KU LEUVEN

FACULTY OF ECONOMICS AND BUSINESS

Institutional and environmental implications for innovation and entrepreneurship



Dissertation presented to obtain the degree of Doctor in Business Economics

by

Felix Bracht

Number 782 2022



Institutional and environmental implications for innovation and entrepreneurship

Dissertation presented to obtain the degree of Doctor in Business Economics

by

Felix Bracht

Number 782 2022

Daar de proefschriften in de reeks van de Faculteit Economie en Bedrijfswetenschappen het persoonlijk werk zijn van hun auteurs, zijn alleen deze laatsten daarvoor verantwoordelijk.

Examination Committee

Supervisor:

Prof. Dr. Dirk Czarnitzki	KU Leuven

External Members:

Dr. Andrew Toole	U.S. Patent and Trademark Office
Prof. Dr. Steven Vanhaverbeke	Rotterdam School of Management

Internal Member:

Prof. Dr. Hans Degryse	KU Leuven

Chair:

Prof. Dr. Stijn Kelchtermans	KU Leuven

Acknowledgements

This thesis would not have been possible without the support and encouragement of a number of people.

First and foremost, I thank my supervisor Dirk Czarnitzki for giving me the opportunity to start my PhD. Dirk, I consider myself lucky to have had you as my supervisor. You gave me all the freedom to explore my research ideas and work on topics of my interest. At the same time, I was always able to rely on your support. These conditions made it possible to develop my rich and complete skill mix that allows me to explore even the most challenging research questions.

Second, I would like to thank my co-authors of the first chapter of this PhD dissertation, Steven Vanhaverbeke, and Jeroen Mahieu. Our project was a focal point in my academic career. You gave me the great opportunity to benefit from your experiences as recent PhD graduates. I am strongly convinced that your guidance helped me to avoid common pitfalls that many other PhDs make. I am grateful for all the knowledge you have shared with me. I see our project as the ramp from which I have jumped on a steep learning curve.

Third, I would like to thank the co-author of the third chapter of this PhD dissertation, Dennis Verhoeven. Thank you for starting this project with me which was my entry to discover the amazing world of python. I am especially grateful for our lengthy Zoom calls and the critical discussion we had. You always challenged me to take a step further. Your persistence to find, gather and clean the most complex datasets made me a true python geek.

Fourth, gratitude also goes to the other members of my examination committee Professor Hans Degryse and Doctor Andre Toole for their constructive

comments and suggestions. Your valuable insights greatly improved this dissertation.

Fifth, I would like to thank my former colleagues from ECOOM, Jesse and Laura. Even though I had to share some of my PhD time for the Innovation Surveys, I have never regretted any minute of my work. Jesse thanks for your amazing Stata do-files that allowed me to become a bit of a Stata geek like you. Laura thank you for all the fun times at ECOOM.

I would also like to thank all other colleagues at MSI and ECOOM. Many of them become my friends over the past four years. Thank you, Andres, Dries, Florence, Geon, Jordan, Marcel, Marcelina, Marjana, Markus, Maarten, Michael, Max, Peter, Thomas, and Wytse, for all the time we shared. The coffee breaks upstairs, the Friday-evening drinks and dinners, and all the MSI events.

Finally, special thanks to my family for their love and support. You have always encouraged me to follow my ideas and let me make my own choices. Thank you for building the foundation of my career.

Felix Bracht
Leuven, July 2022

Contents

Acknowledgements **i**

Table of Contents **iii**

List of Figures **vi**

List of Tables **viii**

General Introduction **1**

Capital Market Friction 2
Negative Externalities 3
Contribution 4
Outline of the Dissertation 6

1 The Signaling Value of Legal Form in Debt Financing **10**

1.1 Introduction 10
1.2 Theory 16
1.2.1 Legal form as a signal of default risk 18
1.2.2 The role of lender type 20
1.3 Legal Background 21
1.4 Data and Descriptive Statistics 25
1.5 Relationship between Legal Form and Debt Financing 31
1.6 Results 33
1.6.1 Pooled OLS 33
1.6.2 Heterogeneity Analysis 37

1.7 Robustness tests 39
1.7.1 Instrumental variable regression 39
1.7.2 Regression Discontinuity 42
1.7.3 Difference-in-Differences 43
1.7.4 Changes in paid-in capital vs. legal form 46
1.8 Conclusion 47

2 Patent Collateral and Access to Debt **51**
2.1 Introduction 51
2.2 Conceptual framework and empirical identification strategy . 53
2.3 Data sources and descriptive statistics 56
2.3.1 Data sources 56
2.3.2 Descriptive statistics 57
2.3.3 Matching 58
2.4 Estimation Results 60
2.4.1 Main results 60
2.4.2 Placebo test 64
2.5 Conclusion 65

3 Air Pollution and Innovation **68**
3.1 Introduction 68
3.2 Empirical strategy 72
3.2.1 Measures for air pollution and innovation 72
3.2.2 Instrumental variables 74
3.2.3 Econometric Model 76
3.3 Data & Measures 77
3.3.1 Descriptive findings 80
3.3.2 Summary statistics 83
3.4 Main Results 84
3.4.1 Baseline 84
3.4.2 Count Model 86
3.4.3 Accounting for spatial and serial correlation 88
3.4.4 Further robustness checks 88
3.4.5 Heterogeneity Regions 89

3.5 Mechanisms 93
3.5.1 Inventor Mobility 95
3.5.2 R&D expenditures 98
3.5.3 Mortality 101
3.6 Discussion 103

General Conclusion **107**
Limitations and Avenues for Future Research 111

References **114**

Appendix **131**
A Chapter 1 132
B Chapter 2 146
C Chapter 3 150
C.1 Data cleaning inventor relocation 162

List of Figures

1.1 German and Austrian newly established firms over time 24
1.2 RDD with German low- and high-capital LLCs 43
1.3 RDD with Austrian low- and high-capital LLCs 47

3.1 Correlation between IV and $PM_{2.5}$ 82
3.2 Variation in predicted $PM_{2.5}$ concentration by NUTS-3 region . 85
A1 Dynamic difference-in-differences of long- and short-term debt 132
A2 DiD with Austrian low- and high-capital LLCs 133
B1 Coefficient plots for the dynamic difference-in-difference estimation using the Dutch sample 147
B2 Coefficient plots for the dynamic difference-in-difference estimation using the Swedish sample 147
C1 Thermal Inversion 150
C2 Ventilation Coefficient 150
C3 Annual average number of patent filings per NUTS-3 region . 151
C4 Annual average $PM_{2.5}$ level per NUTS-3 region 151
C5 Dropped NUTS-3 regions with total number of patent filings equal or below the 5th percentile 152
C6 Coefficient plot of robustness results. 158
C7 Annual average $PM_{2.5}$ concentration by Urban-Rural classification 158
C8 Inventors relocating between NUTS-3 regions for the sample period 2001-2012 159

C9 Inventors relocating between NUTS-3 and regions outside Europe for the sample period 2001-2012. 160

List of Tables

1.1 Descriptive Statistics: Full Sample 28
1.2 Descriptive Statistics: Survey Sample 30
1.3 OLS: Full Sample 34
1.4 OLS: Survey Sample 36
1.5 OLS Full Sample: Relationship vs. Transactional Banks 38
1.6 Instrumental Variable Estimation 41
1.7 Difference-in-Difference Regression 45

2.1 Summary statistics for the Dutch sample 58
2.2 Summary statistics for the Swedish sample 58
2.3 Summary statistics for the matched sample of Dutch firms . . . 59
2.4 Summary statistics for the matched sample of Swedish firms . 59
2.5 Difference-in-difference regression estimating the impact of patent pledging on debt level in the Netherlands 61
2.6 Difference-in-difference regression estimating the impact of patent pledging on debt level in Sweden 63

3.1 Summary statistics 84
3.2 $PM_{2.5}$ on the number of patent applications 85
3.3 Split sample based on regions median $PM_{2.5}$ concentration . . 91
3.4 Split sample based on Urban-Rural classification 93
3.5 Migrating inventors and air pollution 97
3.6 PubMed publications and air pollution 99
3.7 Patent citations and air pollution 101

3.8 Total deaths and air pollution 102
A1 Variable Description 134
A2 Newly established firms in Germany and Austria over time . . 135
A3 Data Cleaning - German Sample 135
A4 Descriptive Statistics: DiD 136
A5 OLS: Survey Sample with same outcome variables used for the Full Sample 137
A6 OLS: Survey Sample with full controls I 138
A7 OLS: Survey Sample with full controls II 139
A8 OLS: Alternative Measures from Survey Data 140
A9 OLS Survey Sample: Relationship vs. Transactional Banks . . . 141
A10 OLS: Trade Credit Dependence 142
A11 Foreign Ownership and external Financing 143
A12 Regression Discontiniuity Design: Survey Sample 144
A13 Descriptive Statistics: Austrian Sample 144
A14 Regression Discontiniuity Design: Austria 145
A15 Difference-in-Difference Regression: Austria 145
B1 Summary statistics for patent-pledging Dutch firms 146
B2 Summary statistics for patent-pledging Swedish firms 146
B3 Summary statistics for the Dutch placebo sample 148
B4 Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in the Netherlands 148
B5 Summary statistics for the Swedish placebo sample 149
B6 Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in Sweden 149
C1 Summary for the predicted $PM_{2.5}$ concentrations for the regressions shown in Table 3.2 152
C2 Poisson fixed effects regression 153
C3 Accounting for spatial and serial correlation 154
C4 Different thresholds for a low VC 154
C5 Different thresholds for dropping low patenting NUTS-3 regions 155

C6 Different sample periods 155
C7 Patenting and weather controls 156
C8 Patenting and air pollution with individual weather controls . 157
C9 Supplementary summary statistics 159
C10 Migrating inventors and air pollution for a restricted sample where the relocation year of an inventor can be well defined . . 160
C11 Immigrating inventors and air pollution 161
C12 Immigrating inventors and air pollution for a restricted sample where the relocation year of an inventor can be well defined . . 161

General Introduction

Entrepreneurship and innovation are important sources of economic growth. Since Schumpeter's early idea of creative destruction, *'entrepreneurship'* and *'innovation'* have been closely linked. In his theory, entrepreneurs introduce new products and processes that replace outdated ones and push forward the frontiers of technology, which in turn enables economic growth (Schumpeter, 1911). However, neither all entrepreneurs are innovative, nor all innovations are generated by entrepreneurs. Some individuals are forced into entrepreneurship due to a lack of alternative options in the labor market, formally known as 'necessity entrepreneurs' (Schoar, 2010). Such entrepreneurs contribute little or nothing to innovation and growth (Levine and Rubinstein, 2017). On the other hand, the entry of new firms can trigger incumbents to innovate and escape competition (Aghion et al., 2005). Thus, it is important to distinguish between entrepreneurship and innovation. Empirical evidence shows that both are important factors for economic growth. Entrepreneurs contribute to total job creation (Haltiwanger, Jarmin and Miranda, 2013), promote knowledge spillover (Audretsch, Bönte and Keilbach, 2008), and competition (Aghion et al., 2009). Furthermore, endogenous growth theory has put innovation at the center stage in explaining economic progress (Aghion and Howitt, 1990; Romer, 1990). The theory builds on Solow (1956) pioneering work demonstrating that technological progress is needed to sustain long-run economic growth.

However, there are limiting factors to economic growth. Capital market frictions and negative externalities result in substantial deadweight loss, as explained in the following sections. Both sources of inefficiency apply to en-

trepreneurship and innovation. This has motivated a large body of literature to investigate the economic costs associated with market frictions and factors mitigating their negative impact.

Capital Market Frictions

In perfect capital markets with full information, contracting is costless. This means that the actions of individuals and firms are fully observable and all agents receive the capital they need at zero transaction costs (Fama, 1978). Internal and external capital are perfect substitutes (Modigliani and Miller, 1958). However, scholars have agreed that such conditions rarely hold. In the presence of asymmetric information between the borrower and the investor, even profitable investment projects do not receive financing (Stiglitz and Weiss, 1981). Thus, the literature often assumes that capital markets are imperfect and that certain agents are financially constrained. In particular, the financing of entrepreneurship and innovation is characterized by a high degree of information asymmetry. Newly established companies have limited information that lenders and investors can verify (Berger and Udell, 1998). Furthermore, investments in innovation are often highly firm-specific, and the outcome of the innovation process is uncertain (Nelson, 1959). All of these properties increase the risk of adverse selection or moral hazard that discourages external investors (Arrow, 1972).

The idea of imperfect capital markets is supported by empirical findings showing that wealthy individuals are more likely to start a business because external financing is too costly (Hurst and Lusardi, 2004; Glenn et al., 2004). Similarly, empirical studies across different sectors and countries provide strong evidence for innovative firms being financially constrained (Aghion et al., 2012; Brown, Martinsson and Petersen, 2012; Brown and Petersen, 2009).

These findings have motivated researchers to investigate factors that mitigate capital market friction. The pioneering work of Spence (1973) introduced the signaling framework to solve information asymmetry. In the context of capital market imperfections, high-quality borrowers can address information asymmetry by engaging in costly actions that serve as signals about their type

to outside investors. If the signal is too costly for low-quality borrowers but easily visible for outsiders, investors will be able to distinguish between low- and high-quality borrowers resulting in a separating equilibrium. Hence, a large body of literature examines signals by borrowers mitigating financing constraints. Empirical studies show that voluntary information in financial statements (Kausar, Shroff and White, 2016), auditor reputation (Pittman and Fortin, 2004), or the prestige of the board of directors (Certo, 2003) can serve as a signal to investors. Moreover, collateral can serve as a signal for high-quality borrowers as well (Jimenez, Salas and Saurina, 2006). Concerning innovation financing, the literature points out that patents can serve as a signal by conveying observable characteristics of the innovation process (Long, 2002; Hottenrott, Hall and Czarnitzki, 2016).

Negative Externalities

Besides capital market frictions, negative externalities can impose significant costs on entrepreneurs and innovators. Negative externalities are usually caused by discommodities such as pollution. The costs of pollution are often not fully internalized and must also be paid for by third parties that are not responsible for it (Buchanan and Stubblebine, 1962). One of the key externalities is air pollution that causes harm to humans, animals, or materials. This is because the atmosphere is a common good that can be consumed for free. Neither individuals nor firms can be excluded from consuming air (Stavins, 2011). Consequently, missing property rights make it difficult to establish a market for air where costs of pollution are fully internalized (Coase, 1988).

At the same time, the negative health effects of air pollution are multifaceted and severe. The WHO (2016) prioritized air pollution as world's highest environmental health risk factor. This view is supported by evidence of adverse health effects documented in the medical literature. Inhaled pollutants can cause inflammation in the lungs imparing the gas exchange and subsequntly cellular functions throughout the entire body (Viehmann et al., 2015). Furthermore, pollutants can enter the bloodstream through the lungs and influence the cardiovascular system (Oberdörster et al., 2004). Epide-

mological studies show that air pollution is associated with cardiovascular morbidity and mortality (Brook et al., 2010). In addition, there is evidence that air pollution affects the psychology of individuals, including cognitive ability (Power et al., 2016; Clifford et al., 2016), anxiety (Lu et al., 2018) and life satisfaction (Levinson, 2012).

These heterogeneous health effects of air pollution translate into multiple channels of economic outcomes. For example, air pollution affects human capital by increasing mortality. In addition, there are less obvious channels through which air pollution affects economic outcomes. Documented psychological effects of air pollution can impact individuals' behavior and cognitive performance. Thus, the negative externalities of air pollution are still not well understood. This poses a problem for policymakers who must evaluate abatement programs in a cost-benefit analysis (Landrigan et al., 2018).

A recent stream of literature in economics has started to examine how adverse health effects materialize in economic outcomes (Zivin and Neidell, 2018). Lichter, Pestel and Sommer (2017) provide causal evidence for a reduction in soccer players' productivity – measured by the number of passes given – due to ambient air pollution. The loss in labor productivity has also been documented for more cognitive demanding tasks (Chang et al., 2019). In addition, there is evidence that air pollution affects the supply of labor. Hanna and Oliva (2015) show that the reduction in air pollution due to the closure of a refinery in Mexico City led to an increase in labor supply. Although these small-scale case studies are informative, it is difficult to translate their results into systematic conclusions on the effects of pollution on economic output. Dechezleprêtre, Rivers and Stadler (2019) make an important step forward to address this issue and estimate the causal impact of air pollution on the aggregated economic activity in Europe. They find that a 10% increase in air pollution causes a 0.8% decrease in GDP.

Contribution

The introduction above emphasized the importance of entrepreneurship and innovation for economic growth. Moreover, the following sections demon-

strated how financing constraints and air pollution impose significant costs on the economy. The sections also highlighted the progress that has been made in related literature. This dissertation will contribute to the ongoing work around the two sources of inefficiencies in the context of entrepreneurship and innovation. The first two chapters of this dissertation contribute to the understanding of factors that mitigate financing constraints in the field of entrepreneurship and innovation. The last chapter shifts the focus on estimating the negative externalities of air pollution for innovation. In the following, I will briefly explain the gaps in the literature and how the different chapters contribute to the ongoing work.

Chapter 1 examines how the choice in legal form serves as a signal to external investors. The prior literature documents different signaling strategies of firms to reduce information asymmetries and alleviate financing constraints. However, most documented signals do not address information asymmetry in the early stages of the firm. For example, the disclosure of voluntary information in financial statements or the selection of high-reputation auditors is not a choice for entrepreneurs at the founding stage. Instead, the choice of legal form is typically made when founding a firm. Hence, this chapter contributes to the literature by providing evidence for a signal that addresses information asymmetry in the early stages of firms. In particular, the chapter provides empirical evidence that entrepreneurs choosing a limited liability company with low paid-in capital experience lower access to debt financing compared to their high paid-in capital counterparts. These findings are consistent with the idea that investors use the entrepreneur's legal form choice as a screening device to sort out perceived high-risk firms from low-risk firms.

Chapter 2 focuses on the financing constraints of innovative companies. The prior literature examines the signaling value of patents to reduce information asymmetries. However, this is just one mechanism for patents in mitigating financing constraints. Firms can also pledge patents for loan collateral to ease access to finance. This chapter accounts for patent collateralization and examines how patent pledging can increase firms' access to debt finance. The empirical findings show that firms pledging patents can significantly increase their level of debt compared to similar firms that do not pledge patents. There-

fore, this chapter demonstrates how patents pledged as loan collateral provide a fruitful source of external financing and mitigate financing constraints.

Chapter 3 contributes to the estimation of the economic costs of air pollution. Although prior work estimates the cost of air pollution on the GDP within the same year, these estimates do not account for the effect of air pollution on aggregate inventive output. This is because inventions typically take several years to realize economic benefits through product and process improvements. In particular, the chapter estimates the causal effect of air pollution on innovation in Europe. The results show that the average annual reduction in air pollution in Europe leads to 1.7% more patented inventions. A back-of-the-envelope calculation reveals that this increase in innovation created a benefit of 21.3 billion euros annually. Hence, this chapter provides information on the cost of air pollution that has not yet been considered. This cost estimation can help policymakers in evaluating abatement policies.

The next section provides a detailed summary of all three chapters.

Outline of the Dissertation

Chaper 1 - The Signaling Value of Legal Form in Debt Financing

Recent empirical studies investigate the use of signals by credit providers. For example, the signaling value of voluntary financial statement audits (Kausar, Shroff and White, 2016), auditor reputation (Pittman and Fortin, 2004), or the prestige of the board of directors (Certo, 2003). In this chapter, we posit that the firm's choice of legal form serves as a signal of the quality of startups. In particular, we argue that the choice to set up a company with either high or low paid-in capital can provide incremental information to creditors, which in turn can impact firms' access to finance. Our reasoning strongly follows the signaling theory, which states that managers can separate themselves from lower-quality firms by making use of a costly signal. When there are non-negligible screening costs, outside investors will rely on observable signals that correlate with creditworthiness. We argue that choosing a legal form with

higher paid-in capital requirements signals low credit default risk to outside lenders thereby alleviating concerns of adverse selection. This is because low-risk types face a higher marginal rate of substitution between a loan's interest rate and size of the collateral (paid-in capital), but relatively lower opportunity costs and expected reputational costs associated with default. Furthermore, investors can easily observe the firm's legal form within the company name. We provide several pieces of empirical evidence for stark differences in the access of debt for firms incorporated under two different legal forms in Germany. The two legal forms are similar in almost all dimensions but differ in minimum capital requirements. All of our empirical findings suggest that the difference in the access to debt for the two groups can only be explained by firm's choice of legal form and are unlikely to be driven by other observable or unobservable firm characteristics. These findings are consistent with the idea that the choice of legal forms with lower minimum capital requirements is perceived as a negative signal by credit providers.

Chapter 2 - Patent Collateral and Access to Debt

While chapter 1 examines the signaling value of legal form in debt financing, chapter 2 investigates the role of patents in easing access to debt. The prior literature shows that patents can mitigate financing constraints and can be an important source of financing. Hottenrott, Hall and Czarnitzki (2016) show that patents reduce financing constraints by disclosing information to investors, described as the signaling value of patents. However, this is just one mechanism for patents to mitigate financing constraints. Firms can also pledge patents for loan collateral to ease access to finance. This channel has attracted surprisingly little attention in the empirical literature. In this chapter, we address the literature gap and estimate the effect that the event of a patent pledge has on the pledgor's access to external capital. To do so, we make use of detailed firm and patent level data from Sweden and the Netherlands where the registration of collateralized patents is mandatory. Our empirical findings indicate that firms pledging patents could raise on average 1.4 million euro debt in the Netherlands and 1.2 million euro debt in Sweden. In addition, we

show that only a handful of patent filing firms pledged their patents leaving a huge source of external finance untouched. A back-to-envelope calculation reveals that non-pledging firms will benefit from external financing of more than 5.1 billion euro in the Netherlands and 13.4 billion euro in Sweden if they pledge their patents. Hence, we demonstrate that patents are a lucrative source of external finance that many firms have not yet exhausted.

Chapter 3 - Air Pollution and Innovation

Chapters 1 and 2 contribute to the broad literature on capital market frictions. Chapter 3 shifts the focus on negative externalities caused by air pollution as another source of inefficiency. In this chapter, we study the effect of $PM_{2.5}$ as one of the primary pollutants on the number of patent filings as a common measure for inventive output. To address the problem that air pollution is likely endogenous to innovation, we use weather data to construct two instrumental variables that induce exogenous variation in $PM_{2.5}$ concentration levels. Our estimation shows that a $0.17 \mu g/m^2$ decrease in $PM_{2.5}$ concentration – the average yearly reduction in Europe over the period studied – leads to 1.7% more patented innovations. This effect is driven almost exclusively by regions with above-median levels of air pollution, suggesting that up to certain levels of exposure, the effects on innovation are small or nonexistent. The increase in air quality has a similar impact on total innovation for regions with high and intermediate levels of urbanization. This finding suggests that the potential benefits of reducing air pollution extend beyond highly urbanized regions. In addition, we rule out important mechansisms that prevent us from aggregating our regional estimates to economy-wide costs that are not captured in existing estimates for negative effects of air pollution on the current GDP. In particular, we show that reallocation of human capital, inventor mortality, or R&D expenditures are unlikely to explain our results. A back-of-the-envelope suggests that the yearly realized reduction in air pollution in Europe has created a benefit of 21.3 billion euros annually. Consequently, air pollution imposes a significant cost to innovation that might justify more stringent abatement programs.

Chapter 1

The Signaling Value of Legal Form in Debt Financing*

1.1 Introduction

Formal debt financing is arguably the most important source of external financing for startups (Cosh, Cumming and Hughes, 2009; Robb and Robinson, 2014). The ability to attract debt financing has also been linked to longer survival time, and higher revenues and employment (Cole and Sokolyk, 2018; Robb and Robinson, 2014). Furthermore, unlike equity financing, it does not require giving up ownership control (Ueda, 2004) and can be less costly, after tax (Graham, 2000). Despite these benefits, many startup encounters difficulties in obtaining external debt financing due to informational opacity and the absence of an observable history of performance that are characteristic to new ventures (Amit, Glosten and Muller, 1990; Cosh, Cumming and Hughes, 2009; Sanders and Boivie, 2004; Schmalz, Sraer and Thesmar, 2017; Villanueva, Van de Ven and Sapienza, 2012; Wiklund, Baker and Shepherd, 2010).

In the absence of a proven track record, an important question for entrepreneurs is how they can signal their company's quality to outside lenders

* This chapter is based on joint work with Jeroen Mahieu (Vrije Universiteit Amsterdam) and Steven Vanhaverbeke (Rotterdam School of Management).

(Cassar, Ittner and Cavalluzzo, 2015; Connelly et al., 2011). A seminal paper by Leland and Pyle (1977) shows that one such signal can be the entrepreneur's own investments. More recently, scholars have found that, for example, founders' human capital (Ko and McKelvie, 2018; Matusik, George and Heeley, 2008), the use of patents (Conti, Thursby and Thursby, 2013; Conti, Thursby and Rothaermel, 2013; Hsu and Ziedonis, 2013), government grants (Islam, Fremeth and Marcus, 2018), or third party affiliations (Plummer, Allison and Connelly, 2016) can serve as valuable signals (see Colombo (2021) for an overview).

