approval times fast and administrative cost low. To this end, the application process and eligibility criteria are kept simple. The application process is a two-step process. First, the company an investor seeks to invest in must have its eligibility certified. Then investors submit their applications for the grant. An exemption is provided for companies that are not yet incorporated. In this case, investors may obtain approval before the company is founded. The company is then reviewed after it has been recorded in the commercial register.

To be eligible, companies must be privately held corporations and no older than seven years at the time of the application.[4] Their annual revenues and balance sheet totals must not exceed 10 million Euros, and they must not have more than 50 employees. Companies’ head offices must be within the European Economic Area, and at least one branch or permanent establishment must be located in Germany. Furthermore, the company must not be in financial distress, i.e., not be in a state of insolvency or even bankruptcy. Therefore, the target group of the subsidy program is startup companies. Only 1% of the companies that have applied have more than 40 employees. The average age of the companies whose investors received the grant was two years at the time of approval. Only 3% of applicants were rejected because they exceeded the age threshold.

Importantly for our research design, the guidelines stipulate that companies must operate in

[1] In August 2019 about ten full-time employees were responsible for administrating the program at the BAFA (Deutscher Bundestag, Drucksache 19/12471).
[2] In the original guidelines from 2013, the ceiling was at 250,000 Euros (BAnz AT 10.05.2013 B1).
[3] In the original guidelines from 2013, the ceiling was at 1 million Euros (BAnz AT 10.05.2013 B1).
[4] Up until 2017, the maximum age threshold was set at ten years.

specific industries to be eligible for the grant. Eligible sectors are defined by a list of NACE industry codes that the government considers particularly prone to innovation. The assignment to a specific industry is based on the company's purpose, as specified in the official business register. When applying for the investor grant, firms must provide this information in addition to the NACE code of their main industry. The information is reviewed and validated by BAFA staff using additional resources such as official business register documents and firm websites. The government's definition of innovative industries is highly correlated with R&D-intensities at the sector level (see Figure 4.2). On average, firms operating in eligible industries have higher R&D-intensities than those in non-eligible industries. Yet, many non-eligible sectors also show significant R&D activity at the startup level. Since the first revision of the guidelines in 2014, there have been possible exceptions regarding industry affiliation. Companies that have a valid patent or have received public funding from specific research programs two years before application are also considered eligible. However, the evaluation of the official funding data by Gottschalk et al. (2016) shows that this criterion only applies to 2% of the funded companies. Since the revision of the guidelines in 2017, eligibility can also be certified via proof of innovation, which affects a total of 6% of all eligible companies. However, it is unclear how many of these companies were funded by investors. Next to incomplete applications, lack of innovativeness is the most critical rejection criterion for grant applications (Gottschalk et al., 2016). Industry affiliation is the predominant company criterion on which the funding agency bases the grant decision.

For investors, the following eligibility criteria apply. Investors have to make direct equity investments in the company. These investments must increase company finances. This excludes secondary transactions of existing equity or the subsequent conversion of existing credit lines or subordinated loans into equity. An exception is convertible loan contracts. The program has covered these since the revision of the guidelines in 2017. The grant is paid out once the loan has been converted into equity. Investments from individuals affiliated with the company before applying for the grant are not eligible. The grant has to be reimbursed if the investment relationship between the investor and the young company is terminated before the minimum holding period of three years. In addition, the investor must repay the subsidy if the investor enters into a further relationship with the young company within these three years, e.g., increases the shareholding to over 25% or acquires more than 25% of the voting rights. The above requirements exclude venture capital firms and corporate insiders from the program.

Until May 2019, 5,453 individual investors applied with 8,175 investments for the grant. In total, 6,441 applications from 4,399 individual investors in 1,656 companies have been granted. To put this into perspective, Berger, Egeln, et al. (2020) estimate that about 5,120 firms in high-tech sectors and below the age of four received an investment from a private individual from 2015 to 2018. Based on these estimates, roughly a quarter to a third of all high-tech startups were funded by private investors who received the grant. The average (median) subsidized investment amount per individual investor is 81,679 Euros (50.000 Euros), which corresponds to a subsidy of 16,334 Euros (10.000 Euros) per investment. About half of the investors participating in the program have received between 10.000 and 50.000 Euros, nearly a quarter of investors have received 50.000 to 100.000 Euros in grants, and about 20% of investors received more than 100.000 Euros in grants. In 2019, the annual budget of the program was 46 Mio. Euros, which is roughly equivalent to the previous years. Between 2013 and 2019, half of the funds earmarked for the program in the federal budget were called up. This corresponds to an average call-up amount of around 21 Mio. Euros per year. In total, about 105 Mio. Euros in public funds went into the program in the corresponding period. Based on the funding quota, the program matched approx. 525 Mio. Euros of investments in young and innovative firms between 2013 and 2019. This corresponds to about 13% of early-stage Venture Capital that went into startups in Germany in that period, based on the numbers of Europe's largest Private Equity association *INVEST EUROPE*.

## C.2. Derivation of equilibrium conditions

This section briefly shows the derivation of the equilibrium financing levels in Kortum and Lerner (2000).

- Define $x = \alpha \Pi Y \nu$
- Divide equation (4.2) / (4.3) to arrive at $b/\kappa_t = f_E(\cdot)/f_G(\cdot)$
- Rewrite equation (4.3) as $f_G^{-1}(x) = E_{it}\mu_{it}/Y_{it}$
- Define $g(x) \equiv f_E(f_G^{-1}(x)) = b/\kappa_t$
- Solve for $x$, and get $x = g^{-1}(b/\kappa_t) = h_1(\kappa_t)$
- Plug the previous definition of $x$ into (4.3) and rearrange to get $E/Y = f_G^{-1}(h_1(v))/\mu = h_2(v)/\mu$
- Solve for $Y$ and use $Y = G + bE$, giving $E/G = h_2(\kappa_t)/(\mu - bh_2(\kappa_t))$ which is equilibrium condition (4.5)
- Use $x = \alpha \Pi Y \nu$ and $x = h_1(\kappa_t)$, then solve for $Y$, and arrive at $Y = (\alpha \Pi \nu / h_1(\kappa_t))^{1/(1-\alpha)}$, which is equilibrium condition (4.4)

## C.3. List of industries

**Table C.1.: Industries in sample**

| Observed | N | NACE Rev. 2 |
|---|---|---|
| Eligible | | |
| All periods | 22 | 20, 21, 22, 23, 26, 27, 28, 29, 30, 33, 58, 59, 61, 62, 63, 71, 73, 74, 90, 25.6, 32.5 |
| With gaps | 2 | 60, 13.96 |
| Non-eligible | | |
| All periods | 38 | 10, 11, 13[a] , 14, 15, 16, 17, 18, 24, 25[b], 31, 32[c], 41, 42, 43, 45, 46, 47, 49, 52, 53, 55, 56, 66, 68, 69, 70, 77, 78, 79, 80, 81, 82, 85, 92, 93, 95, 96 |
| With gaps | 8 | 12, 19, 35, 50, 51, 64, 65, 91 |

**Note**: a)NACE 13.96, b) NACE 25.6 c) NACE 32.5

**Table C.2.: NACE codes of eligible industries**

| NACE rev. 2 | Description |
|---|---|
| 13.96 | Manufacture of other technical and industrial textiles |
| 20 | Manufacture of chemicals and chemical products |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| 22 | Manufacture of rubber and plastic products |
| 23 | Manufacture of other non-metallic mineral products |
| 25.6 | Treatment and coating of metals; machining |
| 26 | Manufacture of computer, electronic and optical products |
| 27 | Manufacture of electrical equipment |
| 28 | Manufacture of machinery and equipment n.e.c. |
| 29 | Manufacture of motor vehicles, trailers, and semi-trailers |
| 30 | Building of ships and boats |
| 32.5 | Manufacture of medical and dental instruments and supplies |
| 33 | Repair and installation of machinery and equipment |
| 58 | Publishing activities |
| 59 | Motion picture, video, and television programme production, sound recording, and music publishing activities |
| 60 | Programming and broadcasting activities |
| 61 | Telecommunications |
| 62 | Computer programming, consultancy, and related activities |
| 63 | Information service activities |
| 71 | Architectural and engineering activities; technical testing and analysis |
| 72 | Scientific research and development |
| 73 | Advertising and market research |
| 74 | Other professional, scientific, and technical activities |
| 90 | Creative, arts, and entertainment activities |

**Table C.3.: NACE codes of non-eligible industries**

| NACE rev. 2 | Description |
|---|---|
| 10 | Manufacture of food products |
| 11 | Manufacture of beverage |
| 12 | Manufacture of tobacco products |
| 13 (ex. 13.96) | Manufacture of textiles |
| 14 | Manufacture of wearing apparel |
| 15 | Manufacture of leather and related products |
| 16 | Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting material |
| 17 | Manufacture of paper and paper products |
| 18 | Printing and reproduction of recorded media |
| 19 | Manufacture of coke and refined petroleum product |
| 24 | Manufacture of basic metals |
| 25 (ex. 25.6) | Manufacture of fabricated metal products, except machinery and equipment |
| 31 | Manufacture of furniture |
| 32 (ex. 32.5) | Other manufacturing |
| 35 | Electricity, gas, steam, and air conditioning supply |
| 41 | Construction of buildings |
| 42 | Civil engineering |
| 43 | Specialised construction activities |
| 45 | Wholesale and retail trade and repair of motor vehicles and motorcycles |
| 46 | Wholesale trade, except for motor vehicles and motorcycles |
| 47 | Retail trade, except for motor vehicles and motorcycles |
| 49 | Land transport and transport via pipeline |
| 50 | Water transport |
| 51 | Air transport |
| 52 | Warehousing and support activities for transportation |
| 53 | Postal and courier activities |
| 55 | Accommodation |
| 56 | Food and beverage service activities |
| 64 | Financial service activities, except insurance and pension funding |
| 65 | Insurance, reinsurance, and pension funding (except compulsory social security) |
| 66 | Activities auxiliary to financial services and insurance activities |
| 68 | Real estate activities |
| 69 | Legal and accounting activities |
| 70 | Activities of head offices; management consultancy activities |
| 77 | Rental and leasing activities |
| 78 | Employment activities |
| 79 | Travel agency, tour operator reservation service and related activities |
| 80 | Security and investigation activities |
| 81 | Services to buildings and landscape activities |
| 82 | Office administrative, office support, and other business support activities |
| 85 | Education |
| 91 | Libraries, archives, museums, botanical and zoological Gardens |
| 92 | Gambling and betting activities |
| 93 | Sports activities and amusement and recreation activities |
| 95 | Repair of computers and personal and household goods |
| 96 | Other personal service activities |

# C.4. Description of data and sample

Data in the IAB/ZEW Startup Panel (SUP) comes from a yearly survey among legally independent startups in Germany. The first survey was conducted in 2008 for the reference year 2007. The sample is drawn from the population of German startups and stratified by industries. Startups from high-tech industries are over-represented. When entering the survey, startups must not be older than three years and remain in the survey until their seventh year of operation. Hence the SUP is designed as a replacement sample, where new firms constantly enter the panel. Since the second wave in 2009, 3,500 to 8,000 startups have entered the panel each year. In the first wave, a larger sample of 23,000 startups was surveyed. Between 6,000 and 8,000 startups participate in the survey each year.[5] On average, firms are observed for three periods. When accounting for missing information, this number drops to roughly two. 57% of firms enter the survey in their first year of operation, 26% in their second year, and 16% in their third year. The number of firms and firm-year observations differs markedly between different industries. The largest group of firms (by NACE code) are from the manufacturing industry, followed by firms from the information and communication sector and firms operating in professional, scientific, and technical activities.

**Table C.4.: Number of observations per firm by founding cohorts**

| | Full panel | | | | | | Sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fou. coh. | Eligible | | Non-eligible | | Total | | Eligible | | Non-eligible | | Total | |
| | Med. | Mean | Med. | Mean | Med. | Mean | Med. | Mean | Med. | Mean | Med. | Mean |
| 2005 | 5 | 5.4 | 5 | 5.2 | 5 | 5.3 | 2 | 2.4 | 2 | 2.1 | 2 | 2.3 |
| 2006 | 4 | 4.5 | 4 | 4.2 | 4 | 4.3 | 2 | 2.3 | 2 | 2.3 | 2 | 2.3 |
| 2007 | 3 | 3.7 | 3 | 3.4 | 3 | 3.6 | 2 | 2.3 | 2 | 2.2 | 2 | 2.3 |
| 2008 | 3 | 3.9 | 3 | 3.3 | 3 | 3.6 | 2 | 2.5 | 2 | 2.3 | 2 | 2.4 |
| 2009 | 3 | 3.7 | 3 | 3.4 | 3 | 3.6 | 2 | 2.5 | 2 | 2.3 | 2 | 2.4 |
| 2010 | 4 | 4.0 | 3 | 3.4 | 3 | 3.7 | 2 | 2.5 | 2 | 2.1 | 2 | 2.4 |
| 2011 | 3 | 3.8 | 2 | 3.3 | 3 | 3.5 | 2 | 2.3 | 2 | 2.1 | 2 | 2.2 |
| 2012 | 3 | 3.8 | 3 | 3.3 | 3 | 3.6 | 2 | 2.5 | 2 | 2.2 | 2 | 2.4 |
| 2013 | 3 | 3.5 | 3 | 3.3 | 3 | 3.4 | 2 | 2.2 | 2 | 2.1 | 2 | 2.2 |
| 2014 | 3 | 3.2 | 3 | 3.0 | 3 | 3.1 | 2 | 2.2 | 1 | 1.8 | 2 | 2.0 |
| 2015 | 3 | 2.9 | 3 | 2.7 | 3 | 2.8 | 2 | 1.9 | 2 | 1.8 | 2 | 1.9 |
| 2016 | 3 | 2.4 | 3 | 2.4 | 3 | 2.4 | 1 | 1.6 | 1 | 1.4 | 1 | 1.5 |
| 2017 | 2 | 1.8 | 2 | 1.8 | 2 | 1.8 | 1 | 1.3 | 1 | 1.3 | 1 | 1.3 |
| 2018 | 1 | 1.0 | 1 | 1.0 | 1 | 1.0 | 1 | 1.0 | 1 | 1.0 | 1 | 1.0 |
| Total | 3 | 3.4 | 3 | 3.1 | 3 | 3.2 | 2 | 2.1 | 1 | 1.8 | 2 | 2.0 |

**Note**: Table C.4 shows the median (Med.) and average (Mean) number of observations per firm by founding cohorts and program eligibility. Full panel contains all observations in the IAB/ZEW Startup Panel, sample contains observations that we use in our analysis. For example, for the founding cohort of 2012, the full panel (sample) contains, on average, 3.6 (2.4) observations, and for more than half of the firms founded in 2012, it contains 3 (2) observations.

[5] Note that in 2014 and 2015, the replacement sample was smaller, as firms from the retail sector were not surveyed due to budget constraints.

**Table C.5.: Full panel distribution by founding cohort and first year sampled**

| Founding cohort | First sampled in: t+1 No. | t+1 % | t+2 No. | t+2 % | t+3 No. | t+3 % | Total No. | Total % |
|---|---|---|---|---|---|---|---|---|
| 2005 | 0 | 0 | 0 | 0 | 1,767 | 100 | 1,767 | 100 |
| 2006 | 0 | 0 | 1,934 | 89 | 227 | 11 | 2,161 | 100 |
| 2007 | 1,718 | 71 | 514 | 21 | 185 | 8 | 2,417 | 100 |
| 2008 | 1,430 | 72 | 394 | 20 | 153 | 8 | 1,977 | 100 |
| 2009 | 1,492 | 73 | 410 | 20 | 151 | 7 | 2,053 | 100 |
| 2010 | 1,340 | 68 | 363 | 19 | 254 | 13 | 1,957 | 100 |
| 2011 | 1,287 | 67 | 400 | 21 | 227 | 12 | 1,914 | 100 |
| 2012 | 1,234 | 69 | 363 | 20 | 192 | 11 | 1,789 | 100 |
| 2013 | 1,253 | 65 | 301 | 16 | 386 | 20 | 1,940 | 100 |
| 2014 | 1,269 | 59 | 544 | 25 | 328 | 15 | 2,141 | 100 |
| 2015 | 1,386 | 61 | 606 | 27 | 278 | 12 | 2,270 | 100 |
| 2016 | 1,322 | 50 | 694 | 26 | 614 | 23 | 2,630 | 100 |
| 2017 | 1,265 | 54 | 1,061 | 46 | 0 | 0 | 2,326 | 100 |
| 2018 | 1,543 | 100 | 0 | 0 | 0 | 0 | 1,543 | 100 |
| Total | 16,539 | 57 | 7,584 | 26 | 4,762 | 16 | 28,885 | 100 |

**Note**: Table C.5 shows the distribution of firms by founding cohorts, and the year they were first sampled into the panel. The IAB/ZEW Startup Panel was started in 2008, and founding cohorts 2005/06 are not observed in their first years of operation.

**Table C.6.: Full panel distribution by founding cohort and eligibility**

| Founding cohort | Eligible industry: Non-eligible No. | Non-eligible % | Eligible No. | Eligible % | Total No. | Total % |
|---|---|---|---|---|---|---|
| 2005 | 934 | 53 | 833 | 47 | 1,767 | 100 |
| 2006 | 1,073 | 50 | 1,088 | 50 | 2,161 | 100 |
| 2007 | 1,258 | 52 | 1,159 | 48 | 2,417 | 100 |
| 2008 | 1,032 | 52 | 945 | 48 | 1,977 | 100 |
| 2009 | 1,076 | 52 | 977 | 48 | 2,053 | 100 |
| 2010 | 999 | 51 | 958 | 49 | 1,957 | 100 |
| 2011 | 888 | 46 | 1,026 | 54 | 1,914 | 100 |
| 2012 | 877 | 49 | 912 | 51 | 1,789 | 100 |
| 2013 | 933 | 48 | 1,007 | 52 | 1,940 | 100 |
| 2014 | 1,038 | 48 | 1,103 | 52 | 2,141 | 100 |
| 2015 | 1,174 | 52 | 1,096 | 48 | 2,270 | 100 |
| 2016 | 1,398 | 53 | 1,232 | 47 | 2,630 | 100 |
| 2017 | 1,283 | 55 | 1,043 | 45 | 2,326 | 100 |
| 2018 | 1,021 | 66 | 522 | 34 | 1,543 | 100 |
| Total | 14,984 | 52 | 13,901 | 48 | 28,885 | 100 |

**Note**: Table C.6 shows the distribution of firms by founding cohorts and eligibility for the full IAB/ZEW Startup Panel.

**Table C.7.: Full panel distribution by reference year and eligibility**

| Year | Eligible industry | | | | | |
|---|---|---|---|---|---|---|
| | Non-eligible | | Eligible | | Total | |
| | No. | % | No. | % | No. | % |
| 2005 | 934 | 53 | 833 | 47 | 1,767 | 100 |
| 2006 | 2,007 | 51 | 1,921 | 49 | 3,928 | 100 |
| 2007 | 3,265 | 51 | 3,080 | 49 | 6,345 | 100 |
| 2008 | 3,419 | 51 | 3,350 | 49 | 6,769 | 100 |
| 2009 | 3,675 | 50 | 3,616 | 50 | 7,291 | 100 |
| 2010 | 3,745 | 50 | 3,709 | 50 | 7,454 | 100 |
| 2011 | 3,803 | 49 | 4,022 | 51 | 7,825 | 100 |
| 2012 | 3,609 | 47 | 4,094 | 53 | 7,703 | 100 |
| 2013 | 2,835 | 43 | 3,787 | 57 | 6,622 | 100 |
| 2014 | 3,197 | 45 | 3,881 | 55 | 7,078 | 100 |
| 2015 | 3,660 | 48 | 3,963 | 52 | 7,623 | 100 |
| 2016 | 3,940 | 49 | 4,113 | 51 | 8,053 | 100 |
| 2017 | 4,123 | 51 | 4,038 | 49 | 8,161 | 100 |
| 2018 | 3,840 | 54 | 3,297 | 46 | 7,137 | 100 |
| Total | 46,052 | 49 | 47,704 | 51 | 93,756 | 100 |

**Note**: Table C.7 shows the distribution of firm observations by reference year and eligibility for the full IAB/ZEW Startup Panel.

**Table C.8.: Number of firms and observations per firm by industries**

| NACE (Level 1) | Full Panel | | | | Sample | | | |
|---|---|---|---|---|---|---|---|---|
| | Non-eligible | | Eligible | | Non-eligible | | Eligible | |
| | $N_{Firms}$ | $N_{Obs.}$ | $N_{Firms}$ | $N_{Obs.}$ | $N_{Firms}$ | $N_{Obs.}$ | $N_{Firms}$ | $N_{Obs.}$ |
| 3: Manufacturing | 1,664 | 5,441 | 4,471 | 16,330 | 497 | 938 | 2,253 | 4,878 |
| 4: Electricity and gas | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6: Construction | 3,100 | 9,540 | 0 | 0 | 630 | 1,247 | 0 | 0 |
| 7: Wholesale and retail trade | 3,453 | 10,536 | 0 | 0 | 722 | 1,226 | 0 | 0 |
| 8: Transporting and storage | 590 | 1,677 | 0 | 0 | 152 | 250 | 0 | 0 |
| 9: Accomm. and food service activities | 760 | 2,294 | 0 | 0 | 121 | 212 | 0 | 0 |
| 10: Information and communication | 0 | 0 | 5,464 | 17,467 | 0 | 0 | 2,708 | 5,312 |
| 11: Financial and insurance activities | 418 | 1,230 | 0 | 0 | 164 | 271 | 0 | 0 |
| 12: Real estate activities | 282 | 753 | 0 | 0 | 113 | 167 | 0 | 0 |
| 13: Prof., scien. and techn. activities | 1,831 | 6,039 | 3,870 | 13,662 | 789 | 1,497 | 1,703 | 3,823 |
| 14: Admin. and support service activities | 1,397 | 4,103 | 0 | 0 | 386 | 712 | 0 | 0 |
| 16: Education | 671 | 1,849 | 0 | 0 | 189 | 308 | 0 | 0 |
| 18: Arts, entertainment and recreation | 220 | 700 | 96 | 245 | 69 | 123 | 16 | 21 |
| 19: Other services activities | 598 | 1,829 | 0 | 0 | 68 | 109 | 0 | 0 |
| Total | 14,984 | 45,992 | 13,901 | 47,704 | 3,900 | 7,060 | 6,680 | 14,034 |

**Note**: Table C.8 shows the Number of Firms ($N_{Firms}$) and the total number of firm observations ($N_{Obs.}$) by NACE Codes in eligible and non-eligible industries. The full sample contains all observations in the IAB/ZEW Startup Panel; the working sample contains observations for which we have full information on all variables we employ in our analysis.

# C.5. Description of variables

**Table C.9.: Description of variables**

| Variable name | Type | Description |
|---|---|---|
| | | Financial outcomes |
| Equity (Y/N) | Binary | Firm received equity capital in year $t$. |
| Equity[b] | Continuous | Equity capital used for investments or operating expenses in year $t$. |
| Public subsidy | Binary | Firm received at least one public subsidy in year $t$. |
| Sales | Continuous | Sales in year $t$. |
| | | Innovation Inputs |
| R&D activity[b] | Binary | Indicator whether the firm engages in intramural and/or extramural R&D in year $t$, where R&D is defined "as the systematic creative work to expand the existing knowledge, and the use of the knowledge thus gained to develop new applications." |
| R&D expenditures | Continuous | Amount spent on intra- and extramural R&D activities in year $t$. |
| R&D employees | Count | Number of employees working at least 50% of their working time on R&D related tasks in year $t$. |
| | | Innovation outputs |
| Market Novelty | Binary | Indicator, whether a firm introduced a market novelty in year $t$, defined "as product or service which the company was the first to introduce in the market [globally, domestically (i.e. in Germany), regionally]." |
| Patent applications | Count | Number of patent applications that a firm files in year $t$ at the European Patent Office (EPO). |
| | | Firm characteristics |
| Team | Binary | Startup was founded by a team. |
| Academic | Binary | Founding team member has an academic background. |
| Female | Binary | Female member in founding Team. |
| PhD | Binary | Founding team member holds a PhD. |
| Industry experience | Count | Years of industry experience of founding team. |
| Founding experience | Binary | Founding team member has started a business before. |
| Exit experience | Binary | Founding team member has sold a previous company. |
| Patent | Binary | Business was started with at least one patent. |
| Opportunity | Binary | Startup was founded on a concrete business idea. |
| Size | Continuous | Number of full-time equivalents employed at the company's start. |
| Region | Categorical | Location of startup: East/ West/ Berlin. |
| Industry | Categorical | Business sector of the startup: Hightech manufacturing/ Software & technical service/ Non-hightech. |
| Founding cohort | Categorical | Founding cohort of the startup. |

**Note**: [a]See section C.5.1 for the exact calculation procedure, [b]This matches the OECD's definition of Research and Development activity.

## C.5.1. Measuring key variables

### Equity financing

We approximate the level of equity financing based on total cost accounting measures contained in the IAB/ZEW Startup Panel. In the survey, companies are asked about their investment and operating costs in the reference year and the share of these financed from external funds. In addition, companies are asked about the share of external funds contributed by outside equity capital. The level of outside equity employed in reference year $t$ in firm $i$ is calculated as follows:

$$\tilde{E}_{it} = \left( I_{it}^{fix} \cdot \omega_{it}^{fix,ext} + \left( \sum_{k \in K} c_{it}^{k} \right) \cdot \omega_{it}^{oc,ext} \right) \cdot \omega_{it}^{equity}, \tag{C.1}$$

where $I_{it}^{fix}$ are investments in fixed assets, $\omega_{it}^{fix,ext}$ is the share of fixed assets financed by external funds, $c_{it}$ are operating cost, where $K = \{wages, materials, other\}$, $\omega_{it}^{oc,ext}$ is the share of operating cost financed by external resources, and $\omega_{it}^{equity}$ is the share of external funds provided by outside equity investors. Note that the difference between the level of equity capital employed and the level of outside equity capital provided are the capital outlays and cash reserves that a firm holds. Therefore our measure tends to underestimate the amount of equity capital that firms receive. As our main interest lies in understanding the extent to which outside equity goes into innovation-related activities, this is not a real limitation of the approach. However, one should keep in mind the difference when interpreting the estimates. If firms were holding large shares of the external equity capital as cash reserves and were not able to employ it productively, then we would overestimate the effectiveness of equity capital. The same would hold if firms were issuing equity to pay off debt. However, since equity investors tend to keep financing tight, screen investment opportunities for outstanding debt, and stage their investments into several rounds, the difference between equity capital received and equity capital employed should be relatively small.

**Table C.10.: Distribution of investment and operating cost (in thsd. Euros)**

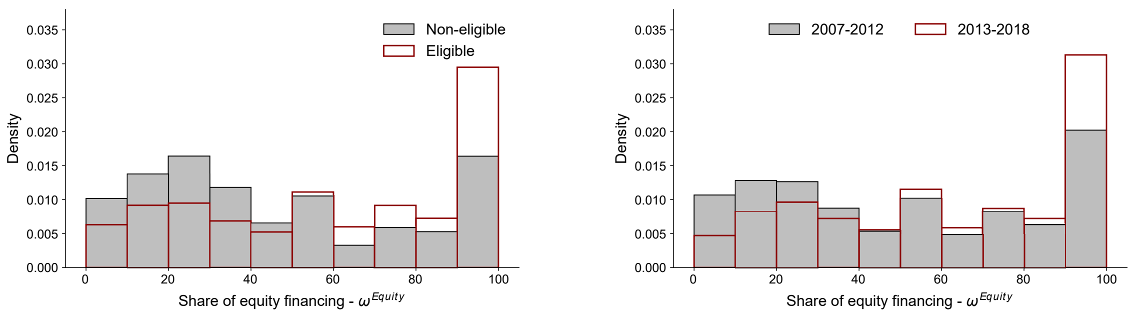
| | All | | Equity | | Non-equity | |
|---|---|---|---|---|---|---|
| | Mean | SE | Mean | SE | Mean | SE |
| $I^{fix}$ | 65.12 | (386.90) | 118.65 | (695.53) | 61.67 | (357.72) |
| $c^{wage}$ | 194.66 | (429.93) | 269.18 | (430.89) | 189.71 | (429.42) |
| $c^{material}$ | 241.03 | (1444.36) | 343.94 | (3258.07) | 234.07 | (1228.43) |
| $c^{other}$ | 49.33 | (601.22) | 64.14 | (166.58) | 48.36 | (619.02) |
| $\sum_k c^k$ | 464.59 | (1959.09) | 653.08 | (3310.76) | 451.52 | (1828.11) |
| $\omega^{fix}$ | 32.31 | (42.32) | 61.74 | (43.65) | 30.45 | (41.54) |
| $\omega^{oc}$ | 25.51 | (37.86) | 67.95 | (36.02) | 22.82 | (36.34) |

**Note**: Note that some firms do not report the cost $c$ separately, but only the total cost $\sum_k c^k$. For those cases, we use the total cost directly.