We posit that entrepreneurs can make use of a different signal, namely the choice of legal form at startup. Selecting a legal form is a highly visible and important choice that all new business owners must make at the start of their venture. In addition, it provides a soft signal of the entrepreneur's own investments within the company because different legal forms have different minimum capital requirements. This is in contrast to many of the signals considered by prior work, which do not represent a choice that is available to all new ventures. The legal organization of a firm may thus act as a valuable signaling strategy for startups in the early stages of their life cycles, as other signals are not available (yet). In addition, the impact of the legal form choice on firms' access to formal debt financing may also have consequences for entrepreneurs' access to other types of financing since debt itself serves as a reliable signal for outside equity investors (Epure and Guasch, 2020).

In this paper, we argue that choosing a legal form with higher paid-in capital requirements signals low credit default risk to outside lenders thereby alleviating concerns of adverse selection.[1] This is because low-risk types face a higher marginal rate of substitution between a loan's interest rate and size of the collateral, but relatively lower opportunity costs and expected reputational costs associated with default. Importantly, we are not merely stating that firms with less paid-in capital face higher financing constraints because they have less equity (e.g., Leland and Pyle (1977)). We hypothesize that firms

[1] The paid-in minimum capital requirement reflects the amount that the entrepreneur needs to deposit in a bank when, or shortly after, incorporating a business. Traditionally, its primary legislative purpose has been to protect creditors from new firms that are set up carelessly (World Bank, 2020)

which choose a legal form with lower paid-in capital face disproportionately more difficulties in attracting the necessary external funding (i.e., an effect driven due to the legal form choice itself; conditional on having the same amount of equity, among other founder and firm characteristics). This effect occurs because the choice of legal form is used as a screening device by credit providers in their lending decision.

Furthermore, we hypothesize that the relation between legal form and the access to outside debt is stronger in the case of small relationship lenders. Large transactional lenders benefit more from technological advances and deregulation (e.g., Berger and Black (2011)) which provide them with other reliable instruments to assess creditors' default risk. Therefore, large lenders are less likely to rely on a startup's legal form as a signal of quality. We thus expect that the difference in financing constraints induced by the legal form choice depends on the type of credit provider that the firm is contracting with.

Documenting that the legal form choice affects firms' financing constraints would have important implications for entrepreneurs, especially in light of the recent paid-in capital reforms that occurred across the globe (World Bank, 2020). Over the last two decades, more than 100 countries have lowered the minimum capital requirements to set up a limited liability company (LLC). Many countries did so by allowing entrepreneurs to choose for a new type of legal form, which has the same perks and benefits as a regular LLC, but with no statutory minimum capital (e.g. in Croatia, Denmark, Germany and Luxembourg).[2] The goal of these legislative changes was to spur entrepreneurship. However, as an unintended consequence, entrepreneurs that opted for a LLC with less paid-in capital might face increased financing constraints.

To test our predictions, we make use of a reform in capital requirements that occurred in Germany. Since 2008, entrepreneurs in Germany can choose a new type of legal form when establishing a limited liability company (LLC), the "Unternehmergesellschaft (haftungsbeschränkt) – UG". This new legal form is commonly referred to as the "mini-LLC" or "low-capital LLC". It is similar in

[2]Other countries, such as Austria, United Kingdom and France, have completely abolished or reduced the minimum capital requirements for all LLCs. We discuss these differences in legislation, and its impact on our results in more detail in section 1.3

almost all dimensions to the regular (high-capital) LLC, the "Gesellschaft mit beschränkter Haftung – GmbH". However, the low-capital alternative does not require the regular minimum paid-in capital of 25,000 euro at start up. An entrepreneur can choose any amount between 1 euro and 24,999 euro to setup such a low-capital LLC. Importantly, firms are required to put the legal form suffix (UG or GmbH) at the end of the company name, which makes it straightforward for outside investors to infer their type. These institutional features are similar to other countries that recently introduced a new LLC with lower capital requirements.[3] The setting thus allows us to nicely identify the signaling value of legal form, because we can compare firms with similar characteristics (e.g. firms with capital of 24.999 euro against firms with 25.000 euro).[4]

An additional useful feature of the German setting is that we can make use of two rich data sources to examine firms' financing constraints: (1) the historical firm records from Orbis, which contain financial data about the full population of German LLCs, and (2) detailed survey data from the IAB/ZEW Start-up Panel. The survey data complements the administrative records with information about firms' financing frictions, as well as a wide variety of information about the founders and their firms.

Our results show that low-capital LLCs are 2 percent less likely to obtain debt, and, conditional on obtaining debt, have approximately 52 percent less debt compared to high-capital LLCs. Importantly, in our analyses we adjust for differences in capital and growth opportunities, and further control for sev-

[3] In Denmark, one can set up a low-capital LLC (IVS), which require paid-in capital between 1 to 49.999 Dkr. A regular high-capital LLC (ApS) in Denmark requires at least 50.000 Dkr in paid-in capital. In Croatia, a low-capital LLC (j.d.o.o.) requires paid-in capital of at least 10.00 HKR, while a high-capital LLC (d.o.o.) requires at least 20.000 HKR in paid-in capital. In Luxembourg , a low-capital LLC (SARL-S) requires paid-in capital between 1 to 12.000 EUR, while a high-capital LLC (SARL) requires at least 12.000 EUR in paid-in capital.

[4] As an alternative setting, one could compare (unlisted) Publicly Limited Companies (PLC) with LLCs. For example, in the UK, one can found a (unlisted) Publicly Limited Company (PLC), which has a minimum capital requirement of 50.000 pound. In contrast, a private LLC in the UK has no capital requirements. Next to capital requirements, however, several other differences exist between these legal forms (e.g. minimum number of founders and financial statement disclosure requirements), which would leave room for alternative explanations of our findings in such a setting.

eral other firm, industry, and founder characteristics, including other signals identified by prior work. Furthermore, we find that low-capital LLCs are more likely to indicate that they experience financing constraints, in particular bank financing constraints. We do not find that low-capital LLCs are less likely to state that they are not in need of external funding. These findings are in line with our signaling explanation, but inconsistent with the idea that low-capital LLCs have a lower demand for external funding.

Consistent with our prediction that small banks rely more on firms' legal form as a signal of their default risk, we find that in regions with a higher share of small relationship banks low-capital LLCs obtain less debt. In addition, we find that in these regions low-capital LLCs are more likely to indicate that they are financially constrained. Taken together, these results lend support to our predictions that especially smaller credit providers limit the supply of debt to low-capital LLCs due to concerns of default risk, adjusting for a variety of potentially confounding factors.

Since the founder's choice of legal form is not random, however, we cannot rule out that there may be unobserved variables influencing the relation between legal form and debt. To mitigate such concerns, we provide an array of robustness tests. First, we instrument the legal form choice with the founder's nationality. We posit this is a valid instrument because reducing low minimum capital requirements to setup a business attract foreign entrepreneurs from countries where minimum capital requirements are higher (Becht, Mayer and Wagner, 2008). In addition, we do not find that foreign founders are able to attract significantly less or more debt. The outcomes of these IV analyses are similar to the OLS estimates obtained earlier.

Second, we make use of a Regression Discontinuity Design (RDD), estimating a local average treatment effect of legal form around the equity threshold that defines low-capital LLCs and high-capital LLCs. In particular, we compare low-capital LLCs that have accumulated equity close to the 25,000 euro threshold with high-capital LLCs that have equity just above the threshold. Hence, firms are on average very similar on a variety of characteristics, including equity, but, by definition, they differ in terms of legal form. Our RDD shows that there is a stark discontinuity in debt financing and degree of financ-

ing constraints, in line with our prior results.

Third, we exploit the fact that low-capital LLCs change their legal form once they reach the 25,000 euro minimum capital requirement. This allows us to compare low-capital LLCs that switch to a high-capital LLC with companies that already opted for high-capital LLC at startup. In doing so, we isolate the impact of changing legal form net of changes in access to finance that would have occurred otherwise and (unobserved) time-invariant firm characteristics. The results show that former low-capital LLCs increase their odds of obtaining outside financing once they turn into a high-capital LLC. This confirms the notion that changing to a high-capital legal form signals higher creditworthiness.

Finally, we provide further evidence that the results are driven by the legal form itself, and not merely by (changes in) the amount of paid-in capital. To do so, we exploit the reduction of paid-in capital requirements in Austria in 2014. For reasons similar to Germany, Austria modified its private corporate law by lowering the paid-in capital requirements for all newly established LLCs. Hence, unlike in Germany, the reform did not introduce a new legal form. If our results are driven by changes in paid-in capital rather than the legal form itself, we would expect a similar increase in debt financing for Austrian firms that are founded with lower minimum capital and subsequently increase paid-in capital to the old minimum capital requirements. This is not the case. In the absence of legal form as a signal of default risk, it appears that outside investors mainly rely on a firm's current level of equity and do not take into account the level of paid-in capital at startup.

Our findings have implications for nascent entrepreneurs and policy makers. We propose the legal form of the firm as one mechanism for entrepreneurs to communicate their quality to outside investors and mitigate the liability of newness. This strategy will be most useful when applying for credit at small relationship banks. Furthermore, several scholars have pointed out that countries with low regulatory requirements have attracted a substantial amount of new businesses, causing regulatory competition among countries (Becht, Mayer and Wagner, 2008; Braun et al., 2013). The pool of new businesses that opt for a legal form with low capital requirements, however, also contain a

non-negligible group of firms that would have set up a business anyway, but with a different legal form (see also Braun et al. (2013)). Our findings indicate a potential downside of this 'deregulation race': it creates a risk for some of these firms to not being able to obtain the necessary debt financing, which ultimately limits their growth potential.

The rest of the paper proceeds as follows. In Section 1.2, we build our theoretical argument. Sections 1.3 and 1.4 discuss our setting and data. Section 1.5 explains how we estimate the relation between legal form and debt financing. Sections 1.6 and 1.7 presents the results and robustness checks. Section 1.8 concludes.

1.2 Theory

Although self-financing of entrepreneurial ventures is prevalent, a majority of entrepreneurs solicits external finance as they only have limited internal funds (Berger and Udell, 2003; Fairlie and Krashinsky, 2012; Gartner, Frid and Alexander, 2012). Hence, acquiring external financing is critical to startup performance. Among the different financing sources, prior work has found that startups rely substantially more on formal debt financing than on equity financing and inside debt financing from friends and family (Cosh, Cumming and Hughes, 2009; Robb and Robinson, 2014). Furthermore, the use of external business debt at the initial year of operations has been linked to superior firm outcomes years later (Cole and Sokolyk, 2018).

Despite this need for outside investments, many startups fail to borrow sufficient capital at reasonable rates (Cosh, Cumming and Hughes, 2009; Schmalz, Sraer and Thesmar, 2017). Unlike established firms, startups lack formal or public records and a proven track record (Santos and Eisenhardt, 2009; Villanueva, Van de Ven and Sapienza, 2012), and have insufficiently established relationships with customers and suppliers (Aldrich and Auster, 1986) to show that their value propositions are viable and the capabilities of the management team. As such, entrepreneurs will have better information on the firm's expected future performance and, consequently, on its ability to repay loans (Sengupta, 1998). Collecting this information is very costly for lenders, partic-

ularly in proportion to the amounts borrowed (Ang et al., 1991). In this case, information asymmetry between entrepreneurs and prospective investors may lead to adverse selection where entrepreneurs with a high credit risk claim to be of high quality. This problem may also be aggravated when there is perfect competition among lenders, and the outcomes of costly screening activities are public information. The resulting free-riding problem lowers external investors' incentives to engage in screening efforts to discover entrepreneurs' true quality (Parker et al., 2018). Consequently, potential investors will be less inclined to provide startups with the necessary resources (Sanders and Boivie, 2004; Wiklund, Baker and Shepherd, 2010).

Signaling theory (Spence, 1973) has been widely used to understand how entrepreneurs credibly convey information about the underlying unobservable quality of their firm through observable actions and attributes to overcome these asymmetric information problems (Colombo, 2021; Connelly et al., 2011). Since the seminal work by Leland and Pyle (1977), scholars have investigated the signaling role of patenting (Conti, Thursby and Thursby, 2013; Conti, Thursby and Rothaermel, 2013), third-party affiliations (Bapna, 2019; Colombo, Meoli and Vismara, 2019; Ko and McKelvie, 2018; Plummer, Allison and Connelly, 2016; Pollock et al., 2010), choice of accounting methods (Cassar, Ittner and Cavalluzzo, 2015), eponymy (Belenzon, Chatterji and Daley, 2017), or founders' human capital (Ko and McKelvie, 2018) amongst others.

Within this literature, few papers have paid attention to the possible signaling role of the choice to incorporate a venture, and, conditional on incorporation the choice of legal form. Yet, the legal organization of a firm may act as a valuable signaling strategy for startups in the early stages of their life cycles as other signals are not available (yet). With regards to the signaling value of incorporation, an early study by Chamley (1983) argues that when there are no costs involved in incorporating a venture, the least able entrepreneurs will choose to incorporate while the able ones do not. The mechanism behind this separating equilibrium is that only the more able types believe the risk of losing their personal assets this way is sufficiently low so that they want to forego the insurance aspect of limited liability to obtain better terms for their borrowings. However, empirical evidence by Cassar (2004) and Storey (1994)

shows a positive relationship between incorporation and bank financing. This may suggest that founders' willingness to incur statutory audit costs and to make information on the business public acts as a signal of credibility and an indicator of growth potential.

1.2.1 Legal form as a signal of default risk

This paper postulates that similar to the incorporation choice, outside lenders also rely on a new venture's choice of legal form to infer its underlying risk.[5] An important distinction between different types of legal forms is the amount of paid-in capital that is required to found a company.[6] This is a crucial aspect because founders are liable for the amount of paid-in capital in case of bankruptcy. In this paper, we argue that choosing a legal form with high-capital is a credible signaling strategy for low-risk firms when 1) the legal form is observable to lenders, and 2) low-risk firms do not have an incentive to "pretend" to be a high-risk firm by choosing the low-capital form, and vice versa (i.e., incentive compatibility constraints) (Connelly et al., 2011; Kirmani and Rao, 2000; Spence, 1973).

First, the legal form can easily be inferred from the company's legal documents (cf. also Section 1.3). Second, models of the use of collateral as a signaling mechanism in credit markets with imperfect information (Besanko and Thakor, 1987*a*,*b*; Bester, 1985, 1987; Boot, Thakor and Udell, 1991; Chan and Thakor, 1987) argue that low-risk firms will select credit contracts with lower interest rates but higher collateral requirements than high-risk types. This is because low-risk types have a higher marginal rate of substitution between a loan's interest rate and size of the collateral; low-risk types are more

[5] The notion of risk can be interpreted in many different ways. For the purposes of this paper, risk refers to a firm's likelihood to pay back its loans.

[6] Many countries have a public and private limited liability legal form. Almost all countries require more paid-in capital for founding a public firm (e.g. UK, France, Germany, Spain, Italy, Sweden, Finland, Denmark, Austria, Norway, among others). For example, in the UK, one can found a (unlisted) Publicly Limited Company (PLC), which has a minimum capital requirement of 50.000 pound. A private LLC in the UK has no capital requirements. Next to capital requirements however, several other differences exist between these legal forms (e.g. minimum number of founders and financial statement disclosure requirements).

inclined to accept a higher increase in collateral for a given reduction in interest payments than high-risk types. High-risk types know they are more likely to default, thereby avoiding having to repay the loan but losing their collateral. Similarly, when the interest rate is fixed but loan size varies, high-risk ventures will be more likely to pick a low-capital legal form even though this implies they will receive smaller loans than low-risk entrepreneurs. Because the legal form, unlike the exact amount of available capital, is easily observable, lenders will likely rely on the legal form choice to infer the default risk of a firm.

Relatedly, because entrepreneurs forego alternative investment opportunities for the amount of paid-in capital invested in the firm, low- and high-risk types face differing opportunity costs of founding a high-capital firm. Since the expected returns for low-risk projects are greater due to the lower likelihood to default, ceteris paribus, it is relatively less costly for low-risk types to invest the required paid-in capital in the firm. This is similar to Leland and Pyle (1977) who argue that when entrepreneurs retain a significant ownership share in their firm this signals high expected future cash flows due to the opportunity cost of equity ownership.

While these arguments revolve around individual preferences and opportunity costs, there may also be a collective component involved. In particular, when their individual default risk is imperfectly observed, entrepreneurs choosing a high-capital legal form may benefit from a positive collective reputation of high-capital firms (Levin et al., 2009; Negro, Hannan and Fassiotto, 2015; Tirole, 1996). In turn, this induces them to be more committed to a successful outcome because the reputational cost of defaulting for this group is high, which may lead to a stigma of failure (Landier, 2005). On the contrary, entrepreneurs choosing a low-capital form may inherit a bad reputation, which reduces their incentive to avoid default, because investors believe failure within this group is common and not very informative. In this sense, entrepreneurs in the low-capital group are stuck in a 'bad reputation trap' due to the self-fulfilling nature of expectations (Coate and Loury, 1993). From this perspective, there is another reason for why choosing a high-capital legal form is more costly for high-risk entrepreneurs: when lenders respond more negatively when a high-capital firm defaults (by not offering entrepreneurs a loan

in the future when they would found a new venture, for example), high-risk types have a higher likelihood to incur this reputational cost.

Combined, these characteristics suggest the existence of a separating equilibrium, in which default risk is negatively related to the likelihood of choosing a high-capital legal form, rather than a pooling equilibrium in which outside investors would not be able to distinguish between entrepreneurial firm types.

1.2.2 The role of lender type

So far, we have argued that we expect high-capital startups to be more likely to obtain outside debt financing due to the signaling value of legal form. However, our baseline hypothesis can be more pronounced depending on the type of lender. The heterogeneity in lender types and their relationship to firm outcomes has received considerable attention in the finance literature. In particular, the conventional view is that relationship lending is the obvious - if not the only - way to cope with the informational opacity surrounding new ventures in contrast to transactional lending. Relationship lending can mitigate opacity issues because it relies mainly on "soft" information acquired by lenders through continuous, personalized, direct contacts with startups, their founders, and the local community in which they operate (Berger and Udell, 2006). Much of the early literature therefore suggested that small banks are more capable of serving young, small firms because of the difficulties associated with quantifying and transmitting soft information through the communication channels and hierarchy of large organizations (Berger et al., 2005; Berger and Udell, 2002; Cole, Goldberg and White, 2004; Stein, 2002).

More recently, however, a number of studies have challenged the conventional wisdom and indicate that due to technological advances and deregulation large, multimarket, and nonlocal banks have a comparative advantage in serving small, young firms using hard-information lending technologies (Berger, Goulding and Rice, 2014; Berger and Black, 2011; Berger and Udell, 2006; De la Torre, Pería and Schmukler, 2010). In particular, some of the technologies applied to lending to small, young ventures benefit from economies of scale and scope. For example, the effectiveness of credit scoring models that

rely on statistical properties to assess risk goes up with the number of clients and loans (De la Torre, Pería and Schmukler, 2010). Similarly, Hughes et al. (2019) provide evidence that large banks are more efficient at credit evaluation and monitoring than their small counterparts. In fact, they find that larger banks experience lower rates of loan default even though they lend to riskier firms. Consistent with these predictions, Jagtiani, Lemieux et al. (2016) find that small banks accounted for only 43 percent of small business loans in 2015 in the US, compared to 77 percent in 1997.

Another reason for why small banks that rely on relationship lending are at a disadvantage when it comes to risk assessment of startups is that the signaling value of soft information is likely to be low. This is because a valuable signal needs to be verifiable by outsiders (Aghion and Tirole, 1997; Baker, Gibbons and Murphy, 2002; Hart, 1995). For a signal to be verifiable, the interpretation of the signal by the sender and the receiver must be the same. This is a characteristic of hard information. By contrast, soft information is private and not verifiable as it involves a personal assessment and depends upon its context, neither of which can be easily captured and communicated. Hence, it is likely that the information acquired by small banks is of a more noisy nature than the hard information collected by large banks.

Taking all arguments together, we expect that large lenders that use transactional lending technologies are better able to assess the default risk of startups based on hard information. This implies that we expect large lenders to rely less on a firm's legal form as a signal of default risk since they have other reliable instruments at hand to reduce the frictions stemming from information asymmetries between entrepreneurs and prospective investors. In other words, we expect that small lenders are less likely to provide loans to low-capital firms than large lenders.

1.3 Legal Background

To test whether the legal form choice can serve as a screening device for credit providers, we make use of a law change that occurred in Germany. The

German MoMiG[7] reform in 2008 introduced the "Unternehmergesellschaft (haftungsbeschränkt)" (UG) as a second option of a LLC besides the already existing "Gesellschaft mit beschränkter Haftung" (GmbH). The new legal form, UG, is often called in Germany "the low-capital LLC" or "mini-LLC". Throughout the paper, we will label firms that operate under the legal form GmbH as "high-capital LLCs", and firms that operate under the new legal form UG as "low-capital LLCs".

The main reason for the reform was increasing pressure due to the liberalization of regulation in terms of the country of incorporation within the EU. Several landmark rulings by the European Court of Justice (ECJ) between 1999 and 2003 justified the incorporation principle by which firms incorporated in one EU Member State are free to do business in any other Member State.[8] Historically, most EU Member States, such as Germany, Austria and France, followed the real-seat principle by which firms had to incorporate where they operate (Gerner-Beuerle et al., 2018). Following the European liberalization, firms took advantage of legal arbitrage opportunities by increasingly incorporating in the UK due to lower minimum capital requirements and setup costs for limited liability firms (Becht, Mayer and Wagner, 2008). However, since countries aim to control the corporate law on firms operating in their jurisdiction this caused a defensive regulatory competition in European corporate law in response to the liberalization (Gelter, 2019).

Germany also reacted on the European liberalization, and implemented the MoMiG reform in 2008. The reform aims to mitigate the flow of incorporations to other Member States by offering a new limited liability firm with lower incorporation costs. The MoMiG reform has been perceived as a great success. It is believed that it has been able to largely stop the practice of German entrepreneurs establishing a business under UK law (Mock, 2016). Moreover, the popular press documents that the reform has led to a sharp increase in en-

[7] Gesetz zur Modernisierung des GmbH-Rechts und zur Bekämpfung von Missbräuchen (MoMiG), 23 October 2008, BGBl I.

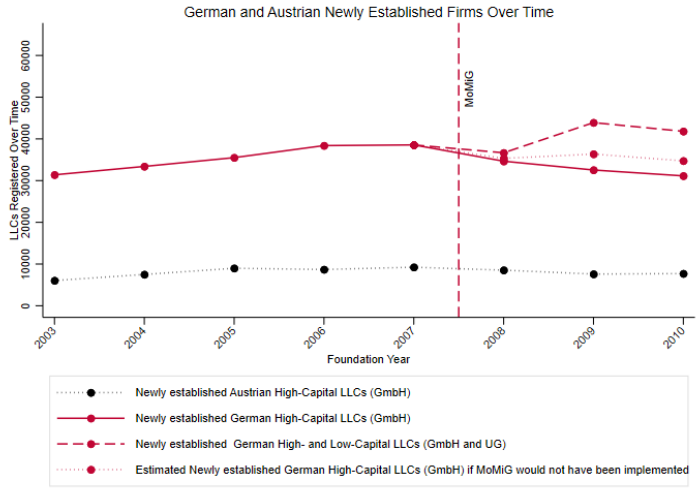
[8] Centros Ltd v. Erhvervs-og Selskabsstyrelsen, Case C-212/97 [1999] ECR I-1459; Überseering BV v. Nordic Construction Company Baumanagement GmbH, Case C-208/00 [2002] ECR I-9919; Kamer van Koophandel en Fabrieken voor Amsterdam v. Inspire Art Ltd., Case C-167/01 [2003] ECR I-10155.

trepreneurial activity within Germany (Anger, 2018; Mathez, 2013). Roughly 5 years after the reform, 10 percent of all LLCs were operating as a low-capital LLC (Mock, 2016). Research from Braun et al. (2013) also suggests that the reform led to a net-increase in entrepreneurship, however, they also find that there was a decrease of 3 percent in regular (high-capital) LLC firms shortly after the reform.

We use historical records of the Orbis database to confirm this finding. Figure 1.1 and the corresponding statistics in Table A2 in the Appendix show that after the MoMiG reform, there are over 15 percent more LLCs established within Germany on a yearly basis between 2003 and 2010. When focusing solely on high-capital LLCs, however, we find that there is a decrease of 7.54 percent. Comparing this to data from neighboring country Austria (which did not implement a change in paid-in capital during this period), we can estimate how many high-capital LLCs in Germany would have been established if the reform would not have taken place. Our results show a very similar trend in terms of number of established firms between Germany and Austria before 2008. However, we do not observe the same decrease in high-capital LLCs in Austria after the MoMiG reform. Using this data, we are able to estimate the number of LLCs that would be established if MoMiG would not have been implemented. The results suggest that there is a substitution effect of 33.69 percent.[9] In other words, roughly one out of three low-capital LLCs would have been established anyway, but under a high-capital LLC legal form. Overall, these findings confirm prior observations that the reform seems to have led to an overall increase in entrepreneurship, but there appears to be also a substantial substitution effect from high- to low-capital LLCs.

[9]The substitution effect is calculated as follows: $33.69\% = (-7,54\% + 1,84\%)/(15,08\% + 1,84\%)$. Note that this percentage only reflects the substitution that would occur between high and a low-capital LLC. The increase in newly established LLCs of 15.08 percent in Germany might also be driven by a substitution effect due to a lower likelihood to choose for other legal forms such as an unlimited liability company (ULC). The Orbis database, however, only includes data of firms that are required to make their financial statements publicly available, and therefore does not include any data about ULCs.

Figure 1.1



This graph shows the number of newly established LLCs for Germany and Austria. The dotted black line shows the annual number of Austrian LLCs. The solid red line shows the annual number of German high-capital LLCs. The dashed red line shows the annual number of German high- and low-capital LLCs. The dotted red line shows the estimated annual number of German LLCs if MoMiG (low-capital LLCs) would not have been implemented.

There are several differences between high-capital LLCs (i.e. GmbH) and the newly introduced low-capital LLC (i.e. UG) that make them a suitable empirical setting to test our theoretical predictions. First, setting up a low-capital LLC only requires 1 euro of paid-in capital instead of the regular 25,000 euro. Hence, the introduction of the low-capital legal form lowered potential financial barriers for setting up a company with limited liability. In addition, low-capital LLCs are required to transfer one quarter of the annual surplus to the retained earnings. Those accumulated reserves can only be used to increase paid-in capital or balance net losses of the current year and the previous year. To avoid the mandatory accumulation of retained earnings, low-capital LLCs must increase paid-in capital to 25,000 euro, which allows them to then automatically change their legal form to a high-capital LLC. Although low-capital LLCs are not legally required to change their legal form, the limited

use of their profits is a strong incentive to change the legal form to GmbH once retained earnings exceed the capital requirements for GmbHs. Moreover, both legal forms have the same legal foundation, which make the switch in legal form simple and does not require costly administrative work, as would be the case with other legal form conversions. This is also confirmed in our dataset, where we find that approximately 99 percent of low-capital LLCs switched legal forms, once they were allowed to do so.

Importantly, the company is required to include the suffix "UG" instead of "GmbH" at the end of the company's name. This requirement makes it relatively easy for outsiders to differentiate between the two types of legal forms because companies are required to mention the full name on their corporate website, as well as on all contracts they sign. This also implies outside credit providers can infer a firm's level of paid-in capital simply by looking at its name. This is a necessary condition for legal form to be an effective signal (cf., Section 1.2). Other regulations, such as taxation, are the same for both legal forms.

1.4 Data and Descriptive Statistics

We use two distinct samples. Our first sample is based on historical records of the Orbis database provided by Bureau van Dijk (BvD).[10] The database contains financial statement information for full population of German limited-liability companies. We use this database to identify low and high-capital LLCs, and construct a range of external financing measures and firm-level control variables using financial statement data. Our second sample is extracted out of the IAB/ZEW Start-up Panel, a firm-level database accessible at the research center of ZEW (IAB and ZEW, 2022). The Start-up Panel contains detailed survey data about a representative set of start-ups operating in Germany. The survey data provides us with more detail information about firms' financing frictions, as well as a wide variety of information about the founders and their firms.

[10] Orbis historical database version February 2019.

We start our data gathering process by downloading all relevant information from the Orbis database. We gather historical names and financial information for German limited liability firms that were founded after 2008 (i.e. the first year where firms could choose to establish a low-capital LLC). The historical names of firms, which contain the required legal form suffix, allow us to identify firms' legal forms over time.[11] We manually cleaned the firms' names and historical legal forms, which allow us to identify if a company was founded as a low-capital LLC or a high-capital LLC.[12]

In the Orbis database, we observe a few high-capital LLCs that are much larger than low-capital LLCs. Prior literature shows that smaller firms are more financially constrained (Hadlock and Pierce, 2010), and firm size affects growth (Czarnitzki and Delanote, 2013). Thus, we restrict the sample to small startup firms to make the group of low-capital and high-capital LLCs more comparable.[13] Furthermore, we trim all continuous financial variables at the 1 percent level on each side of the distribution to eliminate possible outliers. Last, we retrieve data from Orbis-IP, which provides information on patent applications of firms in the Orbis database, and use the information on filed

[11] Specifically, we parse all firm names for common variations and abbreviations of legal form suffixes. Additionally, we validate the obtained legal forms with balance sheet information listing firms' paid-in capital. As mentioned in section 1.3, low- and high-capital LLCs (i.e. firms with the legal form UG and GmbH, respectively) have different capital requirements. Low-capital LLCs have less than 25,000 euro capital whereas high-capital LLCs must have equal or more than 25,000 euro capital. For cases in which paid-in capital does not correspond with the legal form that we observe in the historical firm names, we manually looked up their legal form mentioned in publicly available financial statements on the official section of the German Federal Gazette (see https://www.bundesanzeiger.de/), and adjust the name and legal form accordingly in the database. The procedure implies that we also exclude firms with missing, zero or negative capital.

[12] In addition, we are able to identify the year when a firm switches from a low-capital LLC to a high-capital LLC and surpasses the 25.000 capital requirement threshold. We can thereby identify three different groups: (1) firms that switch from a low-capital to a high-capital LLC; (2) firms that always operate under the low-capital LLC legal form; (3) and firms that are always incorporated as a high-capital LLC. Data about firms that switch legal form will be used in a difference-in-differences specification in section 1.7.3

[13] We use the German Accounting Directive Implementation Act (BilRUG) definition of small firms and only include firms with 50 or less employees and/or 4,840,000 euro total assets and/or 9,680,000 euro in sales to our sample. Less than 1 percent of low-capital LLCs are dropped when imposing these restrictions.

patents to calculate firms annual patent stock.[14] Table A3 in the Appendix displays the changes in sample size when applying the above restrictions.

Table 1.1 shows the summary statistics for low and high-capital LLCs. In our main sample, we observe 136,636 high-capital LLCs and 33,844 low-capital LLCs that were incorporated between 2008 and 2017. Data from the Orbis database already reveal a couple of notable differences between low and high-capital LLCs. First, there appear to be relatively small differences in access to debt; 63 (54) percent of high-capital LLC firm-year observations have long-term (short-term) debt compared to 58 (52) percent for low-capital LLCs. However, there are substantial differences in the level of debt that they receive. On average, high-capital LLCs report to have long-term debt of 244,444 euro compared to only 43,296 euro for low-capital LLCs. Thus, most of the differences in debt between the groups are on the intensive rather than the extensive margin. The descriptive statistics also reveals that the observed differences in debt levels are correlated with differences in terms of capital, accumulated profit, size, age and patents, and indicate the need to control for these characteristics in the regressions.

[14] We account for annual depreciation rate of 15 percent as common in the literature (see e.g. Cuneo and Mairesse (1983)).

Table 1.1: Descriptive Statistics: Full Sample

	High-Capital LLC		Low-Capital LLC	
	N: 478,167		N: 81,421	
	Mean	Std. Dev.	Mean	Std. Dev.
$Low-Capital\,LLC$	0	0	1	0
$Total\,Debt_{(\times 1000)}$	281.310	443.038	46.342	125.899
$Log(Total\,Debt)$	10.990	2.350	9.313	1.931
$Access\,to\,Long-Term\,Debt$	0.627	0.484	0.584	0.493
$Long-Term\,Debt_{(\times 1000)}$	244.444	394.605	43.296	123.584
$Log(Long-Term\,Debt)$	10.872	2.358	9.027	2.124
$Access\,to\,Short-Term\,Debt$	0.542	0.498	0.523	0.499
$Short-Term\,Debt_{(\times 1000)}$	100.866	241.136	17.530	67.807
$Log(Short-Term\,Debt)$	10.552	2.373	8.827	2.056
$Capital_{(\times 1000)}$	28.759	24.114	1.436	2.239
$Accumulated\,Profit/Loss_{(\times 1000)}$	58.057	194.042	7.091	53.785
$Total\,Assets_{(\times 1000)}$	395.406	486.754	61.070	170.564
$Size$	8.805	3.717	7.228	3.225
Age	2.449	1.842	1.796	1.404
$Tangible\,Assets$	0.176	0.219	0.210	0.236
$Patent\,tock$	0.030	0.492	0.007	0.163

This table presents descriptive statistics for the full sample of low- and high-capital LLCs, which is retrieved from the Orbis Historical Database. Corresponding variable definitions can be found in Table A1 in the Appendix. All monetary values are in euro.

In our second sample, we focus on data from the IAB/ZEW Startup Panel. The subsample includes 2,272 high-capital LLCs and 355 low-capital LLCs. In comparison to the Orbis sample, the ZEW startup sample has relatively few observations. However, the main advantage is that we have much more detailed information about our target population, such as information about founders' prior work experience, education, and gender, as well as more detailed information about firms' characteristics and their external financing constraints.

Table 1.2 shows the summary statistics for this subsample of firms that filled in the survey and which we could match to the Orbis database. The composition of firms is highly comparable to our Orbis sample. If anything, firms seem to be, on average, slightly larger in our subsample compared to the Orbis sample (Table 1.1). More important, the survey information provides interesting insights into additional differences between both groups: 23 percent of low-capital LLCs state that they are financially constrained compared to only 18 percent of high-capital LLCs. In addition, high-capital LLCs are 12 percent more likely to indicate that they are not in need of external

financing. This suggests that banks seem to be less willing to provide high levels of debt to low-capital LLCs, although low-capital LLCs have a higher demand for external funding. The data in the Startup Panel further reveal that high-capital LLCs have on average more investments, R&D expenses, and are more likely to export. In addition, the founders of a low-capital LLC have less likely set up a business prior to this venture, are less educated, and were more likely unemployed before they started the business. Hence, a firm's legal form choice seems to be correlated with several founder and firm characteristics. Our survey data allows us to control for these potentially confounding factors in subsequent analysis.

Table 1.2: Descriptive Statistics: Survey Sample

	High-Capital LLC		Low-Capital LLC	
	N: 8,510		N: 896	
	Mean	Std. Dev.	Mean	Std. Dev.
Low – Capital LLC	0	0	1	0
$Total\,Debt_{(\times 1000)}$	394.590	653.246	43.061	71.399
Log(Total Debt)	11.941	1.582	9.675	1.717
Access to Long – Term Debt	0.745	0.436	0.614	0.487
$Long-Term\,Debt_{(\times 1000)}$	286.718	555.439	30.362	55.815
Log(Long – Term Debt)	11.429	1.778	9.021	2.096
Access to Short – Term Debt	0.607	0.488	0.555	0.497
$Short-Term\,Debt_{(\times 1000)}$	136.565	359.703	18.144	47.542
Log(Short – Term Debt)	11.108	1.831	9.242	1.859
Access to Bank Loans	0.316	0.465	0.116	0.322
%Inv. Financed by Ext. Funds	0.348	0.421	0.283	0.395
Financing Constraints	0.184	0.388	0.230	0.421
Bank Financing Constraints	0.151	0.358	0.181	0.386
No Funds Needed	0.488	0.500	0.428	0.495
$Capital_{(\times 1000)}$	36.324	72.476	1.818	2.725
$Accumulated\,Profit/Loss_{(\times 1000)}$	77.364	400.502	7.674	38.477
$Total\,Assets_{(\times 1000)}$	508.206	688.939	52.485	87.324
Size	9.864	2.514	7.811	2.492
Age	2.613	1.937	1.767	1.375
Tangible Assets	0.195	0.211	0.197	0.222
Patent Stock	0.152	0.883	0.017	0.205
$Investments_{(\times 1000)}$	64.035	190.718	15.654	89.976
$R\&D Expenses_{(\times 1000)}$	46.634	153.452	9.513	51.429
$Export_{(\times 1000)}$	140.011	459.603	6.253	35.982
Employees at Start – Up	0.502	0.500	0.338	0.474
Founders	1.816	0.966	1.423	0.728
Family Members	0.081	0.360	0.050	0.253
Gender	0.165	0.371	0.179	0.384
Previous Enterprise	0.516	0.500	0.546	0.498
Prior Experience	17.523	9.914	14.335	10.915
Motive : Self – Employment	0.393	0.488	0.311	0.463
Motive : Business Idea	0.465	0.499	0.482	0.500
Motive : No Emp. Opp.	0.083	0.276	0.082	0.275
Motive : Unemployment	0.028	0.166	0.051	0.221
Motive : Better Earnings	0.031	0.172	0.074	0.261
Prior : Self – Employed	0.421	0.494	0.431	0.496
Prior : Employed (Private)	0.583	0.493	0.404	0.491
Prior : Employed (Public)	0.056	0.231	0.084	0.277
Prior : Unemployed	0.063	0.242	0.082	0.275
Prior : Inactive	0.052	0.221	0.124	0.330
Edu : No Degree/HighSchool	0.453	0.498	0.473	0.500
Edu : Bachelor	0.205	0.404	0.239	0.427
Edu : University	0.342	0.475	0.287	0.453

This table presents descriptive statistics for the survey sample of low- and high-capital LLCs, which is retrieved from the IAB/ZEW Start-up Panel. Corresponding variable definitions can be found in Table A1 in the Appendix. All monetary values are in euro.

1.5 Relationship between Legal Form and Debt Financing

The discussion in Section 1.2 argues that firms that choose a legal form that requires less paid-in capital will be perceived to be of lower quality by credit providers. In turn, low-capital LLCs are less likely to obtain the necessary external investments compared to high-capital LLCs, conditional on their level of creditworthiness (i.e. keeping paid-in capital among other characteristics constant, low-capital LLCs will be perceived to have a higher credit risk). To empirically examine this, we estimate the following model using OLS:

$$y_{it} = \beta_1 Low - Capital\,LLC_i + \beta_2 X_{it} + \delta_t + \eta_s + \varepsilon_{it} \tag{1.1}$$

where y_{it} is one of the following variables that measure firms' financing frictions: our first measure is a firm's total amount of outstanding debt. This variable captures the total amount of short- and long-term debt that a firm need to pay back to creditors (i.e., bank- and trade credit). Second, we split total debt into a firm's long- and short-term debt: $Access\,to\,Long-Term\,Debt$ is a dummy variable equal to one if a firm has debt outstanding in year that is due after at least one year, and zero otherwise. $Access\,to\,Short-Term\,Debt$ is a dummy variable equal to one if a firm has debt outstanding that is due within one year. $Log(Long-Term\,Debt)$ and $Log(Short-Term\,Debt)$ is the log of a firm's long-term and short-term debt, conditional on having such type of debt. These variables allows us to assess if the differences are driven by the extensive or intensive margin of debt.[15]

Third, we make use of a set of financing constraints variables that are available in the IAB/ZEW Startup Panel. This set of variables allow us to examine if differences in debt between low- and high-capital LLCs are driven by differences in the supply of debt (e.g., firms are unable to obtain the necessary

[15] For the subsample of firms where we have additional survey data from the IAB/ZEW Start-up Panel, we also measure y_{it} as a dummy variable equal to 1 if a firm received a loan from a bank in year t, 0 otherwise, and alternatively by the percentage of investments financed by externed financing. Results are presented in Table A8 in the Appendix

external debt to finance their investments opportunities), or alternatively by differences in the demand for external debt (e.g. firms do not need debt because of lower growth opportunities). Our first financing constraint measure is a dummy variable equal to one if the firm states that it experiences external financing constraints (*"Financing Constraints"*). Our second measure is a dummy variable equal to one if the firm is not able to acquire the necessary external funds from banks to finance their investment opportunities (*"Bank Financing Constraints"*). A third measure is a dummy variable equal to one if a firm is not externally financially constrained because they do not need external financing (*"No Funds Needed"*).

Our main variable of interest is $Low-Capital\,LLC_i$, a dummy variable equal to one if a firm is operating under a legal form with low-capital requirements (i.e., UG), and zero if it is operating under a legal form with high-capital requirements (i.e., GmbH). Hence, the parameter of interest β_1 measures the difference in debt and financing constraints between low-capital and high-capital LLCs. Importantly, we also include X_{it}, which is a vector of time varying firm-level characteristics that influence both a firm's legal form and its access to external funding. Specifically, we control for firms' total amount of capital and retained earnings, thereby controlling for the difference in equity between firms. We also control for tangible assets over total assets, as a proxy for collateral which may influence firms' credit status (Almeida and Campello, 2007). Furthermore, we control for differences in firm size, measured as the log of tangible fixed assets plus one, because smaller firms are more likely to be financially constrained and might have different growth opportunities (Hadlock and Pierce, 2010). We include firms depreciated patent stock to account for its inventive activity and demand for external funds (Hottenrott, Hall and Czarnitzki, 2016). We also control for differences in firm' age due to the dynamic nature of the demand for financing over a firm's lifecycle. Lastly, we include in all analyses δ_t, which is a time fixed effect capturing macro-economic changes. η_s are industry fixed effects capturing time-invariant differences across industries.

For the subsample of firms that are available in the IAB/ZEW start-up dataset, we can control for a variety of additional firm-level and founder char-

acteristics. Specifically, we control for (1) the log of total investments, (2) the log of R&D expenses, (3) the log of total earnings from export, (4) the number of employees at start-up, (5) the number of founders, (6) the number of family members in the founding team, (7) an indicator variable if one of the founders is female, (8) an indicator variable if one of the founders has set up a company prior to this business, (9) the number of years that the founder has experience in the sector, (10) a set of dummy variables indicating the main reasons to setup the new business (e.g., better earnings opportunity, new business idea, otherwise unemployed, among others), (11) a set of indicator variables indicating the prior employment of the founders (self-employed, employed in public or private sector, unemployed, inactive), and lastly, (12) a set of indicator variables indicating the highest education degree of the founders (university, bachelor, high school, no degree). Hence, it allows us to better control for differences that might exist between firms that opted for either a low- or high-capital LLC. Table A1 in the Appendix presents a detailed description of all variables included in our models.

1.6 Results

1.6.1 Pooled OLS

Table 1.3 shows the results for the OLS analysis of the relation between legal form and debt using the full sample. Column 1 shows that low-capital LLCs have less total debt. Including financial control variables into the regression (Column 2) reduces the size of the coefficient, but it remains statistically and economically significant: low-capital LLCs have on average 52 percent[16] less debt compared to high-capital LLCs. Looking at long-term and short-term debt, there seems to be only an economically significant difference on the intensive margin: low-capital LLCs are on average 2 percent less likely to obtain long-term debt (Column 4), but have 55 percent less debt, conditional on obtaining long-term debt. This suggests that low-capital LLCs are as likely to have access to long-term debt as high-capital LLCs, but receive smaller

[16] $100 \times \left(e^{-0.743} - 1\right)$

amounts. We observe a similar picture for short-term debt (Columns 7-10).

Table 1.3: OLS: Full Sample

	Log(Total Debt)		Access to Long-Term Debt		Log(Long-Term Debt)		Access to Short-Term Debt		Log(Short-Term Debt)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low – Capital LLC	-1.621***	-0.743***	-0.034***	-0.022***	-1.671***	-0.800***	-0.035***	-0.009**	-1.618***	-0.723***
	(0.012)	(0.012)	(0.003)	(0.004)	(0.016)	(0.017)	(0.003)	(0.004)	(0.016)	(0.017)
Capital		0.006***		0.000		0.006***		-0.000***		0.005***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Accumulated Profit/Loss		0.000***		-0.000***		-0.000		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Size		0.336***		0.020***		0.276***		0.017***		0.324***
		(0.002)		(0.000)		(0.003)		(0.000)		(0.003)
Age		0.126***		0.037***		0.043***		-0.013***		0.136***
		(0.008)		(0.002)		(0.011)		(0.003)		(0.012)
Tangible Assets		-1.865***		0.213***		-0.774***		-0.101***		-2.590***
		(0.020)		(0.006)		(0.027)		(0.006)		(0.028)
Patent Stock		0.034		0.007***		0.042		0.005		0.017
		(0.023)		(0.002)		(0.031)		(0.003)		(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	534,355	384,661	530,102	381,936	328,956	257,662	553,561	388,746	298,377	227,375
R-squared	0.320	0.487	0.059	0.086	0.225	0.296	0.030	0.035	0.241	0.342

This table presents estimates from regressions of debt and financing constraint measures on legal form choice for the full sample, which is retrieved from the Orbis Historical Database. Variable definitions are presented in Table A1 in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

As pointed out earlier, these findings might reflect differences in the demand for debt rather than differences in access to debt. To disentangle the demand and supply of credit, we make use of the survey sample where we have more detailed data about firms' financing constraints. In addition, it allows us to adjust for a wide variety of additional potentially confounding variables.

First, we verify the representativeness of the survey sample by using the same outcome variables as used in Table 1.3. We find very similar results compared to when we use the full sample (Table A5 in the Appendix). In a next step, we add the additional firm and founder control variables. Results are presented in Table 1.4.[17] We find that the coefficient on our variable of interest, Low-Capital LLC, only reduces slightly from -0.743 to -0.664 (i.e., a 45 percent difference in debt instead of 52 percent). The inclusion of these additional controls further strengthens our belief that the findings are not driven by differences between low- and high-capital LLCs apart from their legal form. We further validate our results in Table 1.4 by using alternative proxies for (access to) debt that are available in the survey data. Results in Table A8 in the Appendix confirm that low-capital LLCs have 8 percent lower likelihood to have bank loans, and use 9 percent less external funds to finance their investments.

[17] Tables A6 and A7 in the Appendix present results that include the coefficients and standard errors for the additional control variables.

Table 1.4: OLS: Survey Sample

	Log(Total Debt)	Access to Long-Term Debt	Log(Long-Term Debt)	Access to Short-Term Debt
	(1)	(2)	(3)	(4)
Low – Capital LLC	-0.664***	-0.022	-0.956***	-0.062
	(0.098)	(0.039)	(0.183)	(0.043)
Capital	0.002***	-0.000	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Accumulated Profit/Loss	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.354***	0.026***	0.324***	0.018***
	(0.025)	(0.005)	(0.038)	(0.006)
Age	0.068	0.028	0.026	-0.045*
	(0.061)	(0.021)	(0.098)	(0.025)
Tangible Assets	-1.799***	0.163***	-0.672***	-0.160***
	(0.169)	(0.047)	(0.248)	(0.062)
Patent Stock	0.117**	0.002	0.213***	-0.000
	(0.046)	(0.011)	(0.075)	(0.013)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,584	3,561	2,672	3,583
R-squared	0.536	0.116	0.347	0.053
	Log(Short-Term Debt)	Financing Constraints	Bank Financing Constraints	No Funds Needed
	(5)	(6)	(7)	(8)
Low – Capital LLC	-0.407***	0.054*	0.058*	-0.041
	(0.143)	(0.032)	(0.030)	(0.029)
Capital	0.002***	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	-0.000***	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.351***	-0.001	0.003	-0.003
	(0.033)	(0.004)	(0.004)	(0.004)
Age	-0.018	-0.086***	-0.083***	0.081***
	(0.097)	(0.018)	(0.017)	(0.019)
Tangible Assets	-2.773***	0.089*	0.050	-0.126***
	(0.248)	(0.047)	(0.045)	(0.047)
Patent Stock	0.018	0.005	-0.013	-0.034**
	(0.068)	(0.011)	(0.008)	(0.014)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,209	3,575	3,575	3,575
R-squared	0.371	0.094	0.083	0.436

This table presents estimates from regressions of debt and financing constraint measures on legal form choice for the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Tables A6 and A7 in the Appendix present results that include the coefficients and standard errors for the additional control variables. Variable definitions are presented in Table A1 in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Turning to the question whether our findings can be explained by low-capital LLCs demanding less debt, the results in Column 6 in Table 1.4 reveal that low-capital LLCs are more likely to indicate that they are financially constrained. Similarly, we find that low-capital LLCs are more likely to report that they face difficulties obtaining financing from banks (Column 7). Moreover, we do not find that there is a significant difference in firms' need for external financing. If anything, the negative coefficient in Column 8 indicates that low-capital LLCs are less likely to report that they are not financially constrained because they are not in need of external financing. Taken together, we do not find any evidence of lower demand for debt among low-capital LLCs. On the

contrary, they are more likely than their high-capital counterparts to indicate that they are financially constrained.

1.6.2 Heterogeneity Analysis

Having found that low-capital LLCs obtain less debt, we next investigate if certain types of credit providers are more likely to use a firm's legal form as a signal of its default risk. In particular, we expect large credit providers to rely less on a firm's legal form as a signal of default risk (cf., Section 1.2).

To test this prediction, we estimate the same OLS regression as in equation 1, but add the interaction term $Low-Capital\,LLC_i \times Share\,Relationship\,Banks_r$. $Share\,Relationship\,Banks_r$ is a dummy variable equal to 1 if the weighted share of small relationship banks for a NUTS-2 region r is higher than or equal to 75 percent (i.e. when relationship banks dominate a specific region).[18] Since most firms' main bank is located close to their headquarters, our measure should be highly correlated with the likelihood that firms are contracting with small relationship lenders. Hence, we expect the interaction term to be negative indicating that low-capital LLCs obtain less debt in NUTS-2 regions where firms are more likely to have a contract with a relationship bank.

Results are shown in Table 1.5. Given our prior findings, we focus on the intensive margin. As hypothesized, the results in Columns 1 - 3 show that low-capital LLCs in regions with a high share of small relationship banks receive less debt than their counterparts in areas with fewer relationship banks. The effect is most pronounced for long-term debt, which is in line with the notion that short-term debt mainly covers trade credit in our dataset, while long-term debt mainly captures debt from banks. Columns 2 and 3 in Table A9 in the Appendix present the results for financing constraints. Low-capital LLCs in NUTS-2 regions with a high share of relationship banks are more likely to be

[18] We obtained information on all banks in Germany from Orbis for the sample period. The information covers NUTS-2 regions for all branches and average amount of total assets within the sample period. We classify "Savings bank" ("Sparekasse") as relationship banks and calculate the weighted share of relationship banks for each NUTS-2 region. The share of relationship banks is weighted by the average amount of total assets. In our analyses we also control for $Share\,Relationship\,Banks_r$ by including NUTS-2 region fixed effects.

financially constrained. In addition, we find that they are less likely to state that they are not in need of external funds (Column 4 in Table A9). Overall, our results are in line with our hypothesis that relationship lenders are more likely to use the choice of legal form as a signal in their credit decision.