Table C.10 shows the distribution of investments in fixed assets and operating costs and the respective shares financed by external funds in our sample. On average, firms invest about 65 thousand Euros yearly in fixed assets and have an operating cost of about 466 thousand Euros. For firms that receive equity capital, these costs are roughly 1.5 times larger compared to non-equity-financed firms. On average, firms finance about 32% of investments in fixed assets and 26% of operating expenses by external funds. These shares are again much higher for firms that finance with external equity. While the percentage of investments in fixed assets is about twice as high for equity-financed firms, the share in operating cost is three times larger.

**Figure C.1.: Distribution of equity financing share**

**(a) Eligible vs. Non-eligible** **(b) Before policy vs. After policy**




**Note:** Figure C.1 depicts the distribution of the equity financing share in all financing sources employed by firms. Each bin represents a 10% interval. For visualization, values are cut off at 1 Mio. Euros.

Figure C.1 depicts the distribution of the equity financing share in all financing sources. Panel (a) of Figure C.1 shows that eligible firms more often finance larger shares of their total financing with outside equity, whereas non-eligible firms tend to finance a small share with outside equity. After the introduction of the policy, more firms have shifted towards financing larger shares of their investment and operating costs with outside equity, as depicted in Panel (b) of Figure C.1.

Note that the data only allows us to differentiate between different types of venture capital investors from 2015 onwards. From there, we do not distinguish between different types of equity investors in our analysis. However, about two-thirds of firms that use equity financing in the sample from 2015 onward receive capital from private individuals (angel investors). Also, Berger and Gottschalk (2021) find that the share of firms receiving standalone investments from venture capital funds has remained relatively constant in the considered period.

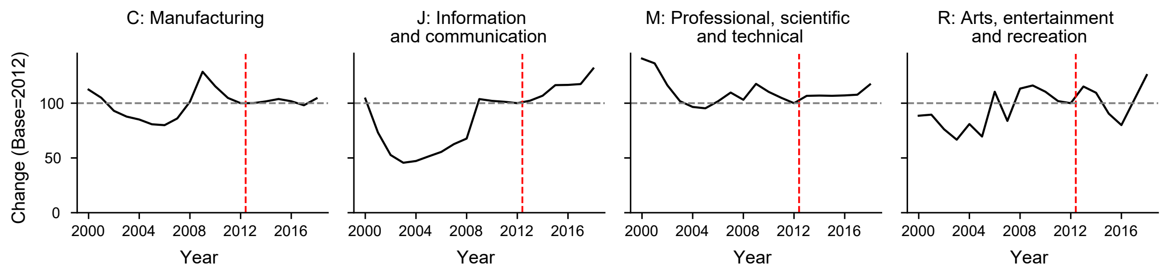
## Innovation activity

Our measures for research and development (R&D) are based on the respective survey items in the SUP. Startups are asked whether they have started R&D projects in the reference year by conducting their own R&D (intramural) or awarding R&D contracts to third parties (extramural).

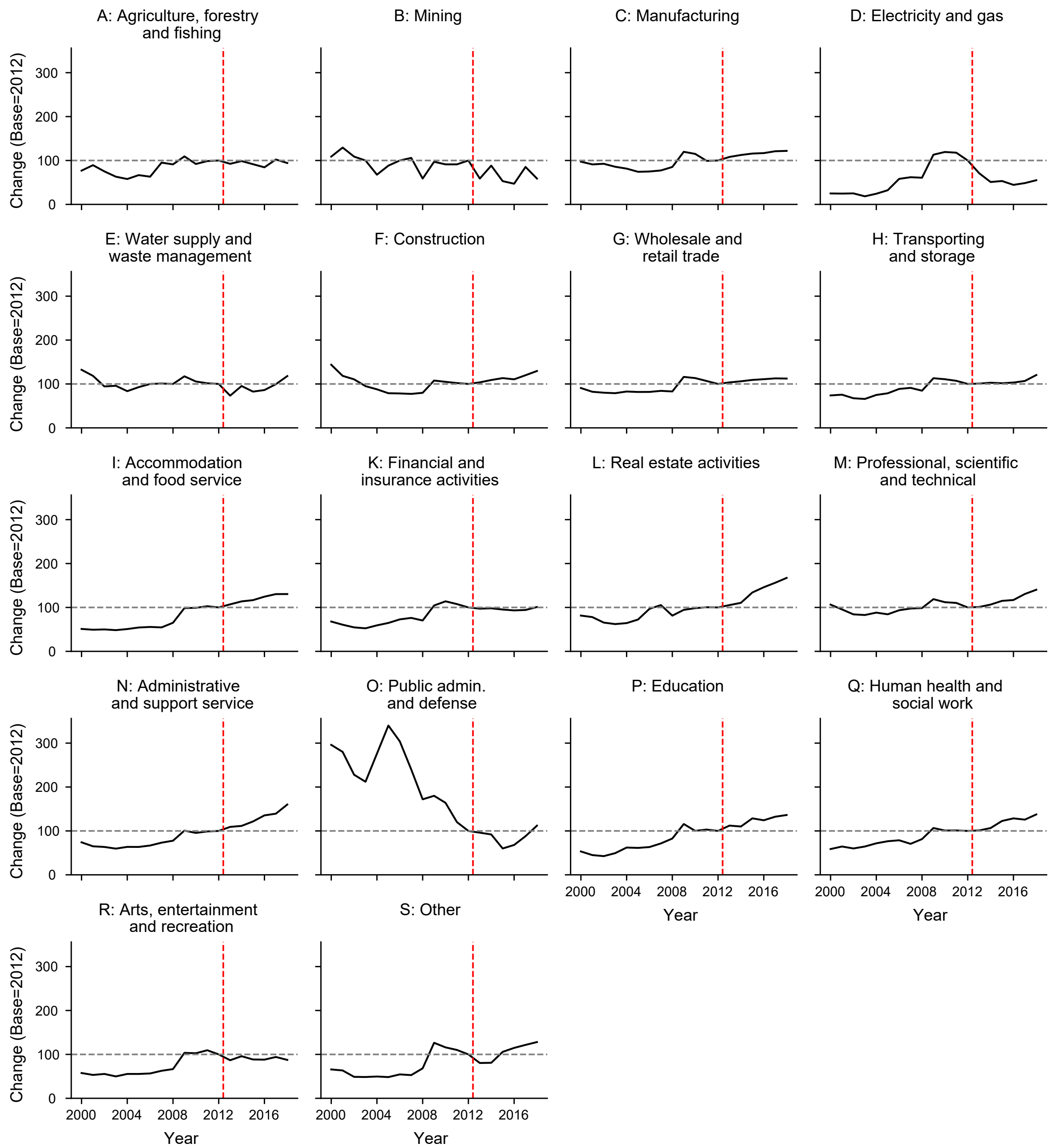
Startups that indicate one of the latter to be true are then asked about the total R&D expenditures in the reference year, including intra- and extramural R&D. The definition of R&D in the survey is consistent with the definition used in the OECD's Frascati Manual definition (OECD, 2018). The survey defines R&D as "systematic creative work to expand existing knowledge and use the acquired knowledge to develop new applications".

## Figure C.2.: Change in incorporations by industries

### (a) Eligible industries

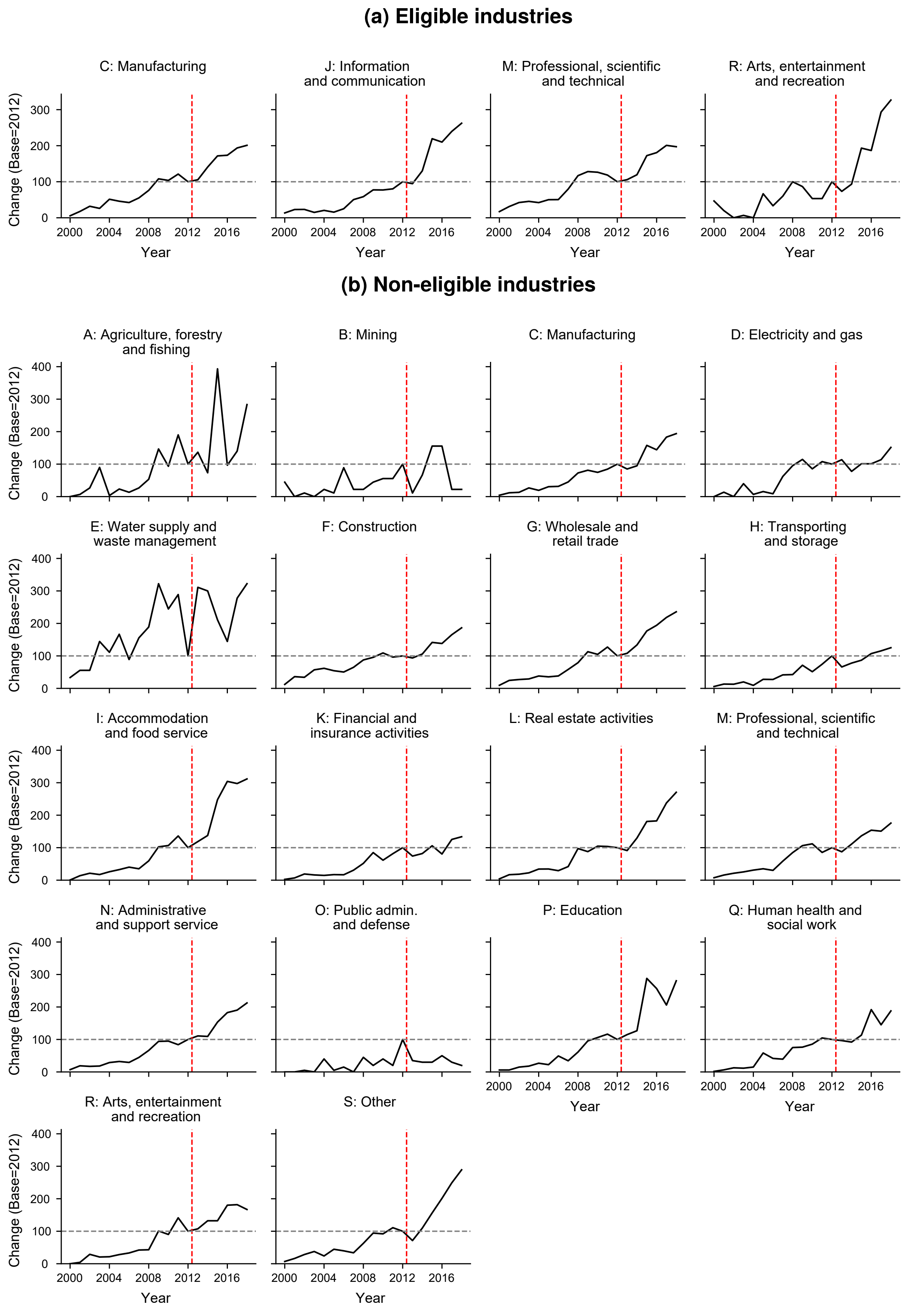



### (b) Non-eligible industries




**Note:** Figure C.2 depicts the change in incorporations relative to the year 2012 prior to the introduction of the INVEST program. Only GmbH, AG, UG, and Limited are considered.

## Figure C.3.: Change in direct investments from individuals by industries



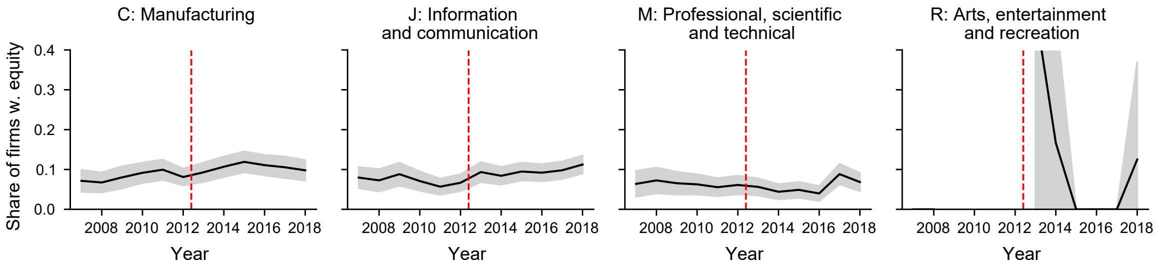

**Note:** Figure C.3 depicts the change in investments from individuals in startups relative to the year 2012 prior to the introduction of the INVEST program. Only GmbH, AG, UG, and Limited are considered.