Table 1.5: OLS Full Sample: Relationship vs. Transactional Banks

	Log(Total Debt)	Log(Long-Term Debt)	Log(Short-Term Debt)
	(1)	(2)	(3)
Low – Capital LLC × Share Rel. Banks	-0.052**	-0.113***	-0.026
	(0.024)	(0.035)	(0.033)
Low – Capital LLC	-0.728***	-0.768***	-0.713***
	(0.014)	(0.020)	(0.019)
Capital	0.006***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Size	0.335***	0.274***	0.324***
	(0.002)	(0.003)	(0.003)
Age	0.121***	0.042***	0.132***
	(0.008)	(0.012)	(0.012)
Tangible Assets	-1.843***	-0.749***	-2.580***
	(0.020)	(0.028)	(0.029)
Patent Stock	0.029	0.038	0.013
	(0.022)	(0.030)	(0.014)
Additional Firm Controls	No	No	No
Founder Controls	No	No	No
Relationship Bank Regions FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	364,960	244,682	215,539
R-squared	0.490	0.298	0.344

This table presents estimates from regressions of debt and financing constraint measures on legal form choice. Variable definitions are presented in Table A1 in the Appendix. We use data from the full sample, which is retrieved from the Orbis Historical Database. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

As an alternative test, we investigate whether the effects are more pronounced for firms that depend on trade credit. Similar to relationship banks, trade credit providers are arguably more likely to rely on soft signals, and typically do not have the time and resources to perform an extensive check of firms' financial statements and business plans (Berger and Udell, 2006). Indeed, the results shown in Table A10 in the Appendix document that low-capital LLCs especially have less debt, and especially short-term debt, when they operate in an industry that more heavily depends on trade credit.

1.7 Robustness tests

The approach outlined above will measure the average relationship between legal form and debt financing after partialling out the influence of a number of observable covariates. Because a founder's choice of legal form is not a random decision, a concern might be that there are still unobserved factors affecting both the choice of legal form and firms' level of debt. To mitigate such concerns, we provide a battery of robustness tests, including an instrumental variable estimation, regression discontinuity design and a difference-in-differences analysis.

1.7.1 Instrumental variable regression

To further minimize concerns of endogeneity, as a first step we instrument firms' legal form choice by the nationality of the founder which is known for the firms in the IAB/ZEW Startup Panel.

We believe that this is a valid instrument because Becht, Mayer and Wagner (2008) show that reducing minimum capital requirements to set up a business attracts foreign entrepreneurs from countries where minimum capital requirements are higher. During our sample time period, capital requirements for LLCs in many neighboring countries (e.g. in the Netherlands, Switzerland and Austria) are higher than the minimum capital requirements for German low-capital LLCs. It is also in line with what we observe in the data available in our sample. We observe that over 10 percent of all low-capital LLCs are founded by foreigners, while foreigners represent only 4 percent of the share of high-capital LLCs. In addition, a large proportion of foreigners that started a LLC in Germany are from neighboring countries.[19] Furthermore, we also find that foreign LLCs attract a similar amount of total debt compared to non-foreign LLCs, which provides us with some empirical support for the exclusion restriction assumption (Table A11 in the Appendix).

In our IV estimation, we first predict the choice of a Low-Capital LLC by a

[19] We observe that the founders of foreign LLCs are mainly Austrian (8.38%), British (4.67%), Dutch (8.38%), Italian (7.66%), Polish (6.71%), Swiss (4.91%), and Turkish (12.34%) citizens.

dummy set to one if the founder has a foreign nationality:

$$Low - Capital\,LLC_i = \beta_1 foreign\,ownership_i + \beta_2 X_{it} + \delta_t + \eta_s + \varepsilon_{it} \qquad (1.2)$$

The second stage is identical to equation (1) but $Low - Capital\,LLC_i$ will be the predicted $Low - \widehat{Capital\,LLC_i}$ from the first-stage regression.

Table 1.6 presents the results. Columns 1 and 3 show the first stage results without and with controls. In line with our assumption, foreign ownership is highly significant and predicts the choice of low-capital LLCs. Column 2 and 4 show the second stage results for the impact of predicted low-capital LLCs on the amount of debt, again without and with additional controls. In both cases, we find that there is a negative relation between being a low-capital LLC and the amount of debt received, although the coefficient is not significant when we include the additional control variables. Columns 5 to 7 present second stage results for our measures of financing constraints. Again, the findings show that low-capital LLCs are more financially constrained than their high-capital counterparts and they are less likely to state they are not in need of external financing. Consequently, instrumenting the choice of legal form with foreign ownership leads to estimates similar to the ones we obtained from the OLS regressions.

Table 1.6: Instrumental Variable Estimation

	Survey Sample - No Controls		Survey Sample - All Controls					
	First stage	Second stage	First stage	Second stage	Second stage	Second stage		Second stage
	Low-Capital LLC	Log(Total Debt)	Low-Capital LLC	Log(Total Debt)	Financing Constraints	Bank Financing Constraints		No Funds Needed
	(1)	(2)	(3)	(4)	(5)	(6)		(7)
Low – Capital LLC		-2.725**		-1.496	1.110**	0.961*		-1.033*
		(1.358)		(1.387)	(0.558)	(0.545)		(0.547)
Foreign Owner	0.103***		0.098**					
	(0.036)		(0.043)					
Capital	-0.001**	0.002*	-0.000***	0.002**	0.000	0.000		-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)		(0.000)
Accumulated Profit/Loss			0.000	-0.000***	-0.000***	-0.000***		0.000***
			(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
Size			-0.023***	0.335***	0.023*	0.024*		-0.026*
			(0.004)	(0.041)	(0.014)	(0.013)		(0.014)
Age			-0.035***	0.039	-0.048*	-0.051*		0.046
			(0.012)	(0.078)	(0.029)	(0.027)		(0.029)
Tangible Assets			0.167***	-1.656***	-0.094	-0.106		0.046
			(0.038)	(0.302)	(0.115)	(0.106)		(0.113)
Patent Stock			-0.001	0.116***	0.007	-0.012		-0.036**
			(0.005)	(0.044)	(0.011)	(0.009)		(0.015)
Additional Firm Controls	No	No	Yes	Yes	Yes	Yes		Yes
Founder Controls	No	No	Yes	Yes	Yes	Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes		Yes
Observations	8,569	8,569	3,584	3,584	3,575	3,575		3,575
R-squared		0.125		0.415	-0.421	-0.349		-0.353

This table presents IV estimates from regressions of debt and financing constraint measures on legal form choice. Variable definitions are presented in Table A1 in the Appendix. We use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

1.7.2 Regression Discontinuity

Second, we make use of a Regression Discontinuity Design (RDD). In this setting, we estimate a local average treatment effect around the equity threshold of 25,000 euro that defines low-capital LLCs and high-capital LLCs. Specifically, we compare a subgroup of low-capital LLCs that have accumulated equity close to the 25,000 euro threshold with high-capital LLCs that have equity just above this threshold. The idea is that firms around this threshold are very similar in observed and unobserved characteristics. Because of this, any remaining difference in debt between firms on different sides of the cutoff value can be attributed to their legal form. We estimate the following model:

$$y_{it} = \beta_0 + \beta_1 I[capital > 25,000] + \beta_2 X_{it} + \varepsilon_{it} \tag{1.3}$$

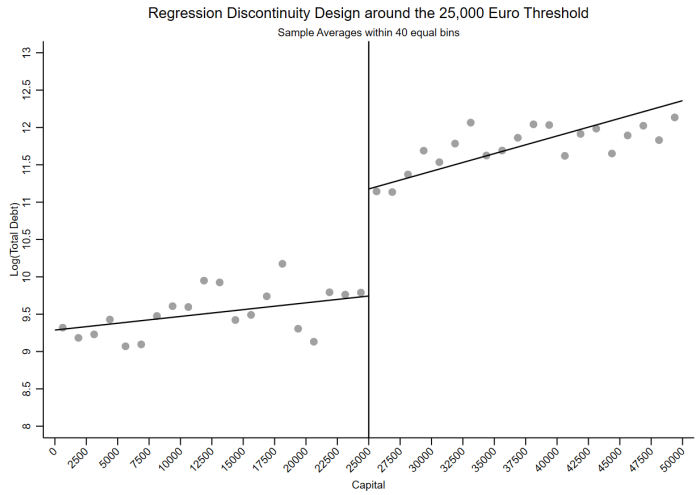
Where y_{it} is similar to before. $I[capital > 25,000]$ is an identity function that takes value one if a firm has more capital than the corresponding threshold in a given year. To increase accuracy, we also control for the same vector X_{it} as in Equation 1.1. Importantly, we estimate Equation 1.3 using a local linear estimation within various bandwidths to assess its robustness.

Before we run our analyses, we plot the relationship between debt and equity to visually examine if a discontinuity is observable around the capital threshold that defines low- and high-capital LLCs.[20] Indeed, Figure 1.2 displays a clear discontinuity in the relation between capital and total debt once firms have accumulated more than 25,000 euro in paid-in capital, something we would not expect to observe if there were no influence of firms' legal form. For other values of capital, we see a clear positive relationship between capital and debt. The "jump" in debt is difficult to align with the interpretation that continuous growth of firms is associated with a continuous increase in need for/use of debt. If this were the case, we would expect to see a linear relationship across the whole distribution. The results of the RDD analysis with total

[20] Specifically, we create 40 equal bins in terms of equity. The first bin represents all firms with 1 to 1250 equity, the second bin represents firms with 1251 to 2500 equity, and so forth. For each group we then display the average amount of total debt that is present.

debt as the outcome variable shown in Panels A (full sample) and B (survey sample) of Table A12 in the Appendix confirm this observation: regardless of the range of the bandwidth, we consistently find that high-capital LLCs have more debt than similar low-capital LLCs. A similar picture emerges when we replace total debt with our measures of demand for financing: high-capital LLCs report to be less financially constrained and are less likely in need of funding.

Figure 1.2



This figure plots the relationship between log of total debt and capital. We used a bandwidth of 25,000 (i.e. capital between 0 and 50,000 euro). The solid line are the fitted values from the local linear regressions. The vertical line is the cut-off point (i.e. 25,000 euro in paid-in capital) that defines the treatment (i.e. low- and high-capital LLCs). The dots represent the average log of total debt in 40 bins.

1.7.3 Difference-in-Differences

As a third method to mitigate concerns about unobservable factors being correlated with both the choice of legal form and firms' level of debt, we exploit changes in firms' legal form. As explained in detail in Section 1.3, low-capital LLCs (automatically) change their legal form into a high-capital LLC once they reach the 25,000 euro minimum capital requirement. In the full sample,

we observe that 1,890 low-capital LLCs change into high-capital LLCs during the sample period. We label this group as $switching\,low-capital\,LLCs$. The remaining 31,954 low-capital LLCs do not change their legal form, and are removed from the sample. The group of firms that incorporated as a high-capital LLC at startup by definition stay high-capital LLCs over the entire period. We label these as $permanent\,high-capital\,LLCs$. Descriptive statistics for the different groups are presented in Table A4 in the Appendix. Panel B of Table A4 already reveals that low-capital LLCs that switch legal form indeed increase their likelihood to obtain long-term debt, and also their total level of debt.

Next, we empirically estimate the impact of the legal form on access to finance by comparing the switching low-capital LLCs with the permanent high-capital LLCs. In particular, we test the following model:

$$y_{it} = \beta_1 Post\,Switch_t \times Low-Capital\,LLC_i + \beta_2 X_{it} + d_t + \alpha_i + \varepsilon_{it} \tag{1.4}$$

The indicator $Post\,Switch_t \times Low-Capital\,LLC_i$ is equal to one if a low-capital LLC has turned into a high-capital LLC in year t or any year following the change. d_t is a time fixed effect capturing macro-economic changes, and α_i are firm fixed effects capturing time-invariant differences across firms. The intuition behind this analysis is that if low-capital LLCs indeed face frictions in obtaining debt financing, changing to a high-capital LLC will relax these constraints by eliminating the negative signal attached to the low-capital legal form. This setup allows us to isolate the impact of changing legal form net of changes in access to finance that would have occurred otherwise and (unobserved) time-invariant firm characteristics such as the founding team and management quality or ownership structure that might play a role. The results shown in Table 1.7 indicate that, on average, the total debt of switching low-capital LLCs goes up by 15 percent after the change of legal form. Again, the results are most pronounced for long-term debt (increase of almost 26 percent), which is most likely to be bank debt.

Table 1.7: Difference-in-Difference Regression

	Log(Total Debt)		Log(Long-Term Debt)		Log(Short-Term Debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Switch × Low – Capital LLC	0.652***	0.141***	0.607***	0.228***	0.634***	0.159***
	(0.038)	(0.030)	(0.057)	(0.053)	(0.057)	(0.049)
Capital		0.003***		0.003***		0.002***
		(0.000)		(0.001)		(0.001)
Accumulated Profit/Loss		-0.001***		-0.001***		-0.001***
		(0.000)		(0.000)		(0.000)
Size		0.233***		0.189***		0.237***
		(0.003)		(0.004)		(0.004)
Age		0.449***		0.146***		0.450***
		(0.014)		(0.023)		(0.026)
Tangible Assets		-0.895***		0.206***		-1.582***
		(0.028)		(0.041)		(0.045)
Patent Stock		0.055***		0.053***		0.054**
		(0.013)		(0.019)		(0.022)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	434,741	317,909	256,277	206,097	226,375	175,789
R-squared	0.881	0.893	0.816	0.794	0.804	0.802

This table presents the results for difference-in-differences regressions of debt. The treated group are firms that switched legal forms from a low-capital LLC to a high-capital LLC in our sample period. The control group are permanent high-capital LLCs (i.e. firms that opted for the legal form high-capital LLC (GmbH) at startup). Variable definitions are presented in Table A1 in the Appendix. We use data from the full sample, which is retrieved from the Orbis Historical Database. In the survey sample, we do not observe sufficient firms that switch legal form. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

The difference-in-differences estimator hinges on the assumption that in the absence of a change of legal form, the trends in debt financing between switching LLCs and their non-switching counterparts would have remained stable. To provide some support for this assumption, we also estimate a dynamic version of Equation 1.4 where we include indicators for the years before and after the change to a high-capital LLC.[21]

The results are shown in Figure A1 in the Appendix. We find that long- and short-term debt start increasing significantly one year after low-capital LLCs have turned into high-capital LLCs. Importantly, we do not observe any

[21] The estimating equation is: $y_{it} = \sum_{\tau=-4,\tau\neq-1}^{+3} \gamma_\tau D_{i\tau} + \beta_2 X_{it} + d_t + \alpha_i + \varepsilon_{it}$. $D_{i\tau}$ is an indicator equal to one if a low-capital LLC switches to a high-capital LLC firm τ years earlier or $-\tau$ later if τ is negative, and zero otherwise. We include indicators for τ = "-4 or more years" before the change to a high-capital LLC to "3 or more years" after switching. In the regression analyses, we omit the indicator of the year before low-capital LLCs have been transformed into high-capital LLCs (τ = -1), so the estimated coefficients should be interpreted as the change relative to the year before the change in legal form.

significantly diverging pre-trends between the two groups. This bolsters our belief that the permanent high-capital LLCs serve as a valid counterfactual.

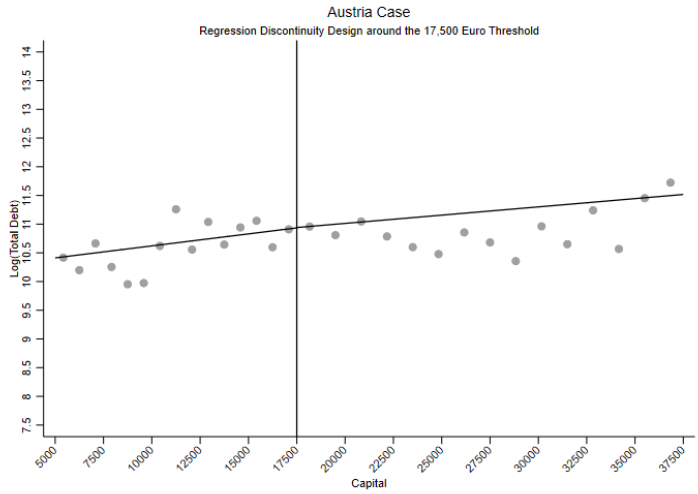
1.7.4 Changes in paid-in capital vs. legal form

As a final robustness test, we want to verify that our findings are indeed driven by the change in legal form and not driven by (an increase in) the amount of paid-in capital. To do so, we exploit an alternative setting: the reduction of paid-in capital requirements in Austria in 2014. In contrast to Germany, the reform in Austria did not introduce a new legal form. Instead, Austria lowered the paid-in capital requirements for newly created LLCs from 17,500 euro in cash to 5,000 euro.[22] This means there is no clear observable signal in the company name for Austrian LLCs. Hence, if our results would be driven by the actual amount of paid-in capital of a firm rather than the signal related to a firm's legal form, we would observe similar effects as presented above. The descriptive statistics for the Austrian sample are described in Table A13 in the Appendix.

As a first test, Figure 1.3 displays a plot of total debt against paid-in capital. Unlike before (cf., Figure A1) we do not observe a discontinuity in total debt around the threshold level of 17,500 euro. Total debt appears to linearly increase with paid-in capital. In line with this observation, the results from a RDD analysis shown in Table A14 in the Appendix indicate no significant difference between firms close to the threshold value. Similarly, results of a difference-in-differences analysis where we compare firms that at a certain point cross the capital threshold with firms that permanently have paid-in capital higher than 17,500 euro show no significant changes in debt once firms cross the capital threshold (cf., Table A15 in the Appendix).

[22] After 10 years the former capital requirements of 17,500 euro must be reached to prevent the dissolution of the firm.

Figure 1.3



This figure plots the relationship between log of total debt and capital for Austrian firms. We used data from firms with capital between 5,000 and 37,500 euro. The solid line are the fitted values from the local linear regressions. The vertical line is the cut-off point (i.e. 17,500 euro in paid-in capital) that defines the placebo (i.e. Austrian low- and high-capital LLCs). The dots represent the average log of total debt in 30 bins.

1.8 Conclusion

In this paper, we examine for a sample of German firms how the choice of a legal form with a low or high paid-in minimum capital requirement affects their access to and their level of debt. We find that entrepreneurs choosing for a legal form with low paid-in capital have roughly equal access to debt compared to their high-capital counterparts, but, conditional on obtaining debt, acquire substantially lower levels of debt. We provide indirect, but compelling evidence that this difference can be explained by the notion that outside investors rely on a firm's legal form as a signal of default risk. Several other plausible explanations for this difference are not supported by the evidence. First, we do not find that low-capital firms have lower demand for debt. Second, concerns of omitted variable bias – including the influence of potentially

correlated signals – do not appear to undermine our main findings. Finally, we find that investors do rely on firms' legal form and not purely on the underlying level of paid-in capital.

Our findings are also important beyond the context of the reduction in limited liability requirements. Next to differences in capital requirements in LLC, most countries also have different legal forms for private and public firms. One of the main differences between these is that public firms are required to have more paid-in capital at startup. Similar as in our setting, public companies may thus be perceived to be of higher quality by lenders. Further research, could verify if the finding in our setting can be extrapolated to this context.

From a theoretical perspective, this study makes several contributions. First, we add to the literature on the use of signals in new venture financing, and, in particular debt financing (e.g., Chua et al. (2011); Eddleston et al. (2016); Han, Fraser and Storey (2009)). While prior work has mostly focused on the role of founders' human and social capital, intellectual property, or third party affiliations, we highlight the role of new ventures' legal structure. Our findings also indicate that "hard" information (Liberti and Petersen, 2019) like legal form can complement the "soft" information typically gathered by small relationship banks, whereas it appears to be of less value to large transactional banks. This confirms the findings of prior studies that the effectiveness of a signal is partly determined by the characteristics of the receiver (cf., Connelly et al. (2011)).

Furthermore, our findings contribute to the ongoing debate on firm entry regulations. While most research shows positive effects of deregulation on firm entry (Klapper, Laeven and Rajan, 2006; Branstetter et al., 2014; Becht, Mayer and Wagner, 2008), we provide evidence that reduced minimum capital requirements to promote firm entry can negatively affect the access to external finance even for firms that might have obtained debt prior to the reform. In our setting, entrepreneurs with profitable business ideas but which opted for a low-capital LLC, will suffer from a negative signaling effect. Thus, a reduction in firm entry regulation might not only promote the creation of businesses by individuals that might otherwise not have opted for an entrepreneurial

career, it will also have negative performance effects for high-quality startups who want to benefit from the lower capital requirements because of reasons unrelated to their creditworthiness. With our paper we hope to better inform these entrepreneurs about the full consequences of the legal form choice.

To conclude, we point to some limitations of our study. These can serve as stepping stones for future research. While we employ a variety of estimation techniques to isolate the effect of legal form, future work could look for quasi-natural variation to more narrowly identify the causal pathways between legal form and debt financing. We look at the impact of legal form on the level of financing. Future work could examine whether loan providers also respond by altering the cost of financing. Recent advances have shown that certain characteristics and actions can "unlock" the signaling value of other firm and market characteristics in the context of new venture financing (Bapna, 2019; Plummer, Allison and Connelly, 2016). It would be interesting to examine whether legal form acts as a complement or substitute to other signals identified by prior work. Furthermore, future studies should investigate the signaling value of legal form in the context of equity financing. While debt providers tend to focus on a startup's stability and ability to repay a loan, equity investors concentrate on a venture's growth potential (Bruns et al., 2008). Therefore, different signals may be desired by debt versus equity providers. Ultimately, while we focus on the financing of startups, more work is needed to uncover the relation between legal firm and firm survival and growth.

Chapter 2

Patent Collateral and Access to Debt*

2.1 Introduction

Innovation is an important source of economic growth, especially for developed countries (Romer, 1990; Aghion and Howitt, 1990). However, investments in research and development (R&D) are hampered by capital restrictions (Nelson, 1959; Arrow, 1972). Given the inherent uncertainty of R&D projects, R&D performers are better informed about the expected outcome of their R&D projects than potential lenders. This information asymmetry can raise transaction costs to an extent that socially desirable innovation projects are not implemented as the cost of external capital rendered them privately unprofitable (Hall and Lerner, 2010). Therefore, many innovative companies are financially constrained (Czarnitzki and Hottenrott, 2011).

The current literature on financing constraints is mainly focused on establishing empirically the existence of financing constraints, and to lesser extent on how to mitigate them. Examples of the latter are analyses of the institutional framework, e.g. banking practice, and the relationships between firms and investors (Beck et al., 2007). Czarnitzki and Hottenrott (2017) have sug-

* This chapter is based on joint work with Dirk Czarnitzki (KU Leuven).

gested that management practices in form of R&D collaboration may help to attenuade financing constraints. Moreover, Hottenrott, Hall and Czarnitzki (2016) show that patents reduce financing constraints by disclosing information to investors, described as the signaling value of patents. In addition to the signalling value of patents, however, firms can also pledge patents for loan collateral to ease access to finance. This channel has attracted surprisingly little attention in the empirical literature.[1] The theoretical literature points out that investors can use collateral as a screening device that mitigates adverse selection (Bester, 1985). Hence, patents pledged as collateral, provide incentives for lenders to commit funding and, at the same time, leave the ownership of patents to borrowers (Steijvers and Voordeckers, 2009). Moreover, the loss of importance of tangible assets in modern knowledge economies (Goldfinger, 1997) forces firms to resort to intangibles for collateral.

In this paper, we estimate treatment effects of patent pledging on the pledgor's access to external capital as measured by debt at the firm level. We obtained information on all pledged patents in Sweden and the Netherlands and constructed two panel databases including financial data. Conditional Difference-in-difference (CDID) analyses for the matched samples of similar non-pledging Swedish and Dutch firms reveal significant increase in the levels of debt following the pledging event. Estimated results show that the patent pledging event causes an increase in debt by about 34% for Dutch pawners and about 20% for Swedish pawners, respectively. These relative changes correspond to higher debt of about 1.4 million euro in the Netherlands and 1.2 million euro in Sweden. However, descriptive statistics show that only a few patenting firms in both countries pledge patents. A back-to-envelope calculation shows that patent owners could raise more than 5 billion euro in the Netherlands and more than 13 billion euro in Sweden if all firms pledge their complete patent portfolios, all else constant. Thus, patents pledged as loan collateral may provide a fruitful source of external financing.

Our regressions also allow comparing the signaling value and the collateral

[1] One might also think of selling or licensing patents. However, in both cases firms will lose their patent or reduce its competitiveness. Moreover, small firms which are mostly affected by financing constraints are less diversified, and could thus lose significant parts of their business model by selling / licensing patents.

value of patents with regard to debt. We find that the patents' collateral value exceeds their signaling value for firms in the Netherlands but not for firms in Sweden.