# C.6. Results

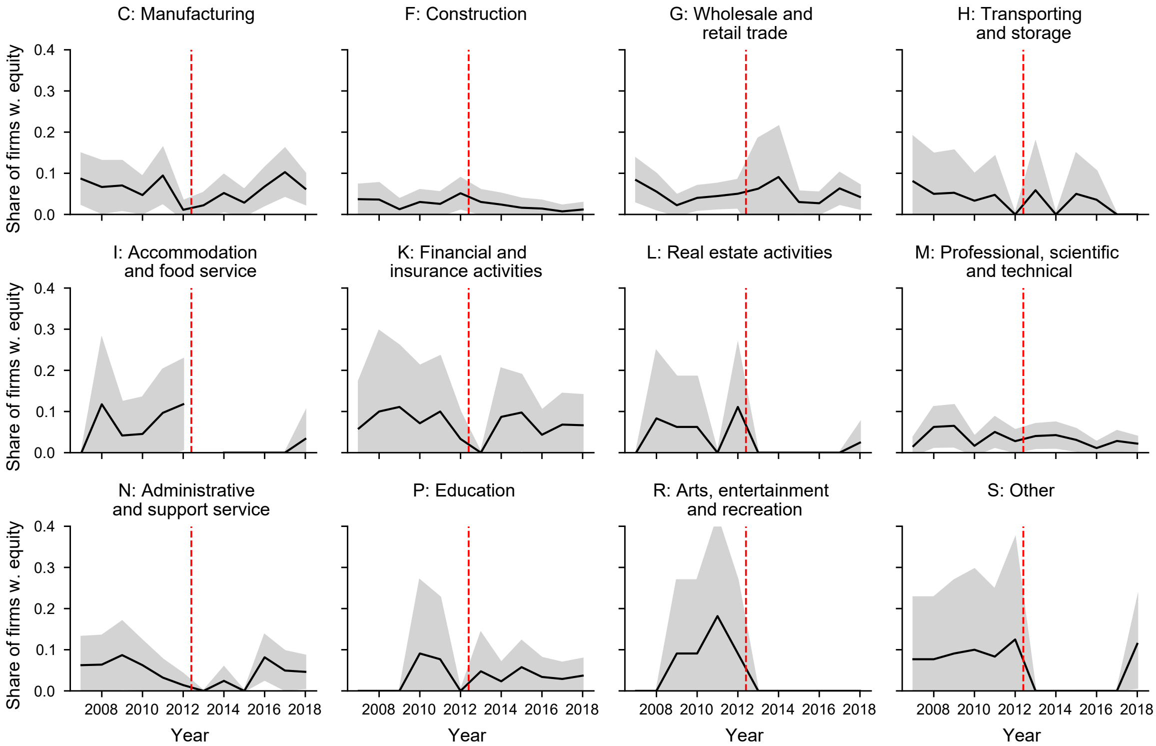
## C.6.1. First stage and time trends

**Figure C.4.: Share of equity-financed startups by industries**

**(a) Eligible industries**




**(b) Non-eligible industries**




**Note:** The gray shaded ared depicts the 95%-confidence intervall.

**Table C.11.: First stage results of program effects on equity financing**

| | Panel A: $\mathbb{1}$[Equity="Yes"] | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Eligible × Post-period | 0.032*** | 0.031*** | 0.031*** | 0.029*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Constant | 0.045*** | 0.046*** | 0.082*** | 0.059*** |
| | (0.003) | (0.003) | (0.011) | (0.011) |
| R2 | 0.036 | 0.040 | 0.120 | 0.135 |
| Clusters | 68 | 68 | 68 | 68 |
| Firm-year obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm obs. | 21,094 | 21,094 | 21,094 | 21,094 |
| | Panel B: ln(1+Equity) | | | |
| | (1) | (2) | (3) | (4) |
| Eligible × Post-period | 0.326*** | 0.321*** | 0.322*** | 0.300*** |
| | (0.062) | (0.061) | (0.061) | (0.058) |
| Constant | 0.476*** | 0.478*** | 0.831*** | 0.569*** |
| | (0.026) | (0.025) | (0.125) | (0.121) |
| **Fixed effects:** | | | | |
| Year | Yes | Yes | Yes | Yes |
| Founding cohort | Yes | Yes | Yes | Yes |
| Industry | Yes | Yes | Yes | Yes |
| Region | | Yes | Yes | Yes |
| **Firm controls:** | | | | |
| Time varying | | | Yes | Yes |
| Time fixed | | | | Yes |
| R2 | 0.038 | 0.042 | 0.125 | 0.141 |
| Clusters | 68 | 68 | 68 | 68 |
| Firm-year obs. | 10,580 | 10,580 | 10,580 | 10,580 |
| Firm obs. | 21,094 | 21,094 | 21,094 | 21,094 |

**Note**: Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size. Standard errors in parentheses clustered at the industry level.
Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## Table C.12.: First stage trends: OLS - Equity financing

| | Dependent variable: $\mathbb{1}$[Equity="Yes"] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Coef. | CI 95% | (2) Coef. | CI 95% | (3) Coef. | CI 95% | (4) Coef. | CI 95% |
| 2007 | -0.026 | [-0.061,0.009] | -0.023 | [-0.059,0.012] | -0.021 | [-0.056,0.013] | -0.016 | [-0.051,0.019] |
| 2008 | -0.014 | [-0.046,0.019] | -0.014 | [-0.047,0.018] | -0.018 | [-0.050,0.014] | -0.015 | [-0.046,0.017] |
| 2009 | -0.009 | [-0.042,0.024] | -0.010 | [-0.043,0.024] | -0.011 | [-0.044,0.022] | -0.008 | [-0.041,0.025] |
| 2010 | 0.007 | [-0.016,0.031] | 0.006 | [-0.017,0.030] | -0.004 | [-0.029,0.022] | -0.000 | [-0.025,0.024] |
| 2011 | -0.015 | [-0.040,0.011] | -0.015 | [-0.041,0.011] | -0.020 | [-0.047,0.006] | -0.020 | [-0.047,0.008] |
| 2013 | 0.021 | [-0.004,0.045] | 0.020 | [-0.005,0.045] | 0.018 | [-0.007,0.043] | 0.016 | [-0.010,0.042] |
| 2014 | 0.014 | [-0.011,0.039] | 0.012 | [-0.013,0.038] | 0.012 | [-0.014,0.038] | 0.010 | [-0.014,0.034] |
| 2015 | 0.021 | [-0.005,0.046] | 0.020 | [-0.005,0.046] | 0.019 | [-0.005,0.043] | 0.019 | [-0.005,0.043] |
| 2016 | 0.030*** | [0.008,0.053] | 0.030** | [0.007,0.052] | 0.025** | [0.003,0.047] | 0.026** | [0.004,0.048] |
| 2017 | 0.031** | [0.006,0.056] | 0.031** | [0.005,0.056] | 0.023* | [-0.002,0.047] | 0.024* | [-0.000,0.048] |
| 2018 | 0.029* | [-0.004,0.061] | 0.027 | [-0.006,0.060] | 0.023 | [-0.010,0.056] | 0.024 | [-0.009,0.057] |
| Constant | 0.050*** | [0.038,0.062] | 0.050*** | [0.039,0.062] | 0.090*** | [0.064,0.115] | 0.065*** | [0.040,0.089] |
| **Fixed effects:** | | | | | | | | |
| Year | Yes | | Yes | | Yes | | Yes | |
| Founding cohort | Yes | | Yes | | Yes | | Yes | |
| Industry | Yes | | Yes | | Yes | | Yes | |
| Region | | | Yes | | Yes | | Yes | |
| **Firm controls:** | | | | | | | | |
| Time varying | | | | | Yes | | Yes | |
| Time fixed | | | | | | | Yes | |
| R2 | 0.036 | | 0.040 | | 0.120 | | 0.135 | |
| Clusters | 68 | | 68 | | 68 | | 68 | |
| Firm-year obs. | 10,580 | | 10,580 | | 10,580 | | 10,580 | |
| Firm obs. | 21,094 | | 21,094 | | 21,094 | | 21,094 | |

**Note**: Coef. gives the difference between eligible and non-eligible firms in the reference year. CI 95% gives the lower and upper bound of the 95%-confidence interval. Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table C.13.: First stage trends: OLS - Equity financing in levels**

| | Dependent variable: ln(1+Equity) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Coef. | CI 95% | (2) Coef. | CI 95% | (3) Coef. | CI 95% | (4) Coef. | CI 95% |
| 2007 | -0.265 | [-0.647,0.117] | -0.239 | [-0.632,0.154] | -0.149 | [-0.531,0.232] | -0.211 | [-0.586,0.163] |
| 2008 | -0.042 | [-0.352,0.268] | -0.051 | [-0.361,0.258] | -0.052 | [-0.347,0.244] | -0.094 | [-0.400,0.211] |
| 2009 | -0.089 | [-0.435,0.257] | -0.093 | [-0.439,0.254] | -0.072 | [-0.414,0.270] | -0.104 | [-0.445,0.236] |
| 2010 | 0.113 | [-0.124,0.351] | 0.098 | [-0.140,0.337] | 0.024 | [-0.219,0.268] | -0.012 | [-0.273,0.248] |
| 2011 | -0.118 | [-0.367,0.131] | -0.128 | [-0.381,0.124] | -0.175 | [-0.450,0.099] | -0.183 | [-0.451,0.084] |
| 2013 | 0.169 | [-0.097,0.435] | 0.164 | [-0.100,0.428] | 0.121 | [-0.157,0.400] | 0.144 | [-0.128,0.416] |
| 2014 | 0.182 | [-0.052,0.415] | 0.160 | [-0.073,0.393] | 0.133 | [-0.082,0.348] | 0.156 | [-0.074,0.386] |
| 2015 | 0.244* | [-0.043,0.530] | 0.243* | [-0.038,0.524] | 0.230* | [-0.022,0.483] | 0.228* | [-0.025,0.482] |
| 2016 | 0.331*** | [0.082,0.580] | 0.325** | [0.074,0.576] | 0.284** | [0.050,0.519] | 0.275** | [0.042,0.508] |
| 2017 | 0.386*** | [0.130,0.641] | 0.381*** | [0.124,0.638] | 0.309** | [0.069,0.550] | 0.297** | [0.055,0.539] |
| 2018 | 0.332* | [-0.022,0.685] | 0.308* | [-0.054,0.671] | 0.280 | [-0.075,0.634] | 0.268 | [-0.089,0.625] |
| Constant | 0.506*** | [0.389,0.622] | 0.511*** | [0.394,0.629] | 0.613*** | [0.344,0.882] | 0.889*** | [0.604,1.174] |
| **Fixed effects:** | | | | | | | | |
| Year | Yes | | Yes | | Yes | | Yes | |
| Founding cohort | Yes | | Yes | | Yes | | Yes | |
| Industry | Yes | | Yes | | Yes | | Yes | |
| Region | | | Yes | | Yes | | Yes | |
| **Firm controls:** | | | | | | | | |
| Time varying | | | | | Yes | | Yes | |
| Time fixed | | | | | Yes | | | |
| R2 | 0.038 | | 0.042 | | 0.141 | | 0.125 | |
| Clusters | 68 | | 68 | | 68 | | 68 | |
| Firm-year obs. | 10,580 | | 10,580 | | 10,580 | | 10,580 | |
| Firm obs. | 21,094 | | 21,094 | | 21,094 | | 21,094 | |

**Note**: Coef. gives the difference between eligible and non-eligible firms in the reference year. CI 95% gives the lower and upper bound of the 95%-confidence interval. Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

## C.6.2. Robustness tests

**Table C.14.: Robustness tests innovation inputs: OLS - R&D activity**

| | Dependent variable: 𝟙[R&D activity="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.175*** | 0.127*** | 0.158*** | 0.108*** | 0.172*** | 0.125*** |
| | (0.014) | (0.012) | (0.018) | (0.017) | (0.014) | (0.012) |
| Public VC | 0.106*** | 0.083*** | 0.107*** | 0.073** | 0.105*** | 0.082*** |
| | (0.031) | (0.027) | (0.033) | (0.028) | (0.031) | (0.026) |
| ln(1+Sales) | -0.004** | 0.000 | -0.004*** | -0.000 | -0.004** | -0.000 |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Subsidy | 0.138*** | 0.120*** | 0.123*** | 0.108*** | 0.152*** | 0.132*** |
| | (0.028) | (0.025) | (0.025) | (0.023) | (0.027) | (0.024) |
| Team | | 0.007 | | 0.005 | | 0.005 |
| | | (0.007) | | (0.007) | | (0.008) |
| Founding exp. | | 0.036*** | | 0.034*** | | 0.036*** |
| | | (0.010) | | (0.009) | | (0.011) |
| Industry exp. | | -0.002*** | | -0.002*** | | -0.002*** |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | 0.041*** | | 0.047*** | | 0.046*** |
| | | (0.011) | | (0.013) | | (0.011) |
| Opportunity | | 0.106*** | | 0.113*** | | 0.110*** |
| | | (0.012) | | (0.012) | | (0.012) |
| PhD | | 0.146*** | | 0.139*** | | 0.141*** |
| | | (0.012) | | (0.012) | | (0.012) |
| Academic | | 0.079*** | | 0.085*** | | 0.083*** |
| | | (0.014) | | (0.014) | | (0.015) |
| Female | | -0.071*** | | -0.077*** | | -0.074*** |
| | | (0.018) | | (0.022) | | (0.020) |
| Patent | | 0.174*** | | 0.178*** | | 0.166*** |
| | | (0.021) | | (0.023) | | (0.020) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.001) | | (0.001) | | (0.001) |
| Constant | 0.410*** | 0.244*** | 0.418*** | 0.245*** | 0.445*** | 0.272*** |
| | (0.017) | (0.020) | (0.016) | (0.019) | (0.019) | (0.023) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.213 | 0.258 | 0.213 | 0.260 | 0.200 | 0.245 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.15.: Robustness tests innovation inputs: OLS - R&D expenditures**

| | Dependent variable: ln(1+R&D expenditures) | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.258*** | 0.208*** | 0.238*** | 0.183*** | 0.257*** | 0.207*** |
| | (0.016) | (0.015) | (0.020) | (0.019) | (0.016) | (0.015) |
| Public VC | 1.300*** | 1.046*** | 1.395*** | 1.040*** | 1.308*** | 1.052*** |
| | (0.362) | (0.314) | (0.398) | (0.334) | (0.358) | (0.306) |
| ln(1+Sales) | 0.000 | 0.041** | -0.004 | 0.037** | -0.003 | 0.039** |
| | (0.019) | (0.015) | (0.019) | (0.015) | (0.021) | (0.017) |
| Subsidy | 1.717*** | 1.531*** | 1.533*** | 1.378*** | 1.871*** | 1.666*** |
| | (0.294) | (0.255) | (0.276) | (0.244) | (0.285) | (0.247) |
| Team | | 0.029 | | 0.018 | | -0.003 |
| | | (0.081) | | (0.093) | | (0.088) |
| Founding exp. | | 0.438*** | | 0.447*** | | 0.453*** |
| | | (0.093) | | (0.098) | | (0.104) |
| Industry exp. | | -0.012*** | | -0.012** | | -0.013*** |
| | | (0.004) | | (0.005) | | (0.004) |
| Exit exp. | | 0.655*** | | 0.703*** | | 0.707*** |
| | | (0.122) | | (0.135) | | (0.126) |
| Opportunity | | 1.184*** | | 1.260*** | | 1.245*** |
| | | (0.149) | | (0.154) | | (0.152) |
| PhD | | 1.573*** | | 1.451*** | | 1.504*** |
| | | (0.134) | | (0.134) | | (0.130) |
| Academic | | 0.915*** | | 0.981*** | | 0.985*** |
| | | (0.154) | | (0.160) | | (0.171) |
| Female | | -0.842*** | | -0.889*** | | -0.875*** |
| | | (0.183) | | (0.202) | | (0.214) |
| Patent | | 1.933*** | | 1.980*** | | 1.843*** |
| | | (0.223) | | (0.261) | | (0.221) |
| Size | | 0.003 | | 0.001 | | 0.001 |
| | | (0.011) | | (0.011) | | (0.012) |
| Constant | 3.894*** | 1.921*** | 3.982*** | 1.923*** | 4.218*** | 2.145*** |
| | (0.221) | (0.286) | (0.218) | (0.275) | (0.249) | (0.317) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.239 | 0.288 | 0.238 | 0.290 | 0.229 | 0.279 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.16.: Robustness tests innovation inputs: OLS - R&D employment**