Our findings contribute to the vast literature on financing constraints. Among others, Harhoff (2000) and Brown, Fazzari and Petersen (2009) provide evidence that innovative firms are financially constrained. Our results show that firms can access external finance by offering patents as loan collateral, hence mitigate financing constraints. Moreover, we contribute to the scarce literature on patent pledging. Mann (2018) provides descriptive evidence that mature US firms pledging patents as collateral have significantly higher total debt. Our results reinforce these findings in the framework of a treatment effects study with both public and private firms in Europe and suggest that collateralized patents causally help firms to access more debt. In addition, our findings can also be interpreted as a contribution to the large literature on patent valuation (Bloom and Van Reenen, 2002; Hall, Jaffe and Trajtenberg, 2005; Czarnitzki, Hall and Oriani, 2006; Gambardella, Harhoff and Verspagen, 2008). The estimated treatment effects reflect a minimum value of the pledged patent as lenders are willing to supply additional capital for these collateralized patents in loan contracts.

The rest of the paper is organized as follows: In Section 2.2 we explain our conceptual framework including the empirical identification strategy. In Section 2.3 we present a description of the data including data sources, descriptive statistics and the construction of a control group. Section 2.4 presents and discusses our findings. Finally, Section 2.5 concludes on implications of our results.

2.2 Conceptual framework and empirical identification strategy

We estimate the impact of patent pledging on firms' access to debt. Specifically, we apply a conditional difference-in-difference (CDiD) framework to estimate the treatment effect of patent collateralization in a loan negotiation.

Thus, we compare the debt level of a firm after the event of a patent pledge with the debt level before this event. As the debt level might be affected by other exogenous macroeconomic characteristics relevant to the firm, we use non-patent-pledging firms as control group in the regression analysis.

To address the selection into the group of pawners, we perform matching to find similar non-pledging firms that are comparable in the pre-treatment period. Specifically, we apply a Mahalanobis distance match in the pre–treatment period on debt, equity, the patent stock and the number of forward citations the firms' patent portfolio receives in the future as well as firms' age and sector. By conducting such a matching in the pre-treatment period, we establish a quasi–experimental setting in which the treatment group and the control group had, on average, in the past similar demands for debt and currently possess similar equity. Furthermore, the patent stock and the forward citations to this patent stock control for the potential collateral that the firms could offer to lenders in terms of quantity and quality of their intellectual assets. We thus interpret positive coefficients for the patent pledging event as estimates of the additional capital that firms could raise because of pleding patents.

We implement the Mahalanobis distance matching as nearest neighbor matching in which we draw up to two nearest neighbors per treated firm. We use a caliper restriction to prevent bad matches, i.e. large Mahalanobis distances, which might introduce bias and draw the neighbors without replacement (Abadie and Spiess, 2021).

In the following, we regress debt on a set of indicators for the periods pre- and post-pledging event for the matched sample. The change of patents collateral status allows controlling for firm-fixed effects. Therefore, any time-invariant firm characteristics, such as management quality or ownership structure, that may be related to firms' access to debt will be differenced out. The specification for the difference-in-difference regression is:

$$y_{it} = \sum_{k} \beta_1 PP_{it} + \beta_2 \boldsymbol{X_{it-1}} + \beta_3 \boldsymbol{d_t} + \alpha_i + \varepsilon_{it} \tag{2.1}$$

Specifying that $t = 0$ is the last pre-treatment period and thus also the period used for matching, the following timeline applies $t = (-2, -1, 0, 1, 2, 3, +4)$.

y_{it} is the natural logarithm of firm i's debt in year t. $PP_{it} = 1$ if a patent has been pledged for all $k \geq t$ periods. $\boldsymbol{X_{it-1}}$ is a vector of time-varying firm-level characteristics that might influence access to debt. We use the one-year lag of firms equity controlling for differences in capital between pledging and non-pledging firms. Furthermore, we control for differences in firm size, measured by the natural log of employees, because it is an important determinant for financing constraints (Hadlock and Pierce, 2010). We include the natural logarithm of firms' patent stock to capture patents' signaling value to investors (Hottenrott, Hall and Czarnitzki, 2016). Last, we include the natural logarithm of the average number of forward citations of firms' annual patent portfolios. This measure serves as a proxy for the quality of firms intangible assets. d_t are a set of time dummies capturing macro-economic changes, and α_i are firm-fixed effects capturing time-invariant differences across firms.

It is possible that the impact of patent pledging varies over time. Therefore, in a second step, we estimate a variation of Equation (1) with multiple pre-pledge and post-pledge indicators for patent pledging firms. This is useful for gauging the overall pattern of the impact of patent collateral. In addition, the coefficients for the pre-pledge periods serve as direct test of the common trend assumption. We thus regress debt on a set of indicators for the years since any patents have been pledged, ranging from $t = -2$ to $t = +4$. The estimation equation is:

$$y_{it} = \sum_{\tau=-2,\tau\neq 0}^{+4} \gamma_\tau PP_{i\tau} + \beta_2 \boldsymbol{X_{it-1}} + d_t + \alpha_i + \varepsilon_{it} \tag{2.2}$$

$PP_{i\tau}$ is an indicator equal one if a firm pledged patents τ years after or $-\tau$ later if τ is negative, and zero otherwise. We include indicators for $\tau = -2$ before the pledging event up to 4+ years after the pledging patents. We omit the indicator the year before the pledging event ($\tau = 0$), so the estimated coefficients should be interpreted as the change relative to the year before the pledging event. Other specifications are identical to Equation 2.1 as described above.

The set-up of our matching routine and the fixed-effects within regression conforms to the recent suggestions of Abadie and Spiess (2021) who argue

that standard errors in CDID applications are biased if the matching is not done without replacement and the subsequent regression does not include all covariates used for the matching. We therefore believe that we establish state-of-the-art inference.

2.3 Data sources and descriptive statistics

2.3.1 Data sources

The empirical analysis is based on detailed firm–level information covering balance sheet and income statement data combined with information on patents owned by the respective firms. Moreover, the analysis utilizes information on pledged patents. The registration of pledged patents is determined by the national patent law and is not mandatory in most countries. However, the Swedish and Dutch patent offices are one of the few national patent offices where the registration of collateralized patents is mandatory (Ministry of Justice Stockholm, 1967; The Minister of Justice Den Haag, 1995). Thus, we restrict our sample to Swedish and Dutch firms.

To construct our data, we make use of the Orbis Global and Orbis IP databases combining rich firm-level and patent-level information. Importantly, Orbis does not only cover listed companies but also private firms. We obtained historical financial data together with filed patents for all Dutch and Swedish companies. Second, we gained access to detailed information about all pledged national patents and valid EP-patents from the Dutch and Swedish Patent Offices. The database contains information about the date the patent was pledged and the patent owner at the pledging date. Information on pledgors covers firm names and addresses, allowing us to match patent pledgors with historical financial data and information on non-pledged patents from Orbis IP. Third, we gather data on the number of forward citations for all patents from PATSTAT.[2] The total number of forward citations that patents receive is a common proxy for the quality or technological importance of patents (Trajtenberg,

[2]We normalize the total number of forward citations by the average number of citations patents receive with the same filing year and technical field.

1990; Hall, Jaffe and Trajtenberg, 2001). We average the number of forward citations over firms' annual patent stocks to proxy the quality of the entire patent portfolio.

Finally, we construct two separate panels for Swedish and Dutch firms, containing detailed financial data together with their stock of patents, the average number forward citations of the patent portfolio and the number of pledged patents on a yearly base. The patent stock is constructed according to the pertpetual inventory method, i.e. it measures the accumulated yearly number of patent applications of the focal firm depreciated at a rate of 15 percent as common in the literature (Cuneo and Mairesse, 1983).

2.3.2 Descriptive statistics

We restrict our data to patenting firms, as non-patenting firms are considered irrelevant for the treatment effects analysis. Furthermore, we have dropped all sectors in which no firm pledged a patent in our period under review. Finally, all financial variables have been trimmed at the 1% level on each side of the distribution to eliminate influential observations.[3]

The final Dutch sample includes 8650 non-pledging firms and 186 patent-pledging firms observed between 1994 and 2018. Firms in the sample pledged patents between 1995 and 2017. In total, the Dutch panel contains about 100,000 firm-year observations. The Swedish sample includes 7226 non-pledging firms and 130 patent pledging firms observed between 1997 and 2018. Firms in the sample pledged patents between 1998 and 2016. For Sweden, our final data contains almost 90,000 firm–year observations.

Tables 2.1 and 2.2 show the summary statistics for the sample of Dutch and Swedish patent-pledging firms and patentees that do not pledge any patent, respectively. Patent-pledging firms in Sweden and the Netherlands show a similar age structure with an average of around 20 years. However, Swedish pledgors are larger then their Dutch counterparts, showing on average more employees and total assets. Non-pledging firms differ in all dimensions from firms offering patents for loan collateral, which suggest a selection of firms

[3]The debt variable has been trimmed at 2% level due to high number of outliers.

into the group of pawners. To address potential selection effects, we conduct a matching analysis to balance the covariates among the treatment and selected control group in the pre-treatment period.

Table 2.1: Summary statistics for the Dutch sample

	Patent pledging firms					Non-pledging firms				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	1731	7940.23	14764.48	0.16	116128.38	99287	4498.24	13510.72	0.10	160524.00
Equity	1731	4329.86	8416.49	0.00	68734.73	99287	4259.89	19074.73	0.00	405889.00
Employees	1155	92.74	169.85	1.00	1393.00	61087	62.25	255.55	1.00	40045.00
Age	1731	22.84	23.28	0.00	116.00	99287	22.16	22.90	0.00	314.00
Patentstock	1731	2.19	2.98	0.00	24.78	99287	1.13	12.13	0.00	1035.30
Forward Cites	1731	0.24	0.31	0.00	2.15	99287	0.17	0.40	0.00	13.37
N	1731					99287				

8650 non-pledging firms and 186 patent pledging firms observed between 1994 and 2018. Firms pledge patents between 1995 and 2017. All monetary values are in Thd. Euros.

Table 2.2: Summary statistics for the Swedish sample

	Patent pledging firms					Non-pledging firms				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	1439	10484.09	27095.14	1.02	196236.00	86890	4922.64	17076.80	0.87	204978.81
Equity	1439	7304.02	18187.47	0.00	189014.34	86890	4424.33	17932.23	0.00	372612.00
Employees	1365	89.24	233.53	0.00	2196.00	80990	50.77	192.70	0.00	9387.00
Age	1439	20.09	18.40	0.00	119.00	86890	21.77	19.29	0.00	119.00
Patentstock	1439	2.97	5.80	0.00	48.62	86890	1.20	5.58	0.00	344.16
Forward Cites	1439	0.36	0.39	0.00	2.76	86890	0.18	0.38	0.00	14.31
N	1439					86890				

7226 non-pledging firms and 130 patent pledging firms observed between 1997 and 2018. Firms pledge patents between 1998 and 2016. All monetary values are in Thd. Euros.

2.3.3 Matching

Tables 2.3 and 2.4 (Columns: Unmatched) show the descriptive statistics for non-pledging firms and pledging firms in the year before patents have been pledged, i.e. the pre-treatment period. Both samples include only the first pledging event per firm since subsequent patent pledging of firms might be endogenous. The mean values of the debt variable and all covariates are statistically different between the groups in the unmatched samples (Tables 2.4 and 2.3). To balance the covariates between patent-pleding and non-pledging firms, we apply a Mahalanobis distance match on pre-treatment debt, equity, firm age, patent stock (and its square to assign more weight to this variable in the matching procedure), and the number of forward citations of firms' patent portfolios. We require an exact match on the economic sector and year.

The matching is implemented as nearest neighbor matching in which we draw up to two neighbors per treated firm. We include a caliper to avoid distant matches which might induce bias otherwise. Tables 2.3 and 2.4 (Columns: Matched) show the same descriptive statistics after the matching process. The matched sample of Dutch firms includes 141 pledgors matched to 275 similar non-pledging firms. The matched sample of Swedish firms include 126 patent pledgors matched to 248 non-pledging firms. There are no significant differences between the groups for the matched variables. Consequently, patent pledging and non-pledging firms are observably similar with respect to firm characteristics determining their access to debt.

Table 2.3: Summary statistics for the matched sample of Dutch firms

	Unmatched			Matched		
	Pledgor	Control	$p > \|t\|$	Pledgor	Control	$p > \|t\|$
Equity	3948.49	2219.45	0.003	1514.86	1463.69	0.891
Debt	8096.03	3561.73	0.000	3090.16	2660.70	0.365
Age	18.77	21.73	0.074	14.97	14.44	0.760
Patentstock	2.43	1.00	0.000	1.79	1.47	0.129
Patentstock^2	15.75	94.45	0.007	7.27	5.83	0.624
Forward Cites	0.20	0.13	0.000	0.17	0.16	0.690
N	186	89452		141	275	

All monetary values are in Thd. Euros.

Table 2.4: Summary statistics for the matched sample of Swedish firms

	Unmatched			Matched		
	Pledgor	Control	$p > \|t\|$	Pledgor	Control	$p > \|t\|$
Equity	5742.14	3632.01	0.173	3537.67	2463.21	0.332
Debt	8966.81	4649.05	0.075	4586.21	2604.76	0.105
Age	14.45	21.52	0.000	13.83	13.52	0.852
Patentstock	2.71	1.16	0.000	2.57	1.88	0.121
Patentstock^2	26.00	27.80	0.838	23.93	15.89	0.406
Forward Cites	0.30	0.14	0.000	0.29	0.26	0.258
N	130	80560		126	248	

All monetary values are in Thd. Euros.

Tables B1 and B2 in the Appendix show the summary statistics for the matched sample of patent pledging firms, separated for the pre- and post-treatment period. The average debt levels increases signficiantly in the period following the colleratization of patents. However, other observable firm charac-

teristics including equity, the number of employees, and the number of patents are higher in post-treatment periods as well. Therefore, the increase in debt levels could be partially explained by an increase in the size of firms. The following difference-in-difference analysis will include controls for firm's equity, employment, patent stock, and the number of forward citations of firms patent portfolio thus, account for potential size effects and effects driven by differences in patents value.

2.4 Estimation Results

2.4.1 Main results

Table 2.5 presents the empirical results for the CDID regressions on the impact of a patent pledging on the debt level for the matched sample of Dutch firms. The first two columns show the results with and without controls for the CDID estimation. Columns 3 and 4 show the results with and without controls for the dynamic CDID estimation taking pre-treatment dummies into account. The variable of interest *"post_pledge"* shows a positive sign with highly significant coefficients at the 1% level. Thus, firms significantly increase debt finance after pledging patents. In terms of magnitude, patent pledging firms increase debt by about 34%[4] relative to the counterfactual situation in which no patent would have been used as collateral.

[4] $100 \times \left(e^{0.29} - 1\right)$

Table 2.5: Difference-in-difference regression estimating the impact of patent pledging on debt level in the Netherlands

	Diff-in-Diff		Dynamic Diff-in-Diff	
Dep. Variable:	Log(Debt)	Log(Debt)	Log(Debt)	Log(Debt)
post_pledge	0.28***	0.29***		
	(0.11)	(0.099)		
pre(t2)_pledge			-0.064	-0.059
			(0.18)	(0.16)
pre(t1)_pledge			0.016	0.0047
			(0.17)	(0.16)
post(t1)_pledge			0.32**	0.32**
			(0.15)	(0.14)
post(t2)_pledge			0.39**	0.39**
			(0.16)	(0.16)
post(t3)_pledge			0.28	0.30*
			(0.17)	(0.17)
post(t4f)_pledge			0.11	0.11
			(0.19)	(0.18)
Log(Equity)		-0.021***		-0.019***
		(0.0041)		(0.0041)
Log(Employees)		0.24***		0.25***
		(0.035)		(0.035)
Log(Patent_Stock)		0.17***		0.15***
		(0.056)		(0.056)
Log(Forward_Cites)		0.76**		0.76**
		(0.31)		(0.31)
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
F	7.09	25.8	3.32	14.5
R-squared	0.82	0.83	0.82	0.83
N	2669	2669	2669	2669

This table presents the results for the difference-in-difference regression estimating the impact of patent pleding on firms' debt level. Regression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B1 in the Appendix graphically visualizes the estimated coefficients of the "dynamic" difference-in-difference analysis. Both coefficients of pre-treatment indicators are insignificant. Thus, we find no evidence for diverging trends between pledging firms and control groups of non-pledging firms in years prior the pledging event. Consequently, the estimated treatment effects are unlikely to be driven by firm specific trends in debt finance for pre-treatment periods. Most importantly, the graph shows a significant jump for

firms' debt levels in post-treatment periods starting in the year of the pledging event. This shows that Dutch firms increase debt immediately after the patent collaterlization.

Table 2.6 presents the empirical results for the difference-in-difference regression concerning the impact of a patent pledging event on debt level for the matched sample of Swedish firms. The first two columns show the results with and without controls for the simple difference-in-difference estimation. Column 3 and 4 show the results with and without controls for the dynamic difference-in-difference estimation, respectively. The average treatment effects for the Swedish sample are smaller than for the Dutch sample. Patent pledging firms in Sweden increase debt by about 20%. Interestingly, post-treatment effects are only significant starting the second and third year following the pledging event. Thus, the increase in debt occurs mainly in the third year after patents have been pledged. A possible explanation for the delay might be that collateralized loans are only taken up sequentially and not in full amount immediately. This is common in, for example, loan contracts for buildings that are under construction.

Table 2.6: Difference-in-difference regression estimating the impact of patent pledging on debt level in Sweden

	Diff-in-Diff		Dynamic Diff-in-Diff	
Dep. Variable:	Log(Debt)	Log(Debt)	Log(Debt)	Log(Debt)
post_pledge	0.30***	0.18**		
	(0.080)	(0.071)		
pre(t2)_pledge			-0.15	0.035
			(0.16)	(0.13)
pre(t1)_pledge			-0.072	-0.011
			(0.14)	(0.13)
post(t1)_pledge			0.17	0.14
			(0.11)	(0.10)
post(t2)_pledge			0.11	0.12
			(0.14)	(0.12)
post(t3)_pledge			0.31***	0.28***
			(0.12)	(0.10)
post(t4f)_pledge			0.31***	0.21**
			(0.10)	(0.088)
Log(Equity)		0.013		0.014
		(0.0091)		(0.0093)
Log(Employees)		0.61***		0.58***
		(0.033)		(0.034)
Log(Patent_Stock)		0.37***		0.41***
		(0.044)		(0.051)
Log(Forward_Cites)		-0.53***		-0.57***
		(0.16)		(0.17)
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
F	14.3	111.4	4.12	49.4
R-squared	0.88	0.91	0.88	0.91
N	4119	4119	4119	4119

This table presents the results for the difference-in-difference regression estimating the impact of patent pleding on firms' debt level. Regression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Control variables for employment and firms patent stock show a positive coefficient in both samples. This is in line with the financial literature that defines firm size as the main determinant of firms' access to debt (Hadlock and Pierce, 2010). Furthermore, the positive coefficient for the patent stock confirms (Hottenrott, Hall and Czarnitzki, 2016) findings on the signaling value of patents to external investors. Our results show that a one percent increase in firms' patent stock is associated with a 17% increase in the debt

levels of Dutch firms and 37% increase in the debt levels of Swedish firms. Thus, Dutch firms can increase their debt by pledging patents more than their Swedish counterparts. However, the signaling value of patents seems to be more pronounced in Sweden. Last, the coefficients for the number of forward citations on the portfolio level show different signs for the Dutch and Swedish samples. This is likely due to the strong correlation with the patent stock variable.[5]

2.4.2 Placebo test

A key assumption for the difference-in-difference analysis is the common trend assumption. In our setting, this means that in the absence of a patent pledging event, the debt levels of treatment and controls groups should have followed the same trend. To further prove the validity of our empirical design, we performe a placebo test for randomly assigned "fake" pledging events in the pre-treatment period of patent pledging Dutch and Swedish firms.[6] Afterwards the assignment of fake pledging events, we estimate the identical difference-in-difference analysis applied in our main analysis. The idea of this placebo test is that the fake pledging event should not alter firms' debt level if the firms follow the same trend in debt finance.

Tables B4 and B6 in the Appendix show the results of the difference-in-difference analysis using "fake" patent pledging events in pre-treatment periods for Sweden and the Netherlands receptively. In both samples the treatment indicator "$post_pledge$" show a small and insignificant coefficient. Hence, fake pledging events in pre-treatment periods do not alter firms' debt level. This further supports the assumption that firms in our main analysis follow the same trend in debt finance in years prior the patent pledging event, and that our actual treatment effects estimations are indeed causal.

[5] Unreported results where we include controls individually show a postive sign for the number of forward citations on the portfolio level in both samples. This is in line with the expectation that patents with higher underlying technological quality (value) are more likely to be pledged.

[6] "Fake" pledge events have been assigned for each patent pledging firm at a random year prior the actual pledging event.

2.5 Conclusion

It is well known that many innovative companies are financially constrained. The literature shows that patents can mitigate such financial frictions through their signaling value by reducing information asymmetries between borrowers and lenders. However, patents can also serve as loan collateral and thereby improve firms' access to debt. This collateral channel has attracted surprisingly little attention in the existing literature.

In this paper, we estimate the impact of patent-pledging on firms' debt level using a quasi-experimental set-up by implemting conditional difference-in-difference regressions. Thus, we provide causal evidence for the increase in firms' debt capacity through the pledging of patents. We show for a sample of Dutch and Swedish patent filing firms that the patent pledging event causes an increase in the level of debt by about 34% for Dutch pawners and about 20% for Swedish pawners.

It is possible to translate our marginal effects into monetary values by multiplying the effect size with the firms' debt level prior to the pledging event. This implies that Dutch (Swedish) firms were able ro raise, on average, 1.38 (1.24) million additional euros debt by offering patents as loan collateral. However, our descriptive statistics show that only a few patent-filing firms pledged their patents compared to the number of patent-owning firms. This implies that innovators in Sweden and the Netherlands currently do not exhaust all financing opportunities. Specifically, non-pledging Dutch (Swedish) firms could raise addtional 5.1 billion euro (13.4 billion euro) external funding in total by offering their patents as loan collateral, all else constant.

We can also revisit prior findings on the positive signaling value of patents. Our results show that firms patent stock is associated with a 17% increase in the debt levels of Dutch firms and 37% increase in the debt levels of Swedish firms. In monetary terms, this means that the signaling value of pledged patents can explain an average increase in debt of 594 thousand euro for Dutch firms and an average increase in debt of 1.8 million euro for Swedish firms.[7]

[7] The calculation of the signaling value is based on the average patent stock prior to the pledging event which is equal to 1.69 (2.91) in the Netherlands (Sweden). Adding

This suggests that the collateral value of patents exceeds their signaling value for firms in the Netherlands but not for firms in Sweden.

Finally, our results can also seen as contribution to the literature on patent valuation that, for example, assesses marginal effects of (quality–weighted) patent stocks on firms' market value (Kogan et al., 2017). We offer a new method to assess minimum values of patent portfolios as our estimated treatment effects may reflect the value of patents to the extent that a lender commits additional financial resources for patents being used as collateral.

There are some important limitations to our results. First, companies do not pledge patents at random. Since we were unable to find a suitable instrument for the pledging event[8], we applied a CDiD regression for a matched sample to mitigate selection effects. However, the matching of a similar control group of non-pleding firms is based on observable firm characteristics. Thus, we cannot exclude the possibility that unobserved firm characteristics drive both firms' access to debt and the decision to pledge patents. Second, our empirical analysis is based on Dutch and Swedish firms which limits the generalizability of our results to countries with a similar economy and legal framework.

the average number of pledged patents (2.26 in the Netherlands and 3.53 in Sweden) leads to an increase in the patent stock by 84.9% (79.44%) in the Netherlands (Sweden). Consequently, the increase in the patent stock by the number of pledged patents corresponds to an increase in debt by about 14% (29%) for Dutch (Swedish) firms.

[8]We have tried to use variation in real estate prices at the location of the companies, the distance between firms and their national patent office, regional variation in the share of relationship banks to total banks and weather shocks at the firm's location. However, neither of the purposed instruments significantly explained patent pledging.

Chapter 3

Air Pollution and Innovation*

3.1 Introduction

Knowing the economic costs of air pollution is important for rational abatement policies (Landrigan et al., 2018). Traditional assessments sum up foregone output due to pollution-induced premature deaths (Cohen et al., 2017). This approach obscures costs associated with less acute health or cognitive effects (Zivin and Neidell, 2018). A body of evidence points out that bad air quality reduces supply and productivity of labor, even in occupations demanding mainly cognitive effort (Zivin and Neidell, 2012; Hanna and Oliva, 2015; Chang et al., 2016, 2019). These 'hidden' costs add up to economically important drops in output. Analyzing European regions, Dechezleprêtre, Rivers and Stadler (2019) find that a 10% increase in air quality causes a 0.8% surge in GDP within the same year. These findings imply that cleaner air is responsible for up to 15% of Europe's GDP growth between 2000 and 2015.

We study the effect of air pollution on aggregate inventive output. This effect does not show up in GDP because inventions typically take several years to realize economic benefits through product and process improvements (Scherer, 1965; Ravenscraft and Scherer, 1982). These lagged benefits may be large be-

* This chapter is based on joint work with Dennis Verhoeven (KU Leuven, Bocconi University and London School of Economics).

cause innovation is a key driver of economic growth (Aghion and Howitt, 1990; Romer, 1990). Therefore, the costs of air pollution may be considerably understated when overlooking its effect on innovation.

We analyze a yearly panel of 1,288 European NUTS-3 regions between 2001 and 2012. We measure inventive output as the total number of patents filed in the year following a given level of exposure to air pollution. This one-year lag accounts for the fact that the process of drafting and filing a patent takes 6-12 months. Our measure of air pollution is the exposure to particulate matter with a diameter of 2.5 micrometers or less ($PM_{2.5}$). These small particles enter the bloodstream through the lungs and affect the functioning of several organs (Underwood, 2017). $PM_{2.5}$ is one of the primary pollutants considered by the World Health Organization (WHO) and is commonly used as a measure of air pollution.

Our identification strategy relies on two weather phenomena that provide plausibly exogenous variation in air pollution.[1] Our first instrument measures a region's exposure to 'thermal inversions' during a given year. These inversions are caused by idiosyncratic atmospheric conditions and 'trap' pollutants near the earth's surface by reversing the negative temperature-height relationship. Our second instrument measures the level of natural ventilation that disperses pollutants. It is a function of wind speed and the height of the 'planetary boundary layer'. This layer determines the volume over which turbulent air flows are able to diffuse pollutants. We include controls for wind speed, precipitation, temperature, humidity and air pressure to account for the possibility that weather conditions correlated to our instruments affect innovation, for instance, by their impact on traffic conditions or mood.

We find that a $0.17 \mu g/m^2$ decrease in $PM_{2.5}$ concentration – the average yearly reduction in Europe over the period studied – leads to 1.7% more patented innovations. This effect is driven almost exclusively by regions with above-median levels of air pollution, suggesting that up to certain levels of exposure, the effects on innovation are small or non-existent. Increased air

[1] Other papers that use weather conditions to instrument air pollution include Hanna and Oliva (2015); He, Liu and Salvo (2019); Dechezleprêtre, Rivers and Stadler (2019).

quality has a similar impact on total innovation for regions with high and intermediate levels of urbanization.[2] This finding suggests that the potential benefits of reducing air pollution extend beyond highly urbanized regions.

Our baseline results measure the effect of air pollution on innovative output for the average region. One concern with aggregating these region-level estimates to economy-wide costs is that they may result from reallocation of human capital rather than decreased productivity. Indeed, if inventors migrate in response to air pollution, inventive output lost in one region may be partially recovered in another one. We rule out this mechanism using address information[3] across inventors' subsequent patent applications to identify migration between regions.[4] We find no statistically or economically significant effect of air pollution on inventor in- or out-migration.[5]

In a final set of analyses, we substantiate our claim that the effect on innovation is indeed not captured by prior assessments. First, we find suggestive evidence that changes in R&D expenditures do not drive our results. Because R&D spending is part of a region's GDP, the damages to innovation through this channel would be partially accounted for by the estimates of Dechezleprêtre, Rivers and Stadler (2019). While our data do not allow for a direct test, we find suggestive evidence to rule out the R&D spending mechanism. We show that our results hold when looking at scientific instead of inventive output. Because the funding of science is unlikely to react to changes in air pollution within a year, we would expect a considerably smaller effect on scientific output if R&D expenditures would drive our main result. In addition, the quality of patents in response to air pollution is not affected. When R&D spending would be materially affected, average invention quality should go up because budget-constrained firms would arguably shut down less promising

[2]For regions with intermediate levels of air pollution, the marginal effect is larger, but because of a lower patent intensity, the overall effect is similar.

[3]Inventors are obliged to disclose their address when applying for a patent

[4]We make use of the inventor name disambiguation algorithm developed in Morrison, Riccaboni and Pammolli (2017) to circumvent the fact that inventors are not assigned a persistent identifier in the patent database.

[5]Prior work has established that location choices depend on air quality (Khanna et al., 2021; Heblich, Trew and Zylberberg, 2021). However, the variation to air pollution induced by our instrument is likely too small to invoke a migration response.

projects first. Second, we find that mortality in general does not react to air pollution in our set-up. If this would be the case, the traditional cost estimates that calculate costs due to productive life-years lost due to pollution-induced mortality would partly account for our main result.

While we do not disentangle the exact mechanisms behind our results, we see two remaining candidates. First, the supply of innovative labor may decrease due to absenteeism or a reduction in hours worked. This is consistent with prior work showing that labor supply decreases in response to air pollution (Hanna and Oliva, 2015; Aragón, Miranda and Oliva, 2017; Chang et al., 2019). Second, air pollution may reduce inventor productivity conditional on hours worked by harming cognitive function. This is consistent with a recent stream of literature that finds considerable effects of air pollution on cognitively demanding tasks (Stafford, 2015; Ebenstein, Lavy and Roth, 2016; Archsmith, Heyes and Saberian, 2018; Künn, Palacios and Pestel, 2019; Nauze, Severnini and John Heinz, 2021).

A back-of-the-envelope calculation using existing estimates of the value of inventions shows that the magnitude of the effect of air pollution on inventive output is large. The average private value of a representative sample of European patents is estimated at 3 million euros (Gambardella, Harhoff and Verspagen, 2008). In addition, innovations induce spillovers valued at twice the amount of their private returns (Bloom, Schankerman and Reenen, 2013). Summing up these two sources of value suggests that the yearly realized reduction in air pollution in Europe has created a benefit of 21.3 billion euros annually. As a consequence, our results suggest that the GDP-effect from Dechezleprêtre, Rivers and Stadler (2019) needs to be revised upwards by at least 10%. This is a lower-bound estimate for two reasons. First, the private returns estimated by inventors are about 5 times lower as compared to stock-market-based estimates from Kogan et al. (2017). Second, estimates in Bloom, Schankerman and Reenen (2013) take into account knowledge spillovers and product market rivalry to estimate social returns. This assessment excludes further societal benefits, which are hard to estimate but considered to be large (Jones and Summers, 2020).

The remainder of the paper proceeds as follows. Section 3.2 outlines the

empirical strategy we employ to estimate the causal effect of air pollution on inventive output. Section 3.3 describes the data and measures used. Section 3.4 discusses the results of our preferred specification, documents several robustness checks, and explores heterogeneity across regions. Section 3.5 provides the evidence to rule out mechanisms related to inventor mobility, R&D expenditures and mortality. Section 3.6 concludes.

3.2 Empirical strategy

3.2.1 Measures for air pollution and innovation

Air pollution. We proxy exposure to air pollution using the level of $PM_{2.5}$ concentration[6] in a region. $PM_{2.5}$ is one of the priority pollutants under EU air quality regulations (European Parliament and Council of the European Union, 2008) and the National Ambient Air Quality Standards (NAAQS) in the United States (US EPA , US Environmental Protection Agency). Other common air pollutants such as nitrogen oxides and ozone are not recorded at a scale suitable for our analyses. Therefore, we cannot disentangle the effects of $PM_{2.5}$ from those of other pollutants insofar these are correlated. We view this as only a small caveat for three reasons. First, $PM_{2.5}$ is considered the most harmful pollutant to cognitive function and physical health and is seen as a reference indicator to track air pollution globally (Power et al., 2016; WHO, 2016). Therefore, it is unlikely that co-pollutants importantly confound the effect. Second, the correlation between $PM_{2.5}$ and other pollutants stems from the fact that they result from similar industrial activities involving combustion. As such, regulations targeting $PM_{2.5}$ reduce co-pollutants as well, indicating that the main implications of this study hold even if co-pollutants partially drive the effects. Third, being the most widely used measure, the use of $PM_{2.5}$ ensures comparability of our results with the largest possible number of prior studies.

Innovation. To proxy innovation output, we use the yearly number of

[6] $PM_{2.5}$ refers to suspended particulates smaller than 2.5 μm in aerodynamic diameter.

patent applications filed for in a region. The patent system is designed as a 'deal' between the public and an innovator. In order to receive the exclusive right to use and sell the patented invention in a jurisdiction, the innovator is required to disclose detailed information about the invention to the public. This publication requirement has the objective to allow others to build further upon the knowledge disclosed in the patent, increasing the efficiency of knowledge generation. As a side effect, patent data provide a window on innovative output for studies of technological change, innovation and economic growth (Griliches, 1990; Schmookler, 1966; Trajtenberg, 1990). In this study, we benefit from the fact that most jurisdictions require inventors to state their address when applying for a patent. Recent efforts to geo-locate these addresses allow us to assign patented inventions to NUTS-3 regions (the European equivalent to US counties).

Three issues regarding patent data deserve attention here. First, not all inventions are patented because, when it is easy to maintain secrecy, the innovator has an incentive to minimize knowledge leaks to competitors. Hence, patents represent a lower bound of innovation output. Second, patents do not provide information on inventive inputs. As such, we cannot disentangle labor supply (hours worked) from labor productivity (output conditional on hours worked). Third, we observe the timing of a patent filing, rather than when inventive activity occurred. We assume the bulk of inventive activity takes place during the calendar year preceding the patent filing. This lag is included to account for the fact that preparing and filing for a patent takes an estimated 6-12 months (Scherer, 1965).[7]

[7] We conducted an interview with a patent attorney to confirm this is a reasonable assumption. Also note that inventors are unlikely to postpone patent filing until much after the conclusion of the inventive activity. Indeed, inventors have a strong interest to file for a patent close to the invention date (Griliches, 1990). The requirements for an invention to qualify for a patent are novelty and non-obviousness. Any evidence that the invention was already known before and, thus, violating the novelty criterion is called prior art. Consequently, the closer the filing and invention date, the smaller the pool of potential prior art.

3.2.2 Instrumental variables

Estimating the causal effect of air pollution on innovation is challenging because of several unobserved confounders. For instance, technological opportunity or profits could affect innovation while co-varying with economic activity, the main driver of pollution. Omitting them would lead us to *underestimate* the damage done by air pollution. Reverse causality problems could further attenuate this bias. Albeit less obvious, air pollution might negatively affect innovation while inventive activity itself could contribute to air pollution. Such a mechanism would further understate the costs of low air quality. We address these endogeneity problems using two meteorological sources of variation.

Thermal inversions. Typically, temperature decreases with height in the lower part of the atmosphere (the troposphere). Less dense warm air moves upwards and dilutes pollutants vertically. Thermal inversions reverse this monotonic relationship. Warmer air at higher altitudes hamper vertical dilution and traps pollutants at ground level (see Figure C1 in the Appendix) (Vallero, 2014). Following Dechezleprêtre, Rivers and Stadler (2019) and Arceo, Hanna and Oliva (2016), we exploit this phenomenon to construct an instrumental variable for air pollution by calculating the annual share of days with a thermal inversion in a region.

Ventilation capability. Our second instrument measures variation in natural *ventilation* of pollutants. The atmospheric literature measures the dispersion speed of pollutants using the ventilation coefficient (VC), i.e. the product of wind speed and boundary layer height (Holzworth, 1967, 1972). Wind speed determines horizontal dispersion of pollutants whereas boundary layer[8] height determines the volume of air among which pollutants can disperse in the atmosphere. On days with a high ventilation coefficient, concentration of air pollutants is low because natural ventilation allows them to dilute quickly. Figure C2 in the Appendix provides a schematic representation of the ven-

[8]The planetary boundary layer is the lower part of the troposphere that experiences most turbulent air flow (which is crucial for diluting pollution) because of its interaction with the surface of the earth. The height of this layer varies based on the earth's topography as well as meteorological conditions.

tilation coefficient. To construct our instrument, we first calculate the daily ventilation coefficient for each region. We then obtain the annual average length of spells of consecutive days with a low ventilation coefficient – which we call *Ventilation Capability*. The logic behind this approach is that spells of consecutive days with limited natural ventilation – rather than the average number of days – drive pollution concentrations.[9]

Relevance assumption. Several atmospheric studies have documented a positive correlation between thermal inversions and air pollution (Gramsch et al., 2014; Xu et al., 2017). Similarly, the negative correlation between the ventilation coefficient and air pollution is well-established (Hou et al., 2018; Genc, Yesilyurt and Tuncel, 2010). Our descriptive findings (section 3.3.1) and first-stage results (section 3.4) show a strong correlation between both instrumental variables and air pollution, justifying the relevance assumption of our IV approach.

Exclusion restriction. Our instruments plausibly affect inventive output only through their effect on air pollution. They provide a source of exogenous variation because they result from large-scale atmospheric dynamics unrelated to human activity (Stull, 1988; Garratt, 1994). As argued in Dechezleprêtre, Rivers and Stadler (2019), the relevant literature provides no evidence of pollution causing thermal inversions rather than vice versa. None of the meteorological literature on the ventilation coefficient claims it is any way human-induced. In addition, our instruments pass the common test for over-identifying restrictions (Hansen, 1982). One potential concern might be that our instruments correlate to other weather conditions that affect innovation through for instance traffic conditions or the mood of inventors. To mitigate this concern, we control for average wind speed, precipitation, temperature, humidity and air pressure. Being exogenous themselves, they account for any

[9] To make this clear, consider two regions that are identical in terms of pollution generation, but face a different daily ventilation coefficient distribution. In one region, low ventilation coefficient days are followed by high ventilation coefficient days, while in the other region low ventilation coefficient days are concentrated in time. Any one day's pollution in the former region will affect humans living there for one day only before ventilation disperses it, while in the latter region one day's pollution will affect humans for multiple days in a row before being dispersed. As a result, the average air pollution in the latter region will be higher.

correlation between innovation and weather conditions.[10]

3.2.3 Econometric Model

Our first-stage regression estimates the impact of our two instruments on $PM_{2.5}$. Unlike actual $PM_{2.5}$ concentration, predicted $PM_{2.5}$ concentration levels are exogenous to innovation and can be used to estimate the causal impact of air pollution on innovation. The first-stage regression has following specification:

$$P_{it} = \alpha_1 TI_{it} + \alpha_2 VC_{it} + \alpha_3 Pop_{it} + \alpha_4 X_{it} + \omega_{ct} + \eta_i + \nu_{it} \tag{3.1}$$

P_{it} is the average population-weighted $PM_{2.5}$ concentration for region i in year t. Following Dechezleprêtre, Rivers and Stadler (2019), we weight $PM_{2.5}$ concentration for population density in order to measure individuals' exposure to air pollution, rather than air pollution itself. The first instrumental variable TI_{it} measures the annual share of days with thermal inversions in region i. The second instrumental variable VC_{it} measures the average length of consecutive days with a low ventilation coefficient in year t for region i. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients in region i. Pop_{it} is the total population for region i in year t.[11] X_{it} is a vector of weather covariates controlling for weather conditions on the ground in region i. It includes annual means for wind speed, temperature, surface pressure, relative humidity and total precipitation. This vector also includes the second-degree-polynomials of all weather variables to account for a more flexible functional form. ω_{ct} are country-year fixed effects and η_i are regional fixed effects. Last, ν_{it} is the error term (which we allow to be clustered at regional level) that captures all unobserved determinants of pollution.

The second-stage regression estimates the causal impact of $PM_{2.5}$ on inven-

[10] In fact, our results show that these weather conditions have a marginal, if any, effect on innovation output in our specification.

[11] We do not control for GDP because it directly affected by air pollution and may correlate to innovation. Therefore, GDP would introduce endogenous selection bias (Pearl, 2009).

tive output and has following specification:

$$Y_{it} = \beta_1 \widehat{P_{it}} + \beta_2 Pop_{it} + \beta_3 X_{it} + \lambda_{ct} + \alpha_i + \varepsilon_{it} \tag{3.2}$$

Y_{it} represents output from inventive activity in year t and is measured by the number of patent filings in the following year by inventors living in region i. $\widehat{P_{it}}$ is the predicted $PM_{2.5}$ concentration from the first-stage. λ_{ct} are country-year fixed effects that account for country-specific time-varying effects, for instance exposure to macroeconomic shocks or changes in national regulations. α_i are region-fixed effects that eliminate any time-invariant effects on pollution and innovation. As such, our specification relies on within-region year-to-year variation in pollution caused by the instruments. Last, v_{it} is the error term for the second stage (allowed to be clustered at regional level) and captures all unobserved determinants of innovation output.

3.3 Data & Measures

Patents. To measure inventive output, we rely on patent data from the EPO PATSTAT database (Spring 2018 edition). We link patent filings to NUTS-3 regions in Europe using the geolocation effort described in de Rassenfosse, Kozak and Seliger (2019). This method retrieves geographic coordinates from inventor addresses using online geolocation services. Because one invention is typically described in various patent documents at different times[12], one inventor may be linked to multiple addresses. The geolocation method assigns geographical coordinates to the inventor address that was disclosed at the earliest observed date. When tracking inventor migration, we use data that allows to trace inventor addresses over time (Morrison, Riccaboni and Pam-

[12]The patent application process typically takes several years. After filing, examiners produce an initial search report documenting the relevant prior art and assessing patent criteria such as novelty and inventive step. In response to this search report, applicants are often required to modify the patent patent application before it is granted. At each of these stages in the process, patent offices publish patent documents that we observe in the database. In addition, innovators seeking protection across different jurisdictions will file several patent applications at different patent offices. All the patent documents related to an invention are grouped into so-called patent families by the PATSTAT database.

molli, 2017). This method assigns a stable inventor identifier across multiple patent documents for patents filed at the European Patent Office (EPO), the World Intellectual Property Office (WIPO), and the US Patent and Trademark Office (USPTO). This dataset is appropriate to identify inventor relocation for two reasons. First, it allows to track individual inventors across patent applications by employing a name disambiguation algorithm. Second, it geolocates addresses from each publication associated to the patented innovation, rather than the priority filing only, as is done in de Rassenfosse, Kozak and Seliger (2019). These features allow us to more precisely detect inventor relocation events because there are more documents from which we can infer an inventor's address. We use the number of times a patent was cited to infer patent quality. This indicator is extracted from the PATSTAT database and counts the number of patented inventions that cite the focal invention.[13]

Scientific publications. To estimate the effect of air pollution on scientific output, we use data from the PubMed database maintained by the National Library of Medicine (NLM) at the National Institutes of Health (NIH). It contains a comprehensive account of scientific publications in biomedical and life sciences. To map publications to regions, we use geocodes from author affiliations listed on the publication (Torvik, 2015). Our measure counts the yearly number of first-author[14] publications in a region. To ensure that we include true scientific output, we only include publications from organizations that Torvik (2015) classifies as 'educational', 'hospital', 'educational-hospital' and 'organization'.

Pollution. We use gridded data on the annual average ground-level fine particulate matter ($PM_{2.5}$) concentrations from Hammer et al. (2020) and Van Donkelaar et al. (2019). These data contain estimated pollution concentrations at a fine spatial resolution of $0.01° \times 0.01°$ by combining Aerosol Optical Depth (AOD) retrievals from satellites with regional ground-level observations.

[13] It uses aforementioned patent family concept to identify an invention from the patent documents it is related to. This approach avoids double-counting of citation linkages between patent documents that represent the same invention.

[14] In the biomedical literature, ghost, gift or honor authorships are not an exception. Using first authors only mitigates this concern by picking up the main contributor to a project (Yang, Wolfram and Wang, 2017).

We combine pollution data with gridded data on the population of Europe from CIESIN (Columbia University, 2018) to obtain the population-weighted $PM_{2.5}$ concentration.[15]

Meteorological information. We obtain atmospheric data from the MERRA-2 dataset (Gelaro et al., 2017) to determine the presence of thermal inversions. This data set contains daily mean temperature and relative humidity for 42 different pressure levels at respective heights. This information allows us to calculate the temperature-height relationship that defines thermal inversions. Following Dechezleprêtre, Rivers and Stadler (2019), we identify the occurrence of a thermal inversion when the temperature is higher at the second-to-lowest level of the atmosphere than at the lowest level. To circumvent the problem that the spatial resolution ($0.5° \times 0.625°$) of these data is too coarse to cover smaller NUTS-3 regions, we interpolate these data to a finer resolution ($0.01° \times 0.01°$)[16]. The thermal inversions instrument is calculated as the annual share of days with a thermal inversion for each region.

Further atmospheric and climate data for the period 2001-2018 come from the family of ERA5 datasets provided by the European Centre for Medium-Range Weather Forecasts.[17] Specifically, we make use of the ERA5 data (Hersbach et al., 2020) and the ERA5-Land data (Muñoz-Sabater, 2019) to calculate the ventilation coefficient and additional weather control variables. We use ERA5 hourly data on the boundary layer height to calculate daily means for each NUTS-3 region.[18] We calculate daily means for temperature, wind speed, surface pressure and precipitation using ERA-5-Land hourly data.[19]. Ventilation Capability (VC) is calculated as the annual average number of consecutive

[15] Population estimates are available every 5 years starting in 2000 and ending in 2020. We always use the closest population estimated to calculate annual weighted $PM_{2.5}$ concentration in year t.

[16] For temperature we use a simple bi-linear interpolation technique because temperature varies between geographic locations rather continuously. As relative humidity is spatially discontinuous, we apply nearest-neighbor interpolation technique.

[17] An overview of all ERA5 datasets can be found on https://confluence.ecmwf.int/display/CKB/The+family+of+ERA5+datasets.

[18] Again, we use bi-linear interpolation to increase spatial resolution from $0.25° \times 0.25°$ to $0.05° \times 0.05°$

[19] These data are provided at a spatial resolution of $0.1° \times 0.1°$, which is sufficient to cover smaller NUTS-3 regions.

days in which the ventilation coefficient is equal or below the 20th percentile of the distribution of ventilation coefficients within a NUTS-3 region.[20]

Geographic indicators. We collect geographic indicators for NUTS-3 regions from Eurostat[21]. We use yearly data on population[22], regional classifications[23] and mortality[24].

3.3.1 Descriptive findings

We restrict the sample period to 2001-2012 to avoid truncation bias due to a drop-off in patent counts during recent years of the database. As a patent application only enters our data set at the time the first patent document is published, time series towards the end of the database show a negative trend. This does not necessarily reflect an actual drop in the number of patent application, but rather the lag by which patent applications are observed. To avoid truncation bias due the fact publication lags could correlate to unobserved determinants of innovation, we restrict our sample to the period 2001 until 2012, well before any truncation starts.

Figure C3 in the Appendix shows the annual average number of patent filings by inventors of a NUTS-3 region for the sample period.[25] Western Germany, southern-UK, northern-France and the Nordic countries have highest patent output, while Eastern European countries and Spain show lower patenting activity. The spatial distribution maps well to measures of R&D intensity and R&D growth reported in the Research and Innovation Performance report published by the European Commission (2020), lending support to our measure of patent filings as an indicator for inventive output.

Figure 3.1 (blue line) documents a decreasing trend in $PM_{2.5}$ concentration over time. On average, $PM_{2.5}$ concentration falls by $0.17 \mu g/m^3$ each year.

[20] We calculate the ventilation coefficient as the product of daily mean wind speed and daily mean boundary layer height.

[21] Eurostat databasse are accessable on https://ec.europa.eu/eurostat/data/database.

[22] We use the "demo_r_pjanaggr3" dataset.

[23] We use the classification of metropolitan regions which can be found on https://ec.europa.eu/eurostat/web/rural-development/background.

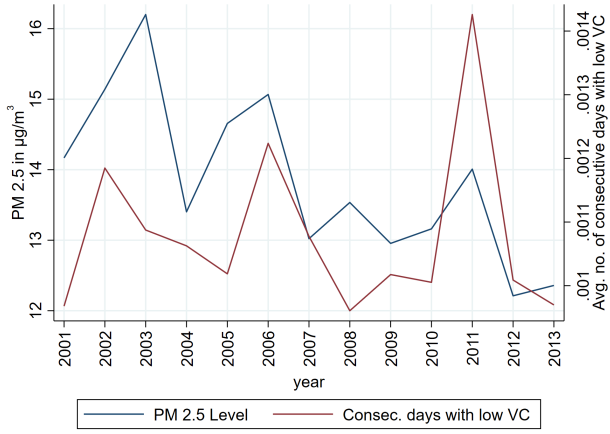
[24] We use the "demo_r_deaths" dataset.

[25] In case multiple regions are assigned to one patent because different inventors on the patent live in different regions, we assign the patents to both regions.

A similar trend appears for nearly all air pollutants in Europe (Koolen and Rothenberg, 2019), indicating a steady improvement of Europe's air quality. Nevertheless, $PM_{2.5}$ concentration varies across EU Member states. Figure C4 in the Appendix shows the annual average $PM_{2.5}$ concentration of NUTS-3 regions in the sample period. Eastern European regions, together with northern Italy, experience higher pollution levels than the rest of Europe. The spatial distribution in $PM_{2.5}$ concentration is in accordance to $PM_{2.5}$ measures from local stations published in the Air quality in Europe report by the European Environment Agency (2020). While informative to validate our measure, the region-fixed effects in our specification purge all cross-sectional variation in innovation and pollution.

Figure 3.1: Correlation between IV and $PM_{2.5}$

(a) Ventilation Capability and $PM_{2.5}$



(b) Thermal Inversions and $PM_{2.5}$

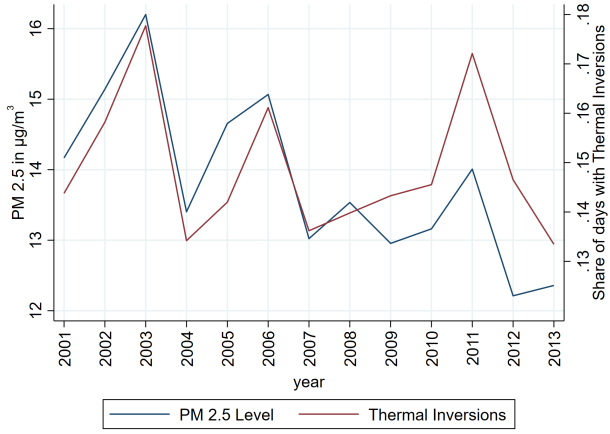


Figure 3.1 shows the yearly variation in $PM_{2.5}$ concentration and the two instrumental variables, thermal inversion and ventilation capability. Trend lines of the instrumental variables show a remarkably strong correlation to $PM_{2.5}$ concentration, providing non-parametric evidence for the strength of our instruments.