| | Dependent variable: ln(1+R&D employees) | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.039*** | 0.034*** | 0.036*** | 0.030*** | 0.040*** | 0.034*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) |
| Public VC | 0.276*** | 0.248*** | 0.292*** | 0.254*** | 0.273*** | 0.244*** |
| | (0.048) | (0.045) | (0.064) | (0.057) | (0.049) | (0.045) |
| ln(1+Sales) | -0.002 | 0.002 | -0.003 | 0.001 | -0.002 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Subsidy | 0.247*** | 0.222*** | 0.218*** | 0.196*** | 0.268*** | 0.240*** |
| | (0.041) | (0.035) | (0.037) | (0.032) | (0.041) | (0.034) |
| Team | | 0.032*** | | 0.030*** | | 0.031** |
| | | (0.011) | | (0.011) | | (0.012) |
| Founding exp. | | 0.017** | | 0.016 | | 0.016* |
| | | (0.008) | | (0.011) | | (0.008) |
| Industry exp. | | -0.001*** | | -0.001 | | -0.001*** |
| | | (0.000) | | (0.001) | | (0.000) |
| Exit exp. | | 0.092*** | | 0.092*** | | 0.102*** |
| | | (0.015) | | (0.016) | | (0.015) |
| Opportunity | | 0.127*** | | 0.128*** | | 0.136*** |
| | | (0.024) | | (0.025) | | (0.025) |
| PhD | | 0.194*** | | 0.174*** | | 0.188*** |
| | | (0.022) | | (0.026) | | (0.022) |
| Academic | | 0.069*** | | 0.079*** | | 0.078*** |
| | | (0.016) | | (0.016) | | (0.018) |
| Female | | -0.062*** | | -0.071*** | | -0.068*** |
| | | (0.018) | | (0.021) | | (0.020) |
| Patent | | 0.202*** | | 0.209*** | | 0.191*** |
| | | (0.037) | | (0.040) | | (0.038) |
| Size | | 0.003 | | 0.002 | | 0.003 |
| | | (0.002) | | (0.002) | | (0.003) |
| Constant | 0.300*** | 0.105*** | 0.311*** | 0.110*** | 0.328*** | 0.119*** |
| | (0.024) | (0.038) | (0.023) | (0.034) | (0.028) | (0.042) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.227 | 0.270 | 0.221 | 0.265 | 0.220 | 0.265 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

### Table C.17.: Robustness tests innovation outputs: OLS - Global market novelty

| | Dependent variable: 𝟙[Global market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.081*** | 0.065*** | 0.076*** | 0.061*** | 0.083*** | 0.066*** |
| | (0.012) | (0.014) | (0.017) | (0.019) | (0.013) | (0.015) |
| Public VC | 0.075** | 0.064** | 0.056 | 0.041 | 0.074** | 0.062* |
| | (0.031) | (0.031) | (0.035) | (0.034) | (0.032) | (0.032) |
| ln(1+Sales) | 0.005*** | 0.006*** | 0.005*** | 0.006*** | 0.005*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Subsidy | 0.039*** | 0.031*** | 0.036*** | 0.029*** | 0.044*** | 0.036*** |
| | (0.010) | (0.008) | (0.010) | (0.008) | (0.011) | (0.009) |
| Team | | 0.002 | | 0.001 | | 0.001 |
| | | (0.006) | | (0.006) | | (0.006) |
| Founding exp. | | 0.003 | | -0.002 | | 0.003 |
| | | (0.005) | | (0.006) | | (0.006) |
| Industry exp. | | -0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | 0.011 | | 0.011 | | 0.016* |
| | | (0.010) | | (0.011) | | (0.009) |
| Opportunity | | 0.044*** | | 0.046*** | | 0.046*** |
| | | (0.006) | | (0.006) | | (0.006) |
| PhD | | 0.052*** | | 0.052*** | | 0.051*** |
| | | (0.009) | | (0.011) | | (0.009) |
| Academic | | 0.030*** | | 0.027*** | | 0.035*** |
| | | (0.007) | | (0.006) | | (0.007) |
| Female | | -0.017** | | -0.023** | | -0.018** |
| | | (0.008) | | (0.010) | | (0.008) |
| Patent | | 0.109*** | | 0.114*** | | 0.109*** |
| | | (0.018) | | (0.018) | | (0.018) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Constant | 0.030** | -0.038** | 0.032** | -0.034* | 0.031** | -0.043** |
| | (0.014) | (0.019) | (0.013) | (0.018) | (0.015) | (0.020) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.071 | 0.092 | 0.068 | 0.091 | 0.071 | 0.093 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.18.: Robustness tests innovation outputs: OLS - Domestic market novelty**

| | Dependent variable: 𝟙[Domestic market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.057** | 0.046** | 0.050** | 0.040 | 0.053** | 0.042* |
| | (0.023) | (0.023) | (0.025) | (0.025) | (0.025) | (0.025) |
| Public VC | 0.009 | 0.003 | 0.015 | 0.008 | 0.009 | 0.003 |
| | (0.020) | (0.019) | (0.023) | (0.022) | (0.021) | (0.020) |
| ln(1+Sales) | 0.004*** | 0.005*** | 0.004*** | 0.005*** | 0.004*** | 0.005*** |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Subsidy | 0.013 | 0.011 | 0.004 | 0.003 | 0.016** | 0.014* |
| | (0.008) | (0.007) | (0.008) | (0.008) | (0.008) | (0.007) |
| Team | | -0.005 | | -0.004 | | -0.006 |
| | | (0.005) | | (0.006) | | (0.006) |
| Founding exp. | | 0.011** | | 0.011* | | 0.010* |
| | | (0.005) | | (0.006) | | (0.005) |
| Industry exp. | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | 0.023*** | | 0.019*** | | 0.027*** |
| | | (0.006) | | (0.007) | | (0.007) |
| Opportunity | | 0.040*** | | 0.041*** | | 0.037*** |
| | | (0.007) | | (0.007) | | (0.008) |
| PhD | | 0.022 | | 0.019 | | 0.022 |
| | | (0.017) | | (0.016) | | (0.018) |
| Academic | | 0.013** | | 0.014** | | 0.015** |
| | | (0.005) | | (0.006) | | (0.006) |
| Female | | -0.000 | | -0.004 | | 0.001 |
| | | (0.010) | | (0.011) | | (0.011) |
| Patent | | 0.019** | | 0.014 | | 0.015* |
| | | (0.009) | | (0.011) | | (0.008) |
| Size | | -0.000* | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Constant | 0.043*** | -0.003 | 0.043*** | -0.004 | 0.044*** | 0.001 |
| | (0.006) | (0.015) | (0.007) | (0.015) | (0.007) | (0.017) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.027 | 0.035 | 0.029 | 0.037 | 0.028 | 0.035 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.19.: Robustness tests innovation outputs: OLS - Regional market novelty**

| | Dependent variable: 𝟙[Regional market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | -0.012*** | -0.013*** | -0.011* | -0.013** | -0.012** | -0.012*** |
| | (0.004) | (0.004) | (0.006) | (0.006) | (0.004) | (0.004) |
| Public VC | -0.006 | -0.006 | -0.005 | -0.005 | -0.003 | -0.002 |
| | (0.008) | (0.008) | (0.011) | (0.011) | (0.009) | (0.009) |
| ln(1+Sales) | 0.001*** | 0.001*** | 0.001** | 0.001** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Subsidy | 0.003 | 0.003 | 0.001 | 0.000 | -0.001 | -0.001 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Team | | 0.004* | | 0.004 | | 0.005** |
| | | (0.002) | | (0.003) | | (0.002) |
| Founding exp. | | 0.001 | | 0.000 | | -0.001 |
| | | (0.003) | | (0.004) | | (0.003) |
| Industry exp. | | -0.000** | | -0.000** | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | -0.001 | | 0.002 | | -0.004 |
| | | (0.005) | | (0.006) | | (0.005) |
| Opportunity | | 0.007*** | | 0.007** | | 0.007** |
| | | (0.003) | | (0.003) | | (0.003) |
| PhD | | -0.003 | | -0.001 | | -0.005* |
| | | (0.003) | | (0.003) | | (0.003) |
| Academic | | -0.006** | | -0.005* | | -0.005* |
| | | (0.003) | | (0.003) | | (0.003) |
| Female | | -0.005 | | -0.004 | | -0.004 |
| | | (0.005) | | (0.006) | | (0.006) |
| Patent | | -0.001 | | -0.003 | | 0.002 |
| | | (0.005) | | (0.005) | | (0.005) |
| Size | | 0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Constant | 0.024*** | 0.025*** | 0.023*** | 0.025*** | 0.022*** | 0.024*** |
| | (0.003) | (0.004) | (0.004) | (0.005) | (0.003) | (0.005) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.013 | 0.014 | 0.015 | 0.017 | 0.015 | 0.016 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.20.: Robustness tests innovation outputs: OLS - Patent applications**

| | Dependent variable: # of patent applications | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.004*** | 0.004*** | 0.003*** | 0.003*** | 0.004*** | 0.004** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Public VC | 0.055*** | 0.054*** | 0.051** | 0.050** | 0.055*** | 0.054*** |
| | (0.017) | (0.017) | (0.021) | (0.021) | (0.018) | (0.018) |
| ln(1+Sales) | -0.001** | -0.001* | -0.001 | -0.000 | -0.001** | -0.001* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Subsidy | 0.013*** | 0.012*** | 0.013*** | 0.012*** | 0.014*** | 0.013*** |
| | (0.003) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Team | | 0.004** | | 0.005* | | 0.005** |
| | | (0.002) | | (0.002) | | (0.002) |
| Founding exp. | | -0.002 | | -0.002 | | -0.002 |
| | | (0.002) | | (0.002) | | (0.002) |
| Industry exp. | | -0.000** | | -0.000** | | -0.000** |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | 0.007* | | 0.008 | | 0.008 |
| | | (0.004) | | (0.006) | | (0.005) |
| Opportunity | | 0.004** | | 0.004** | | 0.004** |
| | | (0.002) | | (0.002) | | (0.002) |
| PhD | | 0.002 | | 0.003 | | 0.002 |
| | | (0.004) | | (0.005) | | (0.004) |
| Academic | | 0.004*** | | 0.004*** | | 0.005*** |
| | | (0.001) | | (0.002) | | (0.002) |
| Female | | 0.001 | | 0.001 | | 0.001 |
| | | (0.002) | | (0.003) | | (0.003) |
| Patent | | -0.006 | | -0.005 | | -0.006 |
| | | (0.005) | | (0.005) | | (0.005) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Constant | 0.013*** | 0.008** | 0.010* | 0.004 | 0.015*** | 0.010*** |
| | (0.004) | (0.003) | (0.005) | (0.004) | (0.005) | (0.003) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| R2 | 0.039 | 0.041 | 0.041 | 0.043 | 0.040 | 0.042 |
| Clusters | 68 | 68 | 67 | 67 | 56 | 56 |
| Firm obs. | 10,580 | 10,580 | 8,290 | 8,290 | 9,169 | 9,169 |
| Firm-year obs. | 21,094 | 21,094 | 16,163 | 16,163 | 18,560 | 18,560 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

### Table C.21.: Robustness tests innovation inputs: 2SLS - R&D activity

| | Dependent variable: $\mathbb{1}$[R&D activity="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.251 | -0.014 | 0.140 | -0.231 | 0.186 | -0.169 |
| | (0.384) | (0.408) | (0.417) | (0.476) | (0.424) | (0.440) |
| Eligible | 0.346*** | 0.404*** | 0.298*** | 0.362*** | 0.350*** | 0.424*** |
| | (0.060) | (0.076) | (0.084) | (0.107) | (0.065) | (0.081) |
| Public VC | 0.067 | 0.153 | 0.116 | 0.241 | 0.098 | 0.230 |
| | (0.190) | (0.194) | (0.212) | (0.231) | (0.213) | (0.211) |
| ln(1+Sales) | -0.003 | -0.000 | -0.004** | -0.002 | -0.004* | -0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Subsidy | 0.135*** | 0.125*** | 0.124*** | 0.116*** | 0.151*** | 0.143*** |
| | (0.028) | (0.025) | (0.028) | (0.027) | (0.030) | (0.025) |
| Team | | 0.010 | | 0.013 | | 0.011 |
| | | (0.011) | | (0.015) | | (0.013) |
| Founding exp. | | 0.037*** | | 0.035*** | | 0.036*** |
| | | (0.010) | | (0.010) | | (0.011) |
| Industry exp. | | -0.002*** | | -0.002*** | | -0.002*** |
| | | (0.001) | | (0.001) | | (0.001) |
| Exit exp. | | 0.048** | | 0.065** | | 0.061** |
| | | (0.023) | | (0.029) | | (0.025) |
| Opportunity | | 0.108*** | | 0.118*** | | 0.115*** |
| | | (0.012) | | (0.013) | | (0.013) |
| PhD | | 0.151*** | | 0.150*** | | 0.151*** |
| | | (0.019) | | (0.020) | | (0.020) |
| Academic | | 0.080*** | | 0.088*** | | 0.086*** |
| | | (0.013) | | (0.013) | | (0.016) |
| Female | | -0.072*** | | -0.081*** | | -0.077*** |
| | | (0.017) | | (0.021) | | (0.019) |
| Patent | | 0.176*** | | 0.182*** | | 0.168*** |
| | | (0.020) | | (0.024) | | (0.021) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.001) | | (0.001) | | (0.001) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 15.5 | 13.1 | 16.2 | 13.2 |
| Robust F | 26.1 | 23.8 | 14.3 | 13.1 | 27.0 | 21.7 |
| Effective F | 25.4 | 24.6 | 14.9 | 13.9 | 24.7 | 22.7 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table C.22.: Robustness tests innovation inputs: 2SLS - R&D expenditures**