3.3.2 Summary statistics

Our sample includes observations for 1288 NUTS-3 regions within 30 countries for the period 2001 - 2012.[26] We trim our measure of $PM_{2.5}$ concentration at 1% at each side of the distribution to remove outliers indicating unrealistically high or low levels of pollution.[27] We drop NUTS-3 regions with only a limited number of patent filings.[28] We do this because we believe patent counts to be a poor indicator of inventive activity for regions with zero or only a handful of patents per year. Therefore, including these regions would plausibly introduce measurement error. Figure C5 in the Appendix shows NUTS-3 regions that are dropped from the baseline analyses, most of which are in the Balkan area. Our baseline result is robust to keeping these regions in the sample.

Table 3.1 shows summary statistics for the sample data. On average, we observe 109 patent filings per year within a NUTS-3 region. This distribution is left-skewed with a median of only 41 filed patents. Hence, we use the natural logarithm of the number of patents (plus one) in subsequent analyses. The annual average population-weighted $PM_{2.5}$ concentration per NUTS-3 region amounts to $13.62 \mu g/m^3$.

[26] The longest period spanned by our data set is 2001-2018, but we drop years after 2012 due to truncation in the data on patent filings (section 3.3.1).

[27] No outliers were detected for the other variables in our models.

[28] The baseline specification drops regions below the 5th percentile in terms of total number of patent filings. Keeping these regions in only slightly decreases the coefficients of interest. Increasing the threshold to the 10th or 15th percentile increases the coefficients, possibly due the fact that innovation intensity correlates to pollution levels.

Table 3.1: Summary statistics

	N	Mean	Std. Dev.	10th	50th	90th
Nb. patent filings	15540	109.68	224.96	3	41	261
Nb. 5-year fw. cites	15540	183.93	397.88	2	58	448
Nb. fw. cites normalized	15540	39.81	80.63	0.45	13.79	97.60
Population (*in thd*)	13706	384.39	436.57	94.33	269.63	734.27
Pop-weighted PM 2.5	15218	13.75	4.83	8.41	12.99	20.61
Nb. thermal inversions	15300	54.88	32.83	13	52	101
Share thermal inversions	15300	0.15	0.09	0.04	0.14	0.28
Ventilation Coefficient (m^2/s)	15156	1649.30	803.33	598	1620	2662
Avg consecutive days with low VC	15156	0.00	0.0003	0.0008	0.0010	0.0015
Surface pressure (Pa)	15156	97979.40	3463.07	93817	98981	101093
Relative humidty (%)	15300	0.74	0.06	0.64	0.74	0.81
Temperature (K)	15156	283.05	2.66	280	283	286
Wind speed (m/s)	15156	2.49	0.94	1.23	2.47	3.62
Precipitation (m)	15156	0.13	0.04	0.09	0.12	0.18
N	15540					

Summary statistics of 1288 NUTS-regions for 30 countries observed over the period 2001 - 2012. Our data includes all EU member states (+ United Kingdom) and EFTA countries. Iceland and Cyprus are not included because both countries are outside the geographical boundaries of our dataset.

3.4 Main Results

3.4.1 Baseline

Table 3.2 presents the baseline results. The instrumental variables strongly predict air pollution. In line with our expectations, both instruments cause an increase in $PM_{2.5}$ concentration. Reassuringly, including both instruments together barely changes their coefficients. Table C1 in the Appendix shows summary statistics of the predicted $PM_{2.5}$ concentrations resulting from our 1st-stage regressions. It examines variation in predicted $PM_{2.5}$ values induced only by the instruments[29]. The last row shows that the standard deviation of fitted $PM_{2.5}$ concentrations is $0.39 \mu g/m^3$ in our preferred specification (third regression in table 3.2). It ranges between $12.83 \mu g/m^3$ and $15.52 \mu g/m^3$. Figure 3.2 plots the standard deviation of these fitted $PM_{2.5}$ concentrations across NUTS-3 regions. Nearly all NUTS-3 regions show similarly strong instrument-induced variation.

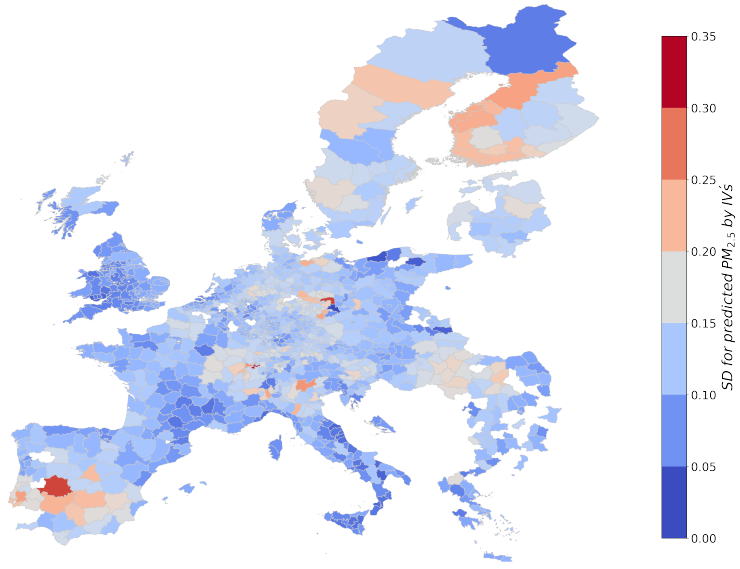
[29] We fix control variables at their mean

Table 3.2: $PM_{2.5}$ on the number of patent applications

	OLS	IV with TI		IV with VC		IV with TI & VC	
Dep. Variable:	Log(Patents)	Log(Patents)	*PM*2.5	Log(Patents)	*PM*2.5	Log(Patents)	*PM*2.5
*PM*2.5	-0.0053	-0.092*		-0.11**		-0.10***	
	(0.0037)	(0.047)		(0.050)		(0.036)	
Share Inversions			3.72***				3.66***
			(0.52)				(0.51)
Share low VC					260.4***		255.6***
					(39.3)		(39.5)
NUTS-3 FE	YES	YES		YES		YES	
Country-Year FE	YES	YES		YES		YES	
Controls	YES	YES		YES		YES	
KP F-stat.		52.1		43.9		44.9	
Hansen J stat. P-Val						0.78	
N	12924	12924	12924	12924	12924	12924	12924

This table presents the results of regressing $PM_{2.5}$ concentration on the annual number of patent applications per NUTS-3 region. The first column shows the results for the OLS regression without using IVs. The second and third column show the second- and first-stage results by using thermal inversions as IV. The fourth and fifth column show the second- and first-stage results by using ventilation capability as IV. The last two columns show the second- and first-stage results by using both IV's. *Share of Inversions* measures the number of days in which thermal inversions occur normalized by the total number of days per year. *Share of low VC* measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the 20*th* percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3.2: Variation in predicted $PM_{2.5}$ concentration by NUTS-3 region



The first column of Table 3.2 shows OLS estimates of a model identical to equation 3.2 where we replace fitted pollution levels to observed ones. The next four columns show the second- and first-stage results by instrumenting $PM_{2.5}$ concentration with thermal inversions or ventilation capability respectively. Finally, the last two columns show the second- and first-stage results by instrumenting $PM_{2.5}$ concentration with both instrumental variables. In line with expectations, OLS estimates are smaller than estimates obtained with the IV regressions, suggesting that omitted variables and reverse causality lead to underestimation of the harmful effects of air pollution (section 3.2). Both instrumental variables lead to similar results (second and fourth column). In our preferred specification (second to last column), an increase in the $PM_{2.5}$ concentration with $1\mu g/m^2$ causes a reduction in the number of patent filings per NUTS-3 region of 10%. This implies an elasticity at the sample mean of 1.36. Our reference increase corresponding to the year-to-year average decrease in pollution in Europe of $0.17\mu g/m^2$ (see section 3.3.1) lies within the variation induced by our instruments mentioned above, and has caused a 1.7% change in inventive output.

The common IV regression test statistics confirm the validity of the assumptions underlying our analyses. First, the Kleibergen-Paap F statistics are high for all IV regressions and above critical values for weak instruments formulated in Stock and Yogo (2002).[30] Second, with a p-value of above 5%, the Hansen test supports the exogeneity assumption of our instruments.

3.4.2 Count Model

In a first robustness check, we apply a count data model rather than a linear model to our data. As the number of patent applications only has non-negative values and its distribution has a relatively large mass on low values, count models could improve the specification of the error term distribution. Count data models with multiple fixed effects that also correct for endogenous regressors have been only recently established (Lin and Wooldridge, 2019). Specifically, we use a poisson fixed-effects model which is robust for under- and overdisper-

[30] F-statistics for the three IV-regressions are all above the 10% Stock and Yogo (2002) critical values.

sion (Wooldridge, 1999). Hence, we assume that the annual number of patent applications per NUTS-3 region follows a poisson distribution. Furthermore, we use a control function approach to account for endogeneity of the $PM_{2.5}$ concentration in the non-linear fixed-effects model.[31] The control function approach predicts residuals from the first-stage regression. Next, predicted residuals together with endogenous $PM_{2.5}$ levels can be consistently estimated in the poisson-fixed-effects regression. This follows the idea that predicted residuals from the first-stage regression will control for endogeneity.[32] The first-stage regression used to predict residuals are identical to equation 3.1. Resulting poisson fixed-effects regression can be written as:

$$Y_{it} = \xi_1 P_{it} + \xi_2 \widehat{v_{it}} + \xi_3 Pop_{it} + \xi_4 X_{it} + \lambda_{ct} + \alpha_i + \varepsilon_{it} \tag{3.3}$$

P_{it} is the actual $PM_{2.5}$ concentration in year t in NUTS-3 region i. $\widehat{v_{it}}$ are predicted residuals obtained from the first-stage regression and account for the endogeneity of P_{it}. Other specifications are identical to equation 3.2 with the important difference that they allow the outcome measure to follow a poisson distribution.

Table C2 in the Appendix shows the results for the poisson fixed-effects regressions for a sample including all NUTS-3 regions. The first column shows results without control function approach. The second column shows results for the control function approach by simply adding the first-stage residuals (equation 3.1) to the poisson fixed-effects regression. We use 500 bootstrap replications to obtain the standard errors, where we re-sample NUTS-3 regions. The coefficient of the $PM_{2.5}$ variable is −0.07, indicating that an increase in the $PM_{2.5}$ concentration by $1 \mu g/m^2$ causes the number of patent filings to drop by 7%. This effect is only slightly smaller than that obtained with the linear

[31] This is important since the regular two-stage least squares estimator might not be consistent in combination with a non-linear second-stage regression.

[32] A simple endogenous model can be written as $y_1 = \beta_1 y_2 + \beta_3 z_1 + u_1$ where y_2 is the endogenous explanatory variable and z_1 a vector of exogenous regressors. The linear projection of y_2 on the exogenous regessors is $y_2 = \alpha_1 z_1 + v_2$ and can be the first-stage in a 2SLS approach. Endogeneity of y_2 arises only if u_1 is correlated with v_2 which can be formalized as $u_1 = \rho_1 v_2 + e_1$. Hence, predicting residuals from first stage $v_2 = y_2 - \alpha_1 z_2$ and plugging them in the first stage $y_1 = \beta_3 z_1 + \beta_1 y_2 + \rho_1 \hat{v}_2 + error$ controls for endogeneity.

regression model. This result leads us to conclude that our results are robust for using a count model specification.

3.4.3 Accounting for spatial and serial correlation

Tobler (1970) formulates the first law of geography as: "Everything is related to everything else, but near things are more related than distant things". Applied to our setting this means that observations for one NUTS-3 region are possibly statistically related to observations from neighboring NUTS-3 regions, raising concerns about spatial autocorrelation. In addition, pollution, weather, and economic data are likely to be correlated over time. To address these concerns, we estimate models that allow standard errors to be spatially and serially correlated (Conley, 1999, 2010). Conley's procedure requires a cutoff for spatial and serial correlation. We estimate two models with different assumptions on the cutoff points allowing for more robust inference.

Appendix Table C3 column 1 shows baseline results with SEs clustered at NUTS-3 level. Column 2 shows results with Conley's SEs assuming a spatial correlation range of 500 kilometers[33] and a serial correlation range of 5 years. Similarly, column 2 shows results with Conley's SE assuming a spatial correlation range of 1000 kilometers and a serial correlation range of 10 years. Standard errors are slightly larger than baseline results when accounting for spatial and serial correlation but results remain significant when accounting for these different degrees of spatial and serial correlation.

3.4.4 Further robustness checks

We conduct several robustness tests to further examine the validity of our results. First, we alter the threshold for the definition of a low ventilation coefficient used to calculate the ventilation capability. Specifically, we define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $10th$, $15th$, $20th$ and $25th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Table C4 in the Appendix shows results for the different ventilation capability measures. Overall,

[33] Distances between NUTS-3 regions are determined by their center points.

results are robust for altering the threshold for a low ventilation coefficient.

Second, we decrease and increase the threshold for excluding NUTS-3 regions with a low number of patent filings (Table C5 in the Appendix). Specifically, we estimate results without dropping any NUTS-3 region and dropping NUTS-3 regions equal or below the $5th$, $10th$ and $15th$ percentile of the distribution for total number of patent filings. Results are robust for excluding NUTS-3 regions based on different thresholds of a low number of patent filings.

Third, we alter the sample period by excluding more recent years. Table C6 in the Appendix presents the results for the different sample periods. Results are robust for restricting the sample period up to the interval 2001-2008.

Fourth, we verify whether the main results are robust for excluding weather covariates. Table C8 in the Appendix shows results for the IV-regression on individual weather covariates. Overall, results are similar regardless of whether we include weather controls or not.

Fifth, table C7 in the Appendix presents results for regressing weather controls on the annual number of patent filings per NUTS-3 region. None of the weather control variables are significantly correlated with the number of patent filings. This suggests that weather does not impact inventive activity in our specification. Hence, the two weather phenomena which we use as instrumental variables are unlikely to impact the inventive activity other than through an increase in air pollution.

Figure C6 presents the coefficient plots for all robustness checks. Estimates are similar across the different empirical specifications confirming the validity of our results.

3.4.5 Heterogeneity Regions

The effects of additional air pollution are not necessarily the same for all regions. Understanding this potential heterogeneity across regions can help informing policy makers about where abatement efforts are best targeted. We first examine effect heterogeneity between high- and low-pollution NUTS-3 regions in order to examine non-linearity of the effects of air pollution – i.e.

whether an increase in air pollution is more harmful to innovation where levels of air pollution are higher. To this end, we split our sample based on the median of region-level mean $PM_{2.5}$ concentration. The first, respectively last, two columns of Table 3.3 show the results of the second- and first-stage regressions for the sub-sample of regions with low, respectively, high levels of pollution. In less polluted regions, the coefficient of interest is small and insignificant. In contrast, negative effects of $PM_{2.5}$ concentration on the number of patent filings are large and highly significant for more polluted regions. For these regions, a $1\mu g/m^2$ increase in the $PM_{2.5}$ concentration reduces the annual number of patent filings by 15%. This finding suggests that harmful effects of pollution are concentrated in regions with relatively high levels of pollution.

Table 3.3: Split sample based on regions median $PM_{2.5}$ concentration

	Low PM 2.5 below Median		High PM 2.5 above Median	
Dep. Variable:	Log(Patents)	$PM2.5$	Log(Patents)	$PM2.5$
$PM2.5$	-0.049		-0.15**	
	(0.049)		(0.067)	
Share Inversions		3.17***		3.89***
		(0.52)		(0.94)
Share low VC		225.7***		210.0***
		(44.9)		(63.4)
Mean # Patents	89.19		130.81	
Mean PM 2.5	10.49		17.05	
NUTS-3 FE	YES		YES	
Country-Year FE	YES		YES	
KP F-stat.	32.1		14.0	
Hansen J stat. P-Val	0.59		0.94	
N	6605	6605	6307	6307

This table presents the results for the split sample into high- and low-polluted NUTS-3 regions. The first two columns show the second- and first-stage results for the sub-sample of low polluted NUTS-3 regions with a mean $PM_{2.5}$ concentration below the median of all regions. The last two columns show the second- and first-stage results for the sub-sample of high polluted NUTS-3 regions with a mean $PM_{2.5}$ concentration above the median of all regions. *Share of Inversions* measures the number of days in which thermal inversions occur normalized by the total number of days per year. *Share of low VC* measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we investigate whether observed negative effects vary with the level of urbanization in a region. This is relevant to policy because effectiveness and costs of abatement programs may vary by level of urbanization. For instance, stimulating electrical driving is more likely to reduce pollution in urban areas, whereas limiting industry emissions might affect less urbanized areas. To understand how the effects of air pollution vary by level of urbanization, we split the sample into regions that are (1) predominantly rural, (2) intermediate and (3) predominantly urban – based on Eurostat's 'Rural Development' indicators[34].

Table 3.4 shows the results for this split sample. The three pairs of columns

[34]For more information, refer to https://ec.europa.eu/eurostat/web/rural-development/methodology.

show the results of the second- and first-stage regressions for the sub-sample of predominantly rural, intermediate and predominantly urban NUTS-3 regions respectively. We do not find a significant effect of air pollution on innovation in predominantly rural areas. Interestingly, negative effects of $PM_{2.5}$ concentration on innovation are strongest for intermediate NUTS-3 regions with an elasticity of 2.36 at the mean $PM_{2.5}$ concentration. In the sub-sample of urban NUTS-3 regions the marginal effects of air pollution are in line with those in the overall sample, with an elasticity at the mean of 1.29. Importantly, urban and intermediate NUTS-3 regions show similar $PM_{2.5}$ levels (see Figure C7 in the Appendix). Hence, the heterogeneity by pollution level is unlikely to explain the difference in these estimates. While the marginal effects starkly differ between urban and intermediate regions, this does not translate in important differences in absolute terms. Because of a higher innovation-intensity in urban regions, a 1% increase in the $PM_{2.5}$ level causes a reduction in the absolute number of patent filings similar to that of intermediate regions (4.8 for urban versus 4.1 for intermediate). A potential explanation for the observed difference in the elasticities might be differences in socio-demographic characteristics of the population in urban and intermediate areas. For instance, people living in urban areas are more highly educated, have higher incomes and are younger (Eurostat, 2017). These factors may affect how prone individuals are to the negative health effects, but also the quality of healthcare they receive. The fact that rural areas are barely affected might be due to lower levels of inventive activity (making it unlikely that patents pick up a lot of variation) or the lower overall levels of pollution in such regions.

Table 3.4: Split sample based on Urban-Rural classification

	Predominantly Urban		Intermediate		Predominantly Rural	
Dep. Variable:	Log(Patents)	$PM2.5$	Log(Patents)	$PM2.5$	Log(Patents)	$PM2.5$
$PM2.5$	-0.092**		-0.17***		-0.0033	
	(0.043)		(0.062)		(0.094)	
Share Inversions		5.43***		2.66***		3.91***
		(1.08)		(0.80)		(0.76)
Share low VC		303.7***		238.2***		148.7**
		(83.3)		(57.4)		(67.9)
Mean # Patents	208.26		96.59		40.84	
Mean PM 2.5	14.14		14.15		13.06	
NUTS-3 FE	YES		YES		YES	
Year FE	YES		YES		YES	
KP F-stat.	18.9		13.7		16.2	
Hansen J stat. P-Val	0.60		0.56		0.25	
N	3370	3370	5746	5746	3704	3704

This table presents the results for the split sample into predominantly rural, intermediate and predominantly urban areas. The first two columns show the second- and first-stage results for the sub-sample of NUTS-3 regions classified as predominantly urban areas. The third and fourth column show the second- and first-stage results for the sub-sample of NUTS-3 regions classified as intermediate areas. The last two columns show the second- and first-stage results for the sub-sample of NUTS-3 regions classified as rural areas. *Share of Inversions* measures the number of days in which thermal inversions occur normalized by the total number of days per year. *Share of low VC* measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5 Mechanisms

In order to aggregate our region-level estimates to economy-wide costs that are not captured in previous estimates, we rule out a number of mechanisms that prohibit us from doing so. First, we examine the extent to which inventor mobility between regions can explain the results. This is important to reliably aggregate our estimates across regions. Indeed, if air pollution causes inventors to relocate to other regions, at least a portion of the human capital loss in one region is recovered by human capital gain in another one. If this mechanism is important, aggregating our estimates would lead to an overestimation of the economic costs induced by innovation.

Second, we investigate to which extent shocks to R&D funding – a crucial

input to the invention process – drive our results. While this mechanism does not preclude us from aggregating the effects across regions, it affects our claim that effects on inventive output are not captured in estimates of the effect of air pollution on short-term economic activity (Dechezleprêtre, Rivers and Stadler, 2019). Indeed, reductions in R&D spending are likely to show up in measures of GDP. We do not observe R&D expenditures for enough firms and regions to directly test this mechanism. However, we provide two pieces of evidence that suggest this mechanism does not explain our results. First, we examine the effect of air pollution on scientific output as measured by PubMed articles produced in a region. We view this as an adequate test because funding cycles in science are too long to immediately respond to air pollution. As such, finding that the effects on science are similar suggests that shocks to funding of R&D are unlikely to explain a large portion of our effect. Second, we study the effect of air pollution on quality-weighted patent counts. If shocks to R&D funding are important in explaining our effect, we would expect that the average quality of inventions increases in response to variation in air pollution. Indeed, if air pollution affects R&D budgets (for instance, because air pollution may increase the expectation of costly regulation), this should reflect either in less R&D projects being started up or in existing R&D projects to be discontinued. Given that a reduction in new projects is not likely to show up in our results because the duration of inventive process, R&D budgets should mainly affect ongoing projects in our setting. If managers face budget constraints, it is likely that they discontinue less promising projects first. This would lead to an increase in average quality of the observed patented inventions.

Finally, we examine effects of air pollution on total mortality in our sample. Such increases in mortality would be picked up by previous estimates of the economic costs of air pollution as assessed by losses in productive life years (Landrigan et al., 2018). Finding that these losses are minimal in our specification, reassures us that the effects we find on inventive output are not captured in the mortality-based assessments.

3.5.1 Inventor Mobility

To identify relocation events and their timing, we chronologically order all inventors' addresses stated on their patents and mark switches between NUTS-3 regions. The relocation year of an inventor can be easily determined when such a switch happens within the same year or within two consecutive years. In this case we assume the relocation year corresponds to the year preceding the filing date of the latest patent stating the inventor's new address.[35] When a switch co-occurs with a gap in time of multiple years, we use the median as relocation year.[36] To exclude unreasonable movement patterns, we conduct the data-cleaning process proposed by Zacchia (2018) (see Appendix C.1). Using these relocation events, we construct our measure of inventor relocation by counting the yearly number of inventor movements out of and into NUTS-3 regions for the sample period 2001-2012. To verify whether the decisions made in terms of selecting the relocation event year drive the results, we re-estimate our regressions using a sample with only relocation events that can be precisely determined. To account for the fact that relocation of more prolific inventors have a relatively large impact on a region's innovation output, we construct an additional measure in which we weight each relocation event by the number of patents respective inventors filed within five years before the relocation year.

It is important to mention that we are only able to observe migration of inventors that file patents before and after a relocation event. Migration before the first filed patent and after the last patent filing as well as multiple moves between two filings cannot be traced. As such, we have data for a sub-sample of relocating inventors. This raises the concern of selection bias because more prolific inventors may be more likely to be (able to afford) moving in response to pollution. While we cannot fully address this issue, the potential bias induced would be conservative because it would lead us to overestimate the number of moves in response to air pollution.

[35] We take the preceding year to account for the 6-12 months lag between invention and patent application.

[36] Decimal numbers are rounded up assuming the relocation year is closer to the patent filed under the new address.

Overall 1,295,300 inventors who filed patents between 1944 and 2013 state addresses in NUTS-3 regions. Only 5.38% of those inventors file patents in two different regions, suggesting that relocation is a rare event. Figure C8 in the Appendix shows relocation events of inventors between NUTS-3 regions for the sample period 2001-2012. Similarly, figure C9 in the Appendix shows relocation events of inventors between NUTS-3 regions and regions outside Europe. Unsurprisingly, most relocation events occur for regions with a high number of patent filings and R&D investments (section 3.3.1) that are plausibly attractive to inventors.