| | Dependent variable: ln(1+R&D expenditures) | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.211 | -0.087 | 0.204 | -0.227 | 0.005 | -0.424 |
| | (0.380) | (0.405) | (0.423) | (0.496) | (0.424) | (0.428) |
| Eligible | 4.503*** | 5.073*** | 3.982*** | 4.562*** | 4.678*** | 5.478*** |
| | (0.484) | (0.632) | (0.716) | (0.975) | (0.528) | (0.659) |
| Public VC | 1.572 | 2.703 | 1.584 | 3.280 | 2.789 | 4.656** |
| | (2.152) | (2.222) | (2.431) | (2.704) | (2.424) | (2.347) |
| ln(1+Sales) | -0.002 | 0.029 | -0.005 | 0.023 | -0.015 | 0.014 |
| | (0.024) | (0.020) | (0.024) | (0.021) | (0.028) | (0.023) |
| Subsidy | 1.737*** | 1.632*** | 1.543*** | 1.479*** | 1.990*** | 1.908*** |
| | (0.340) | (0.299) | (0.322) | (0.307) | (0.364) | (0.306) |
| Team | | 0.104 | | 0.131 | | 0.165 |
| | | (0.127) | | (0.175) | | (0.139) |
| Founding exp. | | 0.437*** | | 0.453*** | | 0.449*** |
| | | (0.092) | | (0.104) | | (0.104) |
| Industry exp. | | -0.016*** | | -0.017** | | -0.022*** |
| | | (0.006) | | (0.009) | | (0.007) |
| Exit exp. | | 0.834*** | | 0.970*** | | 1.086*** |
| | | (0.275) | | (0.360) | | (0.303) |
| Opportunity | | 1.229*** | | 1.318*** | | 1.346*** |
| | | (0.161) | | (0.180) | | (0.167) |
| PhD | | 1.699*** | | 1.627*** | | 1.769*** |
| | | (0.212) | | (0.222) | | (0.230) |
| Academic | | 0.951*** | | 1.023*** | | 1.075*** |
| | | (0.163) | | (0.158) | | (0.198) |
| Female | | -0.871*** | | -0.941*** | | -0.953*** |
| | | (0.169) | | (0.195) | | (0.193) |
| Patent | | 1.956*** | | 2.031*** | | 1.881*** |
| | | (0.220) | | (0.270) | | (0.235) |
| Size | | 0.004 | | 0.003 | | 0.004 |
| | | (0.012) | | (0.011) | | (0.014) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 18.8 | 16.6 | 13.2 | 10.8 | 14.5 | 11.4 |
| Robust F | 28.3 | 26.9 | 12.7 | 11.7 | 28.4 | 23.7 |
| Effective F | 26.4 | 27.0 | 12.9 | 12.2 | 24.8 | 23.8 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table C.23.: Robustness tests innovation inputs: 2SLS - R&D employment**

| | Dependent variable: ln(1+R&D employees) | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.052 | 0.018 | -0.000 | -0.053 | 0.047 | -0.000 |
| | (0.046) | (0.049) | (0.047) | (0.057) | (0.054) | (0.060) |
| Eligible | 0.186*** | 0.280*** | 0.193** | 0.315*** | 0.185*** | 0.298*** |
| | (0.059) | (0.078) | (0.086) | (0.118) | (0.067) | (0.094) |
| Public VC | 0.201 | 0.336 | 0.496* | 0.709** | 0.229 | 0.440 |
| | (0.261) | (0.274) | (0.260) | (0.301) | (0.312) | (0.337) |
| ln(1+Sales) | -0.001 | 0.001 | -0.004 | -0.002 | -0.002 | 0.000 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Subsidy | 0.241*** | 0.227*** | 0.229*** | 0.217*** | 0.264*** | 0.253*** |
| | (0.044) | (0.040) | (0.040) | (0.039) | (0.047) | (0.043) |
| Team | | 0.036** | | 0.053** | | 0.040** |
| | | (0.017) | | (0.021) | | (0.020) |
| Founding exp. | | 0.017** | | 0.018 | | 0.016* |
| | | (0.008) | | (0.012) | | (0.008) |
| Industry exp. | | -0.001** | | -0.002** | | -0.002** |
| | | (0.001) | | (0.001) | | (0.001) |
| Exit exp. | | 0.101*** | | 0.146*** | | 0.122*** |
| | | (0.037) | | (0.048) | | (0.044) |
| Opportunity | | 0.129*** | | 0.140*** | | 0.141*** |
| | | (0.024) | | (0.025) | | (0.025) |
| PhD | | 0.200*** | | 0.210*** | | 0.203*** |
| | | (0.031) | | (0.032) | | (0.036) |
| Academic | | 0.071*** | | 0.087*** | | 0.083*** |
| | | (0.019) | | (0.018) | | (0.022) |
| Female | | -0.063*** | | -0.081*** | | -0.072*** |
| | | (0.016) | | (0.019) | | (0.018) |
| Patent | | 0.203*** | | 0.220*** | | 0.193*** |
| | | (0.038) | | (0.046) | | (0.039) |
| Size | | 0.003 | | 0.002 | | 0.003 |
| | | (0.002) | | (0.002) | | (0.003) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 18.8 | 16.6 | 13.2 | 10.8 | 14.5 | 11.4 |
| Robust F | 28.3 | 26.9 | 12.7 | 11.7 | 28.4 | 23.7 |
| Effective F | 26.4 | 27.0 | 12.9 | 12.2 | 24.8 | 23.8 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

### Table C.24.: Robustness tests innovation outputs: 2SLS - Global market novelty

| | Dependent variable: 𝟙[Global market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | 0.873*** | 0.825*** | 0.970*** | 0.922*** | 0.851*** | 0.811** |
| | (0.254) | (0.264) | (0.301) | (0.312) | (0.319) | (0.342) |
| Eligible | 0.327*** | 0.319*** | 0.294*** | 0.284*** | 0.333*** | 0.323*** |
| | (0.041) | (0.049) | (0.062) | (0.068) | (0.050) | (0.062) |
| Public VC | -0.331** | -0.315** | -0.400*** | -0.385** | -0.326* | -0.316* |
| | (0.135) | (0.138) | (0.150) | (0.154) | (0.172) | (0.180) |
| ln(1+Sales) | 0.008*** | 0.009*** | 0.008*** | 0.009*** | 0.009*** | 0.010*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Subsidy | 0.008 | 0.007 | 0.009 | 0.008 | 0.011 | 0.009 |
| | (0.014) | (0.012) | (0.011) | (0.011) | (0.017) | (0.015) |
| Team | | -0.015* | | -0.019** | | -0.017 |
| | | (0.009) | | (0.009) | | (0.011) |
| Founding exp. | | 0.002 | | -0.004 | | 0.002 |
| | | (0.006) | | (0.008) | | (0.007) |
| Industry exp. | | 0.001* | | 0.001** | | 0.001 |
| | | (0.000) | | (0.001) | | (0.001) |
| Exit exp. | | -0.028* | | -0.036* | | -0.022 |
| | | (0.016) | | (0.019) | | (0.020) |
| Opportunity | | 0.033*** | | 0.033*** | | 0.034*** |
| | | (0.008) | | (0.007) | | (0.009) |
| PhD | | 0.024* | | 0.021 | | 0.024 |
| | | (0.014) | | (0.015) | | (0.016) |
| Academic | | 0.023*** | | 0.019*** | | 0.027*** |
| | | (0.007) | | (0.007) | | (0.008) |
| Female | | -0.010 | | -0.011 | | -0.009 |
| | | (0.008) | | (0.012) | | (0.010) |
| Patent | | 0.101*** | | 0.105*** | | 0.102*** |
| | | (0.016) | | (0.018) | | (0.017) |
| Size | | -0.001 | | -0.000 | | -0.001 |
| | | (0.000) | | (0.000) | | (0.000) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 15.5 | 13.1 | 16.2 | 13.2 |
| Robust F | 26.1 | 23.8 | 14.3 | 13.1 | 27.0 | 21.7 |
| Effective F | 25.4 | 24.6 | 14.9 | 13.9 | 24.7 | 22.7 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p$<$0.01, ** p$<$0.05, * p$<$0.1.

**Table C.25.: Robustness tests innovation outputs: 2SLS - Domestic market novelty**

| | Dependent variable: 𝟙[Domestic market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | -0.382 | -0.443 | -0.463 | -0.573 | -0.583 | -0.714* |
| | (0.339) | (0.371) | (0.388) | (0.440) | (0.372) | (0.414) |
| Eligible | -0.125** | -0.102 | -0.061 | -0.038 | -0.097* | -0.055 |
| | (0.052) | (0.065) | (0.079) | (0.097) | (0.057) | (0.072) |
| Public VC | 0.233 | 0.247 | 0.277 | 0.311 | 0.340* | 0.387** |
| | (0.159) | (0.172) | (0.190) | (0.210) | (0.177) | (0.193) |
| ln(1+Sales) | 0.002 | 0.003** | 0.002 | 0.003** | 0.001 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Subsidy | 0.030** | 0.027** | 0.019 | 0.018 | 0.044** | 0.042*** |
| | (0.014) | (0.013) | (0.014) | (0.013) | (0.018) | (0.016) |
| Team | | 0.006 | | 0.010 | | 0.012 |
| | | (0.011) | | (0.014) | | (0.012) |
| Founding exp. | | 0.012** | | 0.013* | | 0.011* |
| | | (0.005) | | (0.007) | | (0.006) |
| Industry exp. | | -0.001 | | -0.001 | | -0.001* |
| | | (0.001) | | (0.001) | | (0.001) |
| Exit exp. | | 0.048*** | | 0.052** | | 0.066*** |
| | | (0.018) | | (0.022) | | (0.020) |
| Opportunity | | 0.048*** | | 0.051*** | | 0.049*** |
| | | (0.007) | | (0.010) | | (0.010) |
| PhD | | 0.040** | | 0.041** | | 0.049*** |
| | | (0.016) | | (0.016) | | (0.017) |
| Academic | | 0.017** | | 0.019** | | 0.023** |
| | | (0.008) | | (0.008) | | (0.010) |
| Female | | -0.005 | | -0.013 | | -0.008 |
| | | (0.011) | | (0.014) | | (0.014) |
| Patent | | 0.025*** | | 0.021 | | 0.022** |
| | | (0.009) | | (0.013) | | (0.009) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 15.5 | 13.1 | 16.2 | 13.2 |
| Robust F | 26.1 | 23.8 | 14.3 | 13.1 | 27.0 | 21.7 |
| Effective F | 25.4 | 24.6 | 14.9 | 13.9 | 24.7 | 22.7 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table C.26.: Robustness tests innovation outputs: 2SLS - Regional market novelty**

| | Dependent variable: 𝟙[Regional market novelty="Yes"] | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Equity (Y/N) | -0.073 | -0.082 | -0.105 | -0.115 | -0.108 | -0.117 |
| | (0.220) | (0.234) | (0.248) | (0.267) | (0.220) | (0.248) |
| Eligible | -0.037 | -0.031 | -0.028 | -0.022 | -0.031 | -0.025 |
| | (0.034) | (0.042) | (0.051) | (0.060) | (0.034) | (0.044) |
| Public VC | 0.025 | 0.028 | 0.043 | 0.046 | 0.047 | 0.051 |
| | (0.112) | (0.116) | (0.126) | (0.132) | (0.113) | (0.124) |
| ln(1+Sales) | 0.000 | 0.001 | 0.000 | 0.001 | 0.000 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Subsidy | 0.005 | 0.005 | 0.004 | 0.003 | 0.003 | 0.003 |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) | (0.008) |
| Team | | 0.006 | | 0.007 | | 0.008 |
| | | (0.006) | | (0.007) | | (0.007) |
| Founding exp. | | 0.001 | | 0.001 | | -0.001 |
| | | (0.003) | | (0.004) | | (0.003) |
| Industry exp. | | -0.000 | | -0.001 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | 0.003 | | 0.007 | | 0.002 |
| | | (0.012) | | (0.015) | | (0.013) |
| Opportunity | | 0.008* | | 0.008* | | 0.008* |
| | | (0.004) | | (0.005) | | (0.005) |
| PhD | | -0.000 | | 0.002 | | -0.001 |
| | | (0.009) | | (0.010) | | (0.010) |
| Academic | | -0.005 | | -0.004 | | -0.004 |
| | | (0.004) | | (0.003) | | (0.005) |
| Female | | -0.006 | | -0.005 | | -0.005 |
| | | (0.006) | | (0.008) | | (0.007) |
| Patent | | -0.000 | | -0.002 | | 0.003 |
| | | (0.006) | | (0.006) | | (0.005) |
| Size | | 0.000 | | 0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 21.0 | 18.8 | 15.5 | 13.1 | 16.2 | 13.2 |
| Robust F | 26.1 | 23.8 | 14.3 | 13.1 | 27.0 | 21.7 |
| Effective F | 25.4 | 24.6 | 14.9 | 13.9 | 24.7 | 22.7 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table C.27.: Robustness tests innovation outputs: 2SLS - Patent applications**

| | Dependent variable: # of patent applications | | | | | |
|---|---|---|---|---|---|---|
| | Main sample | | Period 2007-2016 | | Excl. retail & oth. serv. | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(1+Equity) | 0.022* | 0.021* | 0.024* | 0.024 | 0.022* | 0.022* |
| | (0.012) | (0.012) | (0.013) | (0.014) | (0.012) | (0.013) |
| Eligible | 0.007 | 0.004 | 0.005 | 0.001 | 0.006 | 0.003 |
| | (0.016) | (0.020) | (0.021) | (0.026) | (0.016) | (0.020) |
| Public VC | -0.046 | -0.043 | -0.062 | -0.061 | -0.048 | -0.046 |
| | (0.070) | (0.072) | (0.087) | (0.091) | (0.073) | (0.078) |
| ln(1+Sales) | -0.000 | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Subsidy | 0.005 | 0.006 | 0.006 | 0.007* | 0.005 | 0.006 |
| | (0.005) | (0.004) | (0.004) | (0.004) | (0.006) | (0.005) |
| Team | | 0.000 | | -0.001 | | 0.000 |
| | | (0.003) | | (0.005) | | (0.004) |
| Founding exp. | | -0.002 | | -0.002 | | -0.002 |
| | | (0.002) | | (0.002) | | (0.002) |
| Industry exp. | | 0.000 | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Exit exp. | | -0.004 | | -0.005 | | -0.003 |
| | | (0.006) | | (0.006) | | (0.006) |
| Opportunity | | 0.001 | | 0.002 | | 0.001 |
| | | (0.002) | | (0.003) | | (0.002) |
| PhD | | -0.005 | | -0.006 | | -0.006 |
| | | (0.007) | | (0.008) | | (0.008) |
| Academic | | 0.002 | | 0.002 | | 0.002 |
| | | (0.001) | | (0.002) | | (0.002) |
| Female | | 0.002 | | 0.004 | | 0.003 |
| | | (0.004) | | (0.004) | | (0.004) |
| Patent | | -0.007 | | -0.008 | | -0.007 |
| | | (0.005) | | (0.007) | | (0.006) |
| Size | | -0.000 | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| **Firm controls:** | | | | | | |
| Time varying | Yes | Yes | Yes | Yes | Yes | Yes |
| Time fixed | | Yes | | Yes | | Yes |
| Craig-Donald F | 18.8 | 16.6 | 13.2 | 10.8 | 14.5 | 11.4 |
| Robust F | 28.3 | 26.9 | 12.7 | 11.7 | 28.4 | 23.7 |
| Effective F | 26.4 | 27.0 | 12.9 | 12.2 | 24.8 | 23.8 |
| Crit. Val. ($\tau$=10%) | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 | 23.1 |
| Clusters | 68 | 68 | 68 | 68 | 57 | 57 |
| Firm obs. | 10,580 | 10,580 | 8,291 | 8,291 | 9,170 | 9,170 |
| Firm-year obs. | 21,094 | 21,094 | 16,164 | 16,164 | 18,561 | 18,561 |