We apply the regression model described in section 3.2.3 to estimate the impact of air pollution on the annual number of inventor relocations. Table 3.5 shows the results for out-migrating inventors. The first column shows results for the OLS estimation by simply regressing the total number of moves away from a region by inventors on $PM_{2.5}$ concentration without using instrumental variables. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. The fourth column shows OLS results for the patent-weighted measure of the number of in-migrating inventors. The last two columns show results for the same outcome variable when instrumenting for $PM_{2.5}$ concentration. OLS estimates are negative and significant indicating that increased $PM_{2.5}$ concentration reduces the likelihood of inventors migrating out of NUTS-3 regions. However, these results are likely to be driven by unobserved factors driving both pollution and migration, i.e. more innovative regions attract more inventors but are also more polluted. The IV regressions do not show statistically or economically significant results. To verify that the estimated coefficients cannot explain our baseline results, consider the upper bound of the 95% confidence interval around the coefficient – 0.12. Taking this as the true effect would imply that inventor migration in response to a $1\mu g/m^2$ increase in $PM_{2.5}$ would increase with 12%. Seeing that the baseline migration rate is about 2 inventors per year, this implies an outflow of inventors with about one fifth of an inventor. With about 0.8 patents per year per migrating inventor, this results in a reduction of 0.16 patents due to migration. The same increase in air pollution reduces the average number of patents in a region by about

11. As such, it becomes clear that, even for this very conservative calculation, migration could only marginally account for our baseline result. Furthermore, Table C10 in the Appendix presents the same regressions for the restricted sample of relocation events where the relocation year is well defined. Again, IV estimates show small but insignificant coefficients. In conclusion, we do not find evidence that air pollution causes inventors to migrate. Tables C11 and C12 in the Appnedix show the results for in-migrating inventors and have the same structure as the tables for out-migrating inventors. Again, IV results for the total number and the weighted number of in-migrating inventors show small and insignificant coefficients. Again, results are robust to the restricted sample of relocation events where relocation year is well defined.

Table 3.5: Migrating inventors and air pollution

	OLS	IV		OLS	IV	
Dep. Variable:	Log(Migr. Inv.)	Log(Migr. Inv.)	*PM*2.5	Log(Migr. Inv. Patents)	Log(Migr. Inv. Patents)	*PM*2.5
*PM*2.5	-0.011***	0.031		-0.017**	0.027	
	(0.0039)	(0.046)		(0.0069)	(0.084)	
Share Inversions			3.78***			3.78***
			(0.50)			(0.50)
Share low VC			227.2***			227.2***
			(40.3)			(40.3)
NUTS-3 FE	YES	YES		YES	YES	
Country-Year FE	YES	YES		YES	YES	
Controls	YES	YES		YES	YES	
KP F-stat.		42.5			42.5	
Hansen J stat. P-Val		0.25			0.27	
N	13671	13671	13671	13671	13671	13671

This table presents the results of regressing $PM_{2.5}$ concentration on the total number ($Log(Migr.Inv.)$) and patent weighted number of migrating inventors ($Log(Migr.Inv.Patents)$) out of NUTS-3 regions. $Log(Migr.Inv.Patents)$ weights the number of migrating inventors by the number of patents inventors filed within 5 year before the relocation. The first column shows results for the OLS estimation by simply regressing the total number of migrating inventors on $PM_{2.5}$ concentration. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. The fourth column shows the OLS results for the patent weighted measure of the number of migrating inventors. The last two columns show results for same outcome variable by instrumenting $PM_{2.5}$ concentration. $Share of Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share of low VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Taken together, we do not find evidence that negative effects of air pollution on innovation pick up inventor migration patterns between regions. These patterns are consistent with the idea that variation in air pollution induced by atmospheric conditions are too idiosyncratic and small to cause inventors to move into or out of a region because of them. In addition, it might be the case that air pollution affects migration of inventors, but rather within the

narrow scope of a NUTS-3 region. Especially since migration costs increase with distance and inventors might have a strong interest to preserve local ties.

3.5.2 R&D expenditures

Scientific output. Table 3.6 shows the results of estimating the effect of $PM_{2.5}$ concentration on the annual number of published journal articles listed in PubMed. In line with the baseline result, the OLS estimate (Column 1) is smaller than the estimate obtained by the IV regression. Coefficients from the IV regressions are statistically significant and imply that an increase in the $PM_{2.5}$ concentration with $1 \mu g/m^2$ causes a reduction in the number of published journal articles per NUTS-3 region of 9%. This negative effect is very similar to negative effects of $PM_{2.5}$ concentration on the number of patent applications. Hence, air pollution affects scientific output about as strongly as inventive output.

Table 3.6: PubMed publications and air pollution

	OLS	IV	
Dep. Variable:	Log(PubMed)	Log(PubMed)	PM2.5
$PM2.5$	-0.0023	-0.086**	
	(0.0041)	(0.042)	
Share Inversions			3.78***
			(0.50)
Share low VC			227.2***
			(40.3)
NUTS-3 FE	YES	YES	
Country-Year FE	YES	YES	
Controls	YES	YES	
KP F-stat.		42.5	
Hansen J stat. P-Val		0.26	
N	13671	13671	13671

This table presents the results of regressing $PM_{2.5}$ concentration on the number of journal articles listed in PubMed ($Log(PubMed)$). The first column shows results for the OLS estimation without using IVs. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. $Share of Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share of low VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Patent quality. To investigate whether air pollution affects the quality of observed inventions, we re-estimate our baseline specification after weighting patent counts for the total number of forward citations patents receive, a common proxy for the quality or technological importance of patents (Trajtenberg, 1990; Hall, Jaffe and Trajtenberg, 2001). We use two different measures for the number of forward citations. First, we count the number of forward citations patents received within a 5-year window. Second, we normalize the total number of forward citations by the average number of citations patents receive with the same filing year and technical field. For both measures we aggregate

the number of forward citations for all patents filed within a NUTS-3 region. The first two columns of Table 3.7 show the second- and first-stage regression results for the 5-year window forward citations measure. The last two columns show the results when using the normalized forward citations measure. Weighting for patent quality makes the negative effect of air pollution slightly stronger, but the coefficient is within the error of margin of our baseline specification. An increase in the $PM_{2.5}$ concentration by $1 \mu g/m^2$ causes patent counts normalized the number of forward citations to drop by 13%, as compared to our baseline estimate of 10% (see section 3.4). Unreported regressions that use the average number of forward citations as an outcome measures show no statistically significant effect of air pollution. In sum, we find no clear evidence that the quality of inventive projects increases upon increased pollution exposure.

Table 3.7: Patent citations and air pollution

	5-year fw. cites		Fw. cites normalized	
Dep. Variable:	Log(Patents)	$PM2.5$	Log(Patents)	$PM2.5$
$PM2.5$	-0.12*		-0.13***	
	(0.062)		(0.042)	
Share Inversions		3.66***		3.66***
		(0.51)		(0.51)
Share low VC		255.6***		255.6***
		(39.5)		(39.5)
NUTS-3 FE	YES		YES	
Country-Year FE	YES		YES	
Controls	YES		YES	
KP F-stat.	44.9		44.9	
Hansen J stat. P-Val	0.77		0.87	
N	12924	12924	12924	12924

This table presents the results of regressing $PM_{2.5}$ concentration on the total number of forward citation for patents filed within a NUTS-3 region. The first two columns show the the second- and first-stage results by measuring forward citations patents received within a 5-year window. The last two columns show the the second- and first-stage results by measuring the total number of forward citations normalized by the number of citations patents received with the same filing year and technical field. *Share of Inversions* measures the number of days in which thermal inversions occur normalized by the total number of days per year. *Share of low VC* measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.5.3 Mortality

Last, we investigate whether the reduction in inventive output can be explained by an increase in mortality induced by air pollution. For this purpose, we apply the regression model described in section 3.2.3 and estimate immediate effects of air pollution on the annual number of deaths and annual death rate per NUTS-3 region. As we do not have reliable estimates of the number of inventor deaths, we conduct this analysis using total deaths per NUTS-3 region obtained from Eurostat. Prior research shows that inventors have high incomes, higher education and high-income parental backgrounds (Bell et al., 2019; Aghion et al., 2017). These socioeconomic factors are negatively corre-

lated with mortality (Torssander and Erikson, 2009). As such, the death rate of the entire population is likely to be higher than the death rate of inventors. Therefore, using the total death rate is likely to overstate the importance of mortality in reducing innovation labor supply.

Table 3.8 presents results for the impact of $PM_{2.5}$ concentration on the natural logarithm of total number of deaths per NUTS-3 region. OLS estimates show negative and significant coefficients indicating positive effects of air pollution on mortality. However, these estimates are likely to be the results of unobserved factors driving both pollution and mortality, i.e. more innovative regions have higher economic activity and wealth, which likely reduce mortality. Instead, both IV regressions for the total number of deaths and the death rate show small and insignificant coefficients. We do not find evidence that baseline results on the reduction in innovation caused by pollution can be explained by increased mortality. Plausibly, the variation in air pollution induced by the instrumental variables is too small to considerably increase mortality.

Table 3.8: Total deaths and air pollution

	OLS	IV		OLS	IV	
Dep. Variable:	Log(Deaths)	Log(Deaths)	PM2.5	Death Rate	Death Rate	PM2.5
*PM*2.5	-0.0011***	0.0027		-0.0012***	0.0028	
	(0.00036)	(0.0038)		(0.00038)	(0.0040)	
Share Inversions			3.43***			3.43***
			(0.50)			(0.50)
Share low VC			241.0***			241.0***
			(40.7)			(40.7)
NUTS-3 FE	YES	YES		YES	YES	
Country-Year FE	YES	YES		YES	YES	
Controls	YES	YES		YES	YES	
KP F-stat.		38.6			38.6	
Hansen J stat. P-Val		0.24			0.30	
N	13230	13230	13230	13230	13230	13230

This table presents the results of regressing $PM_{2.5}$ concentration on the total number of death ($Log(Deaths)$) and the death rate ($Death\,Rate$)) per NUTS-3 region. Death rate does not include population as control. The first and fourth columns show results for the OLS estimation without using IVs. The second and third (fifth and sixth) columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. $Share\,of\,Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share\,of\,low\,VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.6 Discussion

Recent estimates of the effect of air pollution on economic activity suggest that pollution abatement can considerably contribute to growth. This study underscores that reducing air pollution could be even more beneficial than implied by these estimates because it may positively affect innovation. To examine the importance of this channel, we estimate the causal effect of air pollution on innovation using two weather phenomena as sources of exogenous variation.

We find a large negative effect of air pollution on innovation. The estimates suggest that a decrease in pollution of $0.17 \mu g/m^3$ – the yearly average decrease in Europe – on average leads to 1.7% more patented innovations. At the mean pollution level, this implies an elasticity of 1.36. We find no evidence for a concurrent decline in average patent quality, so we can interpret our coefficients as effects on total innovative output. We also find that the negative effect of air pollution is concentrated in regions that are more polluted, suggesting that there is a non-linear relationship between pollution levels and innovation. In NUTS-3 regions above and below the median pollution level, respectively, the elasticities are 2.51 and 0.58. The elasticity for predominantly urban areas is 1.29 and that of areas with intermediate levels of urbanization is 2.36, while both types have similar pollution levels. In absolute levels, however, this difference amounts to about the same number of additional patents (4.8 for the average urban region, 4.1 for the average intermediate region) because urban areas have higher innovation intensity. In addition, we do not find evidence that inventor migration patterns may explain our results. As such, the negative effects of pollution on innovation in one region are unlikely to be made up for by more innovation in a different region through movement of human capital. Given the absence of such spillover effects, we believe that our results can be aggregated to the national and international level. Finally, we find suggestive evidence that shocks to R&D budgets or increased mortality induced by air pollution are unlikely to explain the results. This suggests that the economic costs implied by reduced innovation output are not captured in previous assessments based on reduced human capital and short-term economic output

(Landrigan et al., 2018; Dechezleprêtre, Rivers and Stadler, 2019).

Our study contributes to previous work on the economic effects of air pollution by highlighting an additional channel through which pollution may harm economic activity. Endogenous growth theory has put innovation at the center stage in explaining economic progress (Romer, 1990; Aghion and Howitt, 1990). As innovation is unlikely to translate into firms' short-term productivity increases through improved processes or product quality within (maximum) one year, the observed effect on innovation is largely overlooked by previous assessments. As such, our findings highlight an additional channel through which pollution abatement creates economic value.

However, translating these findings into exact estimates of economic value is a non-obvious exercise. Next to increased profits by firms, innovations create several types of spillovers (Hall, Mairesse and Mohnen, 2010; Jones and Summers, 2020). On the one hand, estimating the contribution of innovation to firms' profits is hard because it is hard to disentangle how much each innovation contributes to lower costs or higher prices. On the other hand, taking into account a host of indirect effects of innovations on welfare is extremely challenging. That being said, the overarching consensus is that the value created by innovation is large, and that the portion of this value captured by the innovator is small (Nordhaus, 2004; Hall, Jaffe and Trajtenberg, 2005; Kogan et al., 2017; Jones and Summers, 2020). One approach to estimate the total economic value implied by our estimates is to combine inventors' estimates of the private value of their (European) patents (3 million euros on average) (Gambardella, Harhoff and Verspagen, 2008) with the ratio of spillovers to private returns as estimated in Bloom, Schankerman and Reenen (2013). This implies an average total value of about 9 million euros for each patented invention. Extrapolating this, leads to a back-of-the-envelop calculation of the expected effect of reducing pollution. In the average region, this would imply that decreasing pollution by $0.17 \mu g/m^3$ leads to a 16.5 million increase in economic value each year. Multiplying this by the number of regions leads to an estimated yearly value of 21.3 billion euros. Relative to the yearly GDP in Europe, this is about 0.014%, which is 10% of the estimates in Dechezleprêtre, Rivers and Stadler (2019).

In addition to adding to the evidence on the costs of air pollution, our findings could help increasing efficiency of abatement policies. For instance, if a country's innovation is clustered in a region with a certain polluting industrial sector, abatement programs targeting this sector may be much more effective than targeting other, equally polluting sectors in less innovation-intensive areas. The heterogeneity in effects uncovered also informs policy makers. Particularly, our finding that the lion's share of the effect comes from highly polluted areas, suggests that targeting low-pollution areas may not be cost-effective (unless the cost of abatement programs across regions vastly differ). This is especially true seeing that highly polluted areas are also areas with high innovation intensity (they have 3.28 times more patents). Similarly, the heterogeneity by level of urbanization can also inform policy makers by highlighting that both highly urban and intermediate regions are important targets for abatement policies. Indeed, if the costs of the policy are similar, decreasing pollution with the same amount will result in roughly the same benefit in terms of innovation output.

While we see our findings as relevant to inform cost-benefit analyses leading to abatement strategies, it is important to stress two limitations of our study. First, we are not able to affirm the importance of different potential mechanisms behind our results. Air pollution may reduce inventive productivity by reducing the hours worked, or by reducing output conditional on hours worked. Because different mechanisms have different implications for abatement policy, it is important to disentangle them in future work. Second, our estimates may be overly conservative. Not all innovative activity is captured in patents. Many innovations are kept secret and do not show up in patent records. In addition, our back-of-the-envelope calculation did not account for the economic value of scientific output and obscures further spillover margins of innovation identified in the literature, which are hard to measure. With these drawbacks in mind, we hope this paper is a useful contribution to the cost-benefit analyses underlying rational abatement policies.

General Conclusion

Financing constraints and air pollution result in substantial deadweight loss. Both sources of inefficiencies also concern entrepreneurs and innovators who are the cornerstones of economic growth. First, the financing of entrepreneurs or innovators, in particular, is characterized by a high degree of information asymmetry. This means that even socially beneficial business ideas or innovation projects might not receive external funding. Second, air pollution causes a wide range of negative health effects which translate into multiple channels of economic outcomes. Hence, the economic costs of air pollution can be large but have not yet been fully uncovered.

This dissertation contributes to ongoing work on the two sources of inefficiencies in the context of entrepreneurship and innovation. First, I contribute to a broad understanding of factors that mitigate financing constraints. The prior literature suggests various signaling strategies to reduce information asymmetries between entrepreneurs and investors. I complement these findings by examining how the choice in legal form serves as a signal to external investors. Furthermore, I extend the findings on the signaling value of patents to mitigate financing constraints. I shift the focus to patents value as loan collateral and show that firms pledging patents can increase their excess to external finance. Second, I contribute to the knowledge of the economic costs of air pollution by estimating the impact of air pollution on innovation. Although prior literature estimates the impact of air pollution on aggregated economic outcomes, these estimates do not account for the long-term effects of air pollution through its impact on innovation.

In the next section, I will summarize the main findings and resulting im-

plications for each of the chapters. Finally, I will discuss important limitations and offer suggestions for future research.

Chapter 1

Chapter 1 examines for a sample of German firms how the legal form choice affects their access to and their level of debt. In Germany, entrepreneurs can choose between two similar legal forms that differ in terms of their minimum capital requirements. We argue that the choice of opting for a legal form with higher paid-in capital can act as a signal for investors to sort them into high-quality lenders because this choice entails higher risks and costs for entrepreneurs. Our empirical estimation shows that firms with a low-capital legal form are 2% less likely to obtain debt, and, conditional on obtaining debt, have approximately 52% less debt compared to observably similar firms that chose a high-capital legal form. Moreover, we find that firms with a low-capital legal form are more likely to indicate that they experience financing constraints, in particular bank financing constraints. We do not find that firms with a low-capital legal form are less likely to state that they are not in need of external funding. These findings are in line with our signaling explanation, but inconsistent with the idea that firms choosing a low-capital legal form have a lower demand for external funding. Importantly, we rule out that these results are simply driven by the difference in minimum capital requirements between the legal forms. Estimations for a sample of firms that change their minimum capital but retain their legal form do not reveal similar effects on the level of debt.

Our findings have important implications for the design of legal forms. In the last decade, several countries have introduced new legal forms with lower minimum capital requirements. These reforms are motivated by findings that show the positive effects of deregulation on the entry of companies (Klapper, Laeven and Rajan, 2006; Branstetter et al., 2014). We provide evidence that reduced minimum capital requirements to promote firm entry can negatively affect access to external finance. In our setting, entrepreneurs with profitable business ideas, who opted for a low-capital legal form, suffer from a negative

signaling effect. Thus, a reduction in firm entry regulation might not only promote the creation of businesses by individuals that might otherwise not have opted for an entrepreneurial career, but it will also have negative performance effects for high-quality startups who want to benefit from the lower capital requirements because of reasons unrelated to their creditworthiness.

Chapter 2

Chapter 2 examines the role of patents in mitigating financing constraints. Long (2002) was amongst the first to argue that patents can serve as a signal to external investors reducing information asymmetries and alleviating financing constraints. However, patents can also serve as loan collateral increasing firms' debt capacity. In this chapter, we account for patent collateralization and estimate the impact of patent pledging on firms' debt levels in Sweden and the Netherlands, where the registration of pledged patents is mandatory. Our results show that pledging patents causes an increase in debt by about 34% for Dutch and by about 20% for Swedish pawners. In terms of monetary values, Dutch companies could raise debt of 1.4 million euros. on average and Swedish companies could raise debt of 1.2 million euros on average. In addition, we revisit prior findings on the positive signaling value of patents. Further analyses indicate that the signaling value of pledged patents can explain an average increase in debt of 594 thousand euros for Dutch firms and an average increase in debt of 1.8 million euros for Swedish firms. Taking all these estimates together, our results suggest that the collateral value of patents exceeds their signaling value for patent pledging firms in the Netherlands but not for their Swedish counterparts. Finally, we find that only a handful of patent filing firms pledged their patents leaving a huge source of external finance untouched. Nonpledging Dutch (Swedish) firms could raise 5.1 billion euros (13.4 billion euros) in external funding in total by offering their patents as loan collateral.

Our results show that patents not only provide a signal for external investors but also serve as valuable collateral in loan agreements. Furthermore, some of our results suggest that the collateral value of patents might even

exceed their signaling value. These findings have important implications for firms and policymakers. Goldfinger (1997) shows that the share of tangible assets is decreasing in modern economies. Thus, the common practice of pledging machinery and real estate will become less important over time. Instead, intangible assets could fill this 'tangible collateral gap'. However, the low number of firms that have pledged patents might indicate barriers preventing firms from using intangible assets as collateral.

Chapter 3

While Chapters 1 and 2 contribute to the broad literature on capital market frictions, Chapter 3 shifts the focus to negative externalities caused by air pollution as another source of inefficiency. Knowing the economic costs of air pollution is important for rational abatement policies. The medical literature provides evidence for a broad set of negative health effects ranging from physical to psychological harm. These multifaced health effects translate into a large number of channels through which air pollution can affect economic outcomes. This explains why current cost estimates of air pollution are still incomplete. In this chapter, we go an important step further and investigate the effect of air pollution on the aggregate inventive output. The negative effects of air pollution on innovation can be large because innovation is a key driver of economic growth (Aghion and Howitt, 1990; Romer, 1990). Our estimation shows that a $0.17 \mu g/m^2$ decrease in $PM_{2.5}$ concentration – the average yearly reduction of the major air pollutant in Europe – leads to 1.7% more patented innovations. We find that this negative effect of air pollution is concentrated in regions that are more polluted, suggesting that there is a nonlinear relationship between pollution levels and innovation. Moreover, our results show that air pollution has a similar impact on total innovation for regions with high and intermediate levels of urbanization. We also provide evidence that neither the reallocation of inventors nor the reduction of R&D expenditures in response to air pollution explains our results. This means that we can aggregate our region-level estimates to economy-wide costs that are not captured in the GDP. A back-of-the-envelop calculation shows that the yearly realized reduction in

air pollution in Europe has created a benefit of 21.3 billion euros annually.

This chapter provides important information about the economic costs of air pollution that have not yet been considered. We show that the negative effects of air pollution on innovation are large but vary by region. These findings have important implications for policymakers. Knowledge of the additional costs of air pollution can justify more stringent abatement policies. Moreover, our insights into heterogeneous effects that differ by region can help to better design abatement programs. Our finding that the lion's share of the effect comes from highly polluted areas, suggests that targeting low-pollution areas may not be cost-effective. Additionally, results for regions with different degrees of urbanization suggest that both highly urban and intermediate regions are important targets for abatement policies.

Limitations and Avenues for Future Research

It is important to note that this disseration has limitations that I will explain for each of the chapters in the following. Some of the limitations provide interesting entry points for future research.

Chapter 1 examines how the choice in legal form serves as a signal to external investors. The empirical analysis exploits the German corporate law that allows entrepreneurs to choose between high- and low-capital private limited forms. We show that entrepreneurs who chose a low-capital legal form, suffer from a negative signaling effect. Although the negative signaling effect imposes a significant cost to entrepreneurs, we cannot derive a conclusion regarding the impact on total welfare. A welfare analysis requires estimating costs to mitigate signaling effects that go beyond this chapter. From the perspective of investors, the use of the legal form choice as a screening device might reduce the costs of a more detailed screening process. Thus, analyzing screening costs for external investors will be an important task for future research. Another interesting avenue for future research provides the country-specific differences in lowering minimum capital requirements to reduce firm entry barriers. While our analysis is based on a country that has lowered minimum capital requirements by introducing a separate legal form, other

countries lowered minimum capital requirements for existing legal forms.[37] Obviously, lowering minimum capital requirements for existing legal forms does not allow investors to discriminate between firms of different legal forms. On the other hand, reduced firm entry barriers cause an increase in low-quality firms that investors have to identify by a more comprehensive screening process. Thus, a separate legal form with lower minimum capital requirements could help investors reduce their screening costs. It remains unclear which type of minimum capital reform is socially optimal. A welfare analysis for both types of minimum capital requirement reforms can fill this gap.

In chapter 2 we estimate the impact of patent pledging on firms' access to debt. This empirical analysis is challenging because firms do not pledge patents at random and patent pledging firms are likely to be different from their non-pledging counterparts. Obviously, firms pledging patents have an increased demand for debt that might also suggest differences in the opportunities to grow. Thus, the selection of firms into the group of pawners can bias results. We try to mitigate concerns about selection effects by matching the group of patent pledging firms with a similar control group of non-pledging firms. However, matching is based on observable firm characteristics. Thus, we cannot exclude the possibility that unobserved firm characteristic drives both firms' access to debt and the decision to pledge patents. Consequently, our empirical analysis does not provide a causal identification. Furthermore, our empirical analysis is based on Dutch and Swedish firms which limit the generalizability of our results to countries with a similar economy and legal framework. Despite the limitations, this chapter provides some interesting avenues for future research. Our results show that only very few firms do pledge patents. This might indicate barriers that either prevent firms from pledging patents or prevent investors from accepting intangible assets as collateral. A cost-benefit analysis for the use of patents as loan collateral can provide some important insights into the low utilization of such a financial instrument. Furthermore, this chapter does answer the question for which purpose patent pledging firms use their external funding. Firms may require

[37] Braun et al. (2013) provides an overview of the different corporate law reforms for countries in Europe.

external funding due to increased growth opportunities. Alternatively, firms might demand funding due to financial distress. In the latter case, patent pledging might prevent unproductive firms from exiting the market and contribute to the growth of zombie firms (Adalet McGowan, Andrews and Millot, 2018). This shows that patent pledging can have different implications on total welfare. Further research on the usage of external funds is needed to conclude the welfare effects of patent pledging.

Finally, Chapter 3 has some important limitations as well. In this chapter, we estimate the negative impact of air pollution on the aggregated inventive output. While we exclude the reallocation of labor, increased mortality of inventors, and the reduction in R&D expenditures as mechanisms behind this relationship, we are not able to disentangle the exact mechanisms behind our results. Specifically, air pollution can reduce innovation output through two different channels. First, the supply of innovative labor may decrease due to absenteeism or a reduction in hours worked. This is consistent with prior work showing that labor supply decreases in response to air pollution (Hanna and Oliva, 2015; Chang et al., 2019). Second, air pollution may reduce inventor productivity conditional on hours worked by harming cognitive function. This is consistent with a recent stream of literature that finds considerable effects of air pollution on cognitively demanding tasks (Stafford, 2015; Ebenstein, Lavy