**Note**: "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. All models include fixed effects for year, founding cohort, industry, and region. Firm controls in Columns (1), (3), and (5) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (2), (4), and (6) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size.
Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Table C.28.: Robustness tests first stage trends: OLS - Equity financing**

| | Dependent variable: $\mathbb{1}$[Equity="Yes"] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Period 2007-2016 | | | | Excluding retail & oth. services | | | |
| | (1) Coef. | CI 95% | (2) Coef. | CI 95% | (3) Coef. | CI 95% | (4) Coef. | CI 95% |
| 2007 | -0.024 | [-0.060,0.012] | -0.016 | [-0.051,0.019] | -0.023 | [-0.058,0.012] | -0.015 | [-0.051,0.022] |
| 2008 | -0.015 | [-0.047,0.018] | -0.015 | [-0.046,0.016] | -0.016 | [-0.048,0.016] | -0.014 | [-0.047,0.019] |
| 2009 | -0.010 | [-0.043,0.023] | -0.008 | [-0.041,0.025] | -0.017 | [-0.054,0.021] | -0.012 | [-0.051,0.028] |
| 2010 | 0.006 | [-0.018,0.029] | -0.001 | [-0.025,0.023] | 0.012 | [-0.012,0.037] | 0.009 | [-0.015,0.033] |
| 2011 | -0.016 | [-0.042,0.011] | -0.019 | [-0.047,0.008] | -0.015 | [-0.042,0.012] | -0.018 | [-0.045,0.010] |
| 2013 | 0.020 | [-0.005,0.045] | 0.017 | [-0.010,0.043] | 0.014 | [-0.010,0.037] | 0.010 | [-0.016,0.036] |
| 2014 | 0.012 | [-0.013,0.037] | 0.010 | [-0.014,0.033] | 0.014 | [-0.015,0.043] | 0.011 | [-0.017,0.038] |
| 2015 | 0.020 | [-0.006,0.046] | 0.019 | [-0.005,0.043] | 0.021 | [-0.008,0.050] | 0.020 | [-0.009,0.049] |
| 2016 | $0.029^{***}$ | [0.007,0.051] | $0.026^{**}$ | [0.005,0.047] | $0.036^{***}$ | [0.012,0.060] | $0.031^{**}$ | [0.007,0.055] |
| 2017 | | | | | $0.036^{***}$ | [0.012,0.061] | $0.028^{**}$ | [0.006,0.051] |
| 2018 | | | | | $0.030^{*}$ | [-0.005,0.064] | 0.027 | [-0.008,0.061] |
| Constant | $0.052^{***}$ | [0.041,0.063] | $0.058^{***}$ | [0.037,0.080] | $0.052^{***}$ | [0.039,0.066] | $0.065^{***}$ | [0.038,0.093] |
| **Fixed effects:** | | | | | | | | |
| Year | Yes | | Yes | | Yes | | Yes | |
| Founding cohort | Yes | | Yes | | Yes | | Yes | |
| Industry | Yes | | Yes | | Yes | | Yes | |
| Region | Yes | | Yes | | Yes | | Yes | |
| **Firm controls:** | | | | | | | | |
| Time varying | | | Yes | | | | Yes | |
| Time fixed | | | Yes | | | | Yes | |
| R2 | 0.041 | | 0.138 | | 0.041 | | 0.143 | |
| Clusters | 67 | | 67 | | 56 | | 56 | |
| Firm-year obs. | 8,290 | | 8,290 | | 9,169 | | 9,169 | |
| Firm obs. | 16,163 | | 16,163 | | 18,560 | | 18,560 | |

**Note**: Coef. gives the difference between eligible and non-eligible firms in the reference year. CI 95% gives the lower and upper bound of the 95%-confidence interval. "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size. Standard errors in parentheses clustered at the industry level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

## Table C.29.: Robustness tests first stage trends: OLS- Equity financing in levels

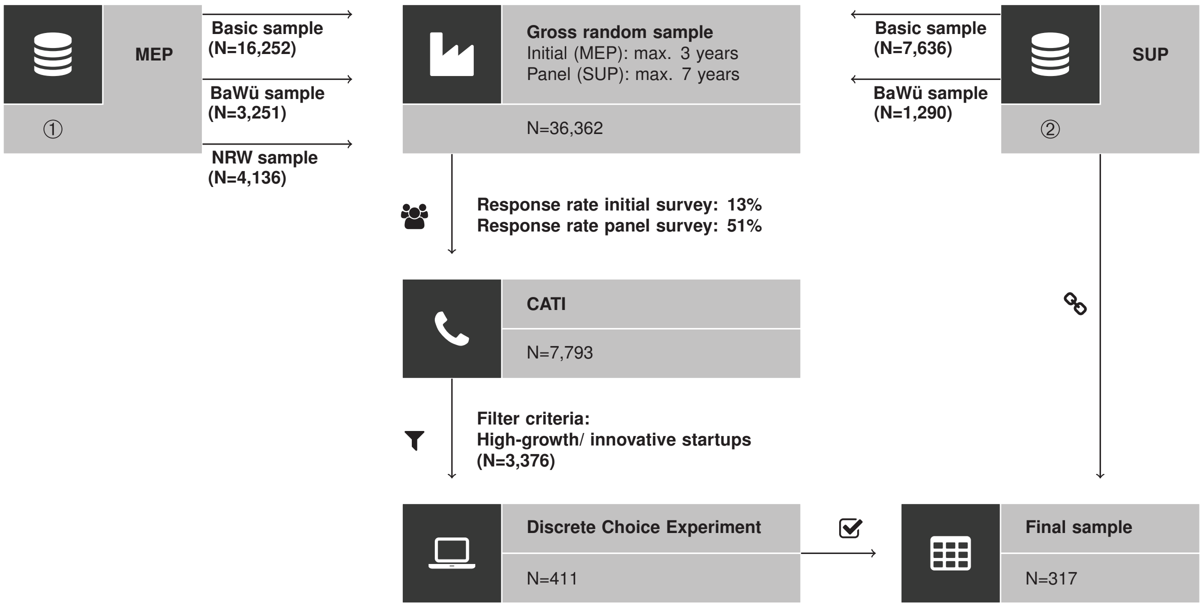
| | Dependent variable: ln(1+Equity) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Period 2007-2016 | | | | Excluding retail & oth. services | | | |
| | (1) Coef. | CI 95% | (2) Coef. | CI 95% | (3) Coef. | CI 95% | (4) Coef. | CI 95% |
| 2007 | -0.236 | [-0.629,0.158] | -0.146 | [-0.524,0.232] | -0.232 | [-0.617,0.153] | -0.133 | [-0.527,0.261] |
| 2008 | -0.050 | [-0.364,0.265] | -0.050 | [-0.346,0.247] | -0.060 | [-0.362,0.241] | -0.035 | [-0.337,0.267] |
| 2009 | -0.093 | [-0.439,0.253] | -0.070 | [-0.409,0.269] | -0.162 | [-0.552,0.227] | -0.105 | [-0.506,0.297] |
| 2010 | 0.096 | [-0.144,0.336] | 0.028 | [-0.213,0.268] | 0.120 | [-0.144,0.385] | 0.084 | [-0.172,0.340] |
| 2011 | -0.128 | [-0.383,0.127] | -0.169 | [-0.445,0.108] | -0.108 | [-0.379,0.164] | -0.136 | [-0.427,0.156] |
| 2013 | 0.170 | [-0.096,0.436] | 0.130 | [-0.150,0.410] | 0.099 | [-0.160,0.359] | 0.060 | [-0.223,0.344] |
| 2014 | 0.165 | [-0.064,0.395] | 0.137 | [-0.075,0.348] | 0.172 | [-0.090,0.435] | 0.130 | [-0.110,0.370] |
| 2015 | 0.240* | [-0.045,0.525] | 0.235* | [-0.020,0.490] | 0.260 | [-0.052,0.573] | 0.247 | [-0.053,0.547] |
| 2016 | 0.323** | [0.075,0.571] | 0.291** | [0.057,0.524] | 0.373*** | [0.106,0.639] | 0.318** | [0.067,0.569] |
| 2017 | | | | | 0.444*** | [0.186,0.702] | 0.354*** | [0.126,0.583] |
| 2018 | | | | | 0.346* | [-0.032,0.723] | 0.314* | [-0.062,0.690] |
| Constant | 0.526*** | [0.415,0.638] | 0.562*** | [0.330,0.794] | 0.532*** | [0.397,0.668] | 0.610*** | [0.311,0.908] |
| **Fixed effects:** | | | | | | | | |
| Year | Yes | | Yes | | Yes | | Yes | |
| Founding cohort | Yes | | Yes | | Yes | | Yes | |
| Industry | Yes | | Yes | | Yes | | Yes | |
| Region | Yes | | Yes | | Yes | | Yes | |
| **Firm controls:** | | | | | | | | |
| Time varying | | | Yes | | | | Yes | |
| Time fixed | | | Yes | | | | Yes | |
| R2 | 0.043 | | 0.145 | | 0.043 | | 0.148 | |
| Clusters | 67 | | 67 | | 56 | | 56 | |
| Firm-year obs. | 8,290 | | 8,290 | | 9,169 | | 9,169 | |
| Firm obs. | 16,163 | | 16,163 | | 18,560 | | 18,560 | |

**Note**: Coef. gives the difference between eligible and non-eligible firms in the reference year. CI 95% gives the lower and upper bound of the 95%-confidence interval. "Period 2007-2016" excludes observations from 2017 onward, when the revised program INVEST 2.0 started. "Excl. retail & oth. serv." excludes firms from the Retail and Service Sectors. Firm controls in Columns (3) include time-varying variables Public subsidy, Public VC, and ln(1+Sales). Column (4) also includes time-fixed variables Team, Female, Academic, PhD, Industry experience, Founding experience, Exit experience, Opportunity, Patent and Size. Standard errors in parentheses clustered at the industry level. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

# D. The Private Value of Entrepreneurial Control

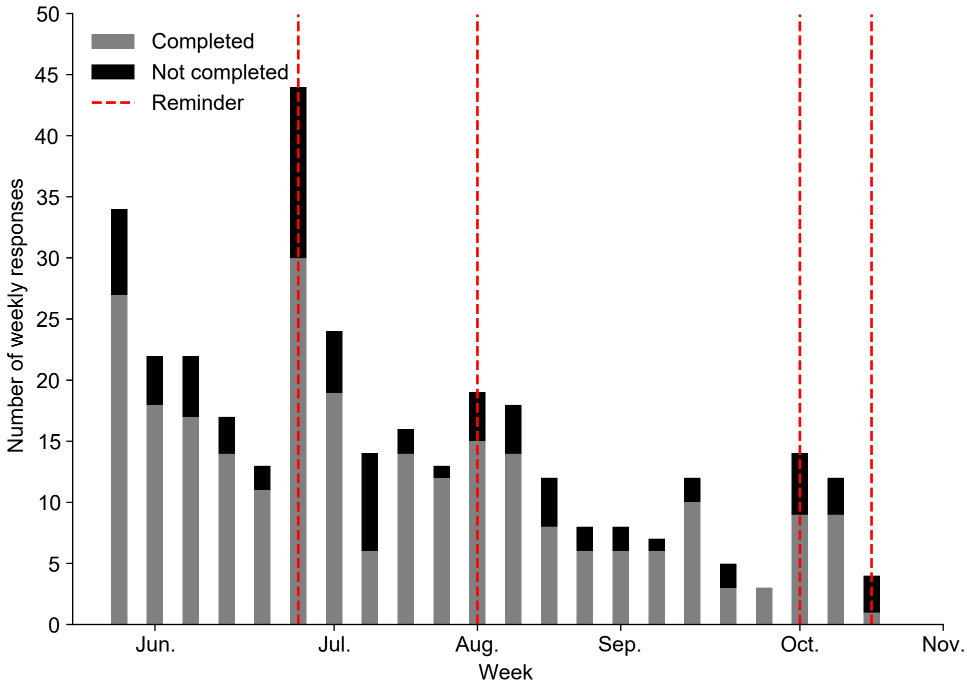
# Appendix

## Figure D.1.: Sampling approach




**Note:** Figure D.1 depicts the sampling procedure. The sampling approach builds upon two databases: the Mannheim Enterprise Panel (1) and the IAB/ZEW Startup Panel (2). In 2019, next to the basic sample, two additional samples for the states of Baden-Württemberg (BaWü) and Northrhine Westfalia (NRW) were drawn. The NRW sample was drawn for the first time, which is why it is not contained in (2). All firms that are drawn into the gross random sample are contacted. The response rate among firms already in (2) is markedly larger. All firms participating in the survey provide information in a computer-assisted telephone interview (CATI). For the online discrete choice experiment (ODCE), firms were selected that fulfill one of the following criteria: i) existing equity investors, ii) contact with equity investors, iii) R&D activity, or iv) growth-oriented. Firms then self-select into participating in the online ODCE. Participants that fully completed the ODCE are contained in the final sample.

**Figure D.2.: Response analysis - Distribution of responses by state of completion**




**Note:** The graph shows the number of responses over our sampling period from May to November 2019. Each bar depicts the number of responses in a given week. The gray part of the bars are responses that were fully completed. In total, four reminders were sent out. The red dotted lines mark the dates of the reminders.

**Table D.1.: Correlations of random coefficients**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Full | VC | By phase: | |
| | | | Startup | Growth |
| Veto rights × Voting majority | 0.77*** | 0.53*** | 0.72*** | 0.74*** |
| | (0.06) | (0.11) | (0.10) | (0.09) |
| Veto rights × Finance support | -0.19 | -0.10 | -0.24 | -0.05 |
| | (0.15) | (0.20) | (0.19) | (0.24) |
| Veto rights × Market access | -0.08 | -0.05 | -0.23 | 0.10 |
| | (0.12) | (0.18) | (0.18) | (0.14) |
| Veto rights × R&D support | -0.18 | -0.28 | -0.14 | -0.18 |
| | (0.19) | (0.21) | (0.20) | (0.36) |
| Veto rights × Strategic support | 0.10 | -0.00 | -0.06 | 0.29 |
| | (0.16) | (0.20) | (0.20) | (0.22) |
| Voting majority × Finance support | -0.11 | -0.24 | -0.07 | -0.16 |
| | (0.13) | (0.17) | (0.18) | (0.19) |
| Voting majority × Market access | -0.26** | -0.24 | -0.31 | -0.15 |
| | (0.10) | (0.15) | (0.16) | (0.13) |
| Voting majority × R&D support | -0.23 | -0.09 | -0.02 | -0.51 |
| | (0.15) | (0.20) | (0.18) | (0.31) |
| Voting majority × Strategic support | -0.01 | -0.14 | -0.06 | 0.07 |
| | (0.13) | (0.18) | (0.18) | (0.18) |
| Finance support × Market access | 0.14 | 0.10 | 0.04 | 0.11 |
| | (0.13) | (0.18) | (0.22) | (0.22) |
| Finance support × R&D support | 0.04 | 0.17 | 0.09 | 0.20 |
| | (0.22) | (0.27) | (0.26) | (0.45) |
| Finance support × Strategic support | -0.23 | 0.17 | 0.12 | -0.45 |
| | (0.17) | (0.23) | (0.24) | (0.31) |
| Market access × R&D support | 0.57** | 0.49* | 0.72*** | 0.55 |
| | (0.18) | (0.21) | (0.15) | (0.38) |
| Market access × Strategic support | 0.31* | 0.27 | 0.38* | 0.27 |
| | (0.15) | (0.21) | (0.19) | (0.20) |
| R&D support× Strategic support | 0.60** | 0.85*** | 0.73*** | 0.30 |
| | (0.22) | (0.13) | (0.16) | (0.45) |
| Pseudo R2 | 0.101 | 0.108 | 0.109 | 0.100 |
| Number of respondents | 317 | 141 | 140 | 177 |
| Number of choices | 3170 | 1410 | 1400 | 1770 |

**Note**: This table shows the correlations between the random coefficients from the mixed logit estimations. Model 1, Full, presents the results for all respondents who completed the survey. Model 2, VC, excludes respondents who have indicated that they are not interested in venture capital financing. Models 3 and 4 split the sample by the respondent firm's growth phase. Model 3 includes respondents in the startup phase who have not yet finished developing their product or have recently begun to market it. Model 4 contains respondents in the growth phase whose products already generate significant sales.
The random coefficients of the underlying mixed logit model follow a fully correlated Gaussian distribution, except for the equity share coefficient, which is set to be fixed. For the simulation of the Gaussian, we used $R = 1000$ draws from a Hammersley point set. We used the Broyden-Fletcher-Goldfarb-Shanno algorithm to maximize the likelihood function, for which all models converged within a reasonable number of iterations. The matrix $\Gamma$ in equation (5.5) is specified as a lower triangular Cholesky matrix, allowing the random coefficients in the model to be correlated. Standard errors for marginal effects have been calculated using the delta method.
Standard errors in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05

## Table D.2.: Robustness checks: Willingness to pay with fixed vs. random price coefficient

| | Panel A: Correlated preference attributes | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | R=10 | | R=50 | | R=100 | | R=250 | | R=500 | |
| | FX | RND | FX | RND | FX | RND | FX | RND | FX | |
| Mean | | | | | | | | | | |
| Equity share | 1.00*** | -2.06*** | 1.00*** | -1.67*** | 1.00*** | -1.78*** | 1.00*** | -1.63*** | 1.00*** | |
| | (0.01) | (0.06) | (0.01) | (0.10) | (0.01) | (0.09) | (0.01) | (0.09) | (0.01) | |
| Veto rights | -10.17*** | -10.24*** | -10.84*** | -11.68*** | -11.07*** | -12.18*** | -11.45*** | -10.15*** | -11.42*** | |
| | (0.09) | (0.80) | (0.11) | (0.61) | (0.11) | (0.73) | (0.13) | (0.62) | (0.13) | |
| Voting majority | -34.07*** | -33.38*** | -36.02*** | -38.38*** | -37.20*** | -37.19*** | -37.42*** | -33.13*** | -37.11*** | |
| | (0.20) | (1.86) | (0.28) | (1.89) | (0.28) | (2.24) | (0.30) | (1.52) | (0.29) | |
| Finance support | 4.91*** | 4.51*** | 4.84*** | 4.50*** | 4.94*** | 5.58*** | 5.15*** | 4.89*** | 4.94*** | |
| | (0.07) | (0.62) | (0.08) | (0.49) | (0.09) | (0.60) | (0.09) | (0.52) | (0.09) | |
| Market access | 11.44*** | 10.93*** | 11.05*** | 11.61*** | 11.31*** | 11.96*** | 11.56*** | 11.56*** | 11.48*** | |
| | (0.09) | (0.89) | (0.12) | (0.71) | (0.12) | (0.96) | (0.12) | (0.83) | (0.12) | |
| R&D support | 4.42*** | 4.42*** | 4.28*** | 4.77*** | 4.55*** | 4.32*** | 4.63*** | 5.04*** | 4.58*** | |
| | (0.07) | (0.65) | (0.08) | (0.57) | (0.09) | (0.60) | (0.09) | (0.58) | (0.08) | |
| Strategic support | 3.92*** | 5.00*** | 3.79*** | 4.55*** | 3.75*** | 4.11*** | 3.85*** | 3.99*** | 3.82*** | |
| | (0.07) | (0.65) | (0.08) | (0.59) | (0.08) | (0.71) | (0.09) | (0.71) | (0.09) | |
| *Number of Respondents* | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 | |
| *Number of Choices* | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | |
| | **Panel B: Uncorrelated preference attributes** | | | | | | | | | |
| | R=10 | | R=50 | | R=100 | | R=250 | | R=500 | |
| | FX | RND | FX | RND | FX | RND | FX | RND | FX | RND |
| Mean | | | | | | | | | | |
| Equity share | 1.00*** | -2.17*** | 1.00*** | -1.88*** | 1.00*** | -1.81*** | 1.00*** | -1.73*** | 1.00*** | -1.72*** |
| | (0.01) | (0.05) | (0.01) | (0.09) | (0.01) | (0.08) | (0.01) | (0.11) | (0.01) | (0.09) |
| Veto rights | -10.85*** | -10.73*** | -11.06*** | -10.77*** | -10.68*** | -10.06*** | -11.13*** | -9.97*** | -10.86*** | -10.45*** |
| | (0.08) | (0.77) | (0.10) | (0.71) | (0.10) | (0.69) | (0.11) | (0.85) | (0.11) | (0.68) |
| Voting majority | -35.27*** | -34.53*** | -36.07*** | -36.04*** | -37.82*** | -35.23*** | -37.70*** | -35.82*** | -36.69*** | -35.33*** |
| | (0.19) | (2.09) | (0.24) | (2.28) | (0.27) | (2.09) | (0.29) | (2.02) | (0.29) | (1.69) |
| Finance support | 4.51*** | 4.36*** | 4.63*** | 4.49*** | 4.64*** | 4.74*** | 4.58*** | 4.61*** | 4.60*** | 4.65*** |
| | (0.06) | (0.57) | (0.08) | (0.54) | (0.08) | (0.55) | (0.08) | (0.59) | (0.09) | (0.54) |
| Market access | 11.07*** | 10.69*** | 10.86*** | 9.70*** | 10.57*** | 10.32*** | 10.93*** | 10.04*** | 10.80*** | 9.99*** |
| | (0.08) | (0.79) | (0.10) | (0.72) | (0.10) | (0.82) | (0.11) | (0.78) | (0.11) | (0.72) |
| R&D support | 3.88*** | 3.84*** | 4.09*** | 3.26*** | 4.08*** | 3.27*** | 4.11*** | 3.80*** | 3.94*** | 3.73*** |
| | (0.06) | (0.57) | (0.07) | (0.52) | (0.08) | (0.51) | (0.08) | (0.66) | (0.08) | (0.53) |
| Strategic support | 3.84*** | 3.74*** | 3.99*** | 3.11*** | 4.01*** | 2.96*** | 3.93*** | 3.22*** | 3.86*** | 3.66*** |
| | (0.06) | (0.56) | (0.08) | (0.50) | (0.08) | (0.55) | (0.08) | (0.53) | (0.08) | (0.58) |
| *Number of Respondents* | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 | 317 |
| *Number of Choices* | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 | 3170 |

**Note**: The table shows the willingness to pay (WTP) for attributes, assuming fixed (FX) and random (RND) price coefficients for varying numbers of draws *R*. The cases of uncorrelated and fully correlated parameters are considered.
The random coefficients of the underlying mixed logit model follow a fully correlated Gaussian distribution, except for the equity share coefficient, which is set to be fixed. For the simulation of the Gaussian, we used $R = 1000$ draws from a Hammersley point set. We used the Broyden-Fletcher-Goldfarb-Shanno algorithm to maximize the likelihood function, for which all models converged within a reasonable number of iterations. Standard errors for marginal effects have been calculated using the delta method.
In Panel A, The matrix $\Gamma$ in equation (5.5) is specified as a lower triangular Cholesky matrix, allowing the random coefficients in the model to be correlated. In Panel B, the matrix is specified as a diagonal matrix, forcing the coefficients to be uncorrelated.
In the case of fully correlated parameters, the model did not achieve convergence for the case of R=500 draws. Revelt and Train (1998) report the same problem for cases where all coefficients are modeled as random.
Standard errors in parentheses. Significance levels: *** p<0.001, ** p<0.01, * p<0.05

### Table D.3.: Heterogeneity of willingness to pay

| | Control | | Support | | | |
|---|---|---|---|---|---|---|
| | Majority vote | Veto | Market | R&D | Finance | Strategic |
| VC fund | 8.032* | 1.957 | 0.033 | -0.549 | 0.247 | -0.086 |
| | (4.709) | (1.191) | (1.307) | (0.712) | (0.935) | (0.927) |
| Angel | -0.378 | 0.826 | 0.166 | -0.686* | 1.250** | 0.279 |
| | (2.447) | (0.721) | (1.054) | (0.376) | (0.524) | (0.445) |
| VC contact | 0.556 | 0.653 | -0.430 | -0.640** | 0.773* | -0.515 |
| | (2.273) | (0.652) | (1.047) | (0.323) | (0.440) | (0.464) |
| R&D | 2.730 | -0.200 | -1.357 | -0.081 | 1.199*** | 0.120 |
| | (2.255) | (0.658) | (1.059) | (0.295) | (0.444) | (0.433) |
| Growth objective | 0.847 | -0.036 | -1.254 | -0.028 | 1.185*** | -0.076 |
| | (1.996) | (0.575) | (0.872) | (0.284) | (0.435) | (0.387) |
| Founder age | 0.138 | 0.015 | -0.001 | 0.027 | -0.042* | -0.030 |
| | (0.115) | (0.032) | (0.046) | (0.017) | (0.023) | (0.020) |
| Female founder | -4.023* | -0.537 | -0.011 | -0.206 | 0.074 | -0.866* |
| | (2.311) | (0.692) | (0.956) | (0.288) | (0.485) | (0.460) |
| Founding exp. | 1.117 | 0.179 | 1.673** | 0.161 | -0.606 | 0.394 |
| | (1.986) | (0.584) | (0.829) | (0.281) | (0.424) | (0.384) |
| Industry exp. | 0.010 | -0.025 | 0.010 | -0.026 | 0.044** | -0.004 |
| | (0.109) | (0.031) | (0.046) | (0.016) | (0.021) | (0.020) |
| Firm age | 0.259 | -0.165 | 0.061 | 0.238*** | -0.013 | 0.083 |
| | (0.588) | (0.180) | (0.255) | (0.084) | (0.114) | (0.112) |
| Sales | -1.317** | 0.004 | -0.104 | 0.054 | -0.477*** | 0.054 |
| | (0.603) | (0.194) | (0.233) | (0.089) | (0.140) | (0.122) |
| Employees | 0.197 | 0.005 | 0.007 | -0.026 | 0.021 | -0.038* |
| | (0.120) | (0.034) | (0.056) | (0.019) | (0.040) | (0.020) |
| Patent | -6.273** | 0.251 | 1.337 | 0.159 | -0.252 | 0.895* |
| | (2.946) | (0.878) | (1.164) | (0.500) | (0.652) | (0.493) |
| **Industry** | | | | | | |
| Hightech services/ software | -4.964* | -0.103 | 1.231 | 0.604 | -0.803 | 0.173 |
| | (2.918) | (0.868) | (1.320) | (0.453) | (0.647) | (0.555) |
| Non-hightech manufacturing | 3.515 | -0.009 | -0.062 | 0.274 | 1.087 | -0.234 |
| | (4.597) | (1.043) | (1.754) | (0.617) | (0.806) | (0.768) |
| B2B services | -2.201 | 0.643 | 0.114 | -0.103 | 0.240 | -0.063 |
| | (4.131) | (1.179) | (1.775) | (0.586) | (0.810) | (0.702) |
| B2C services | 4.018 | -0.293 | -0.535 | -0.154 | 0.473 | -0.112 |
| | (3.740) | (1.042) | (1.596) | (0.547) | (0.708) | (0.743) |
| Construction | 7.508 | 2.146* | -0.538 | 0.226 | 0.857 | 0.278 |
| | (5.100) | (1.242) | (1.952) | (0.635) | (0.807) | (0.817) |
| **Phase** | | | | | | |
| Startup | 2.750 | -0.797 | -1.726 | -1.057** | -0.448 | 0.538 |
| | (3.306) | (1.121) | (1.240) | (0.522) | (0.786) | (0.750) |
| Growth | 0.549 | -0.212 | 0.139 | -1.084* | 0.065 | 0.836 |
| | (3.614) | (1.188) | (1.391) | (0.552) | (0.809) | (0.790) |
| Constant | -41.635*** | -10.947*** | 11.578*** | 3.354*** | 6.793*** | 4.152*** |
| | (6.312) | (1.958) | (2.506) | (1.098) | (1.256) | (1.198) |
| R2 | 0.11 | 0.05 | 0.05 | 0.10 | 0.15 | 0.05 |
| Number of founders | 306 | 306 | 306 | 306 | 306 | 306 |

**Note**: This table shows multivariate regression results between the estimated individual willingness to pay and founder-specific characteristics. Models are estimated using ordinary least squares. Heteroskedasticity robust standard errors in parentheses.
Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

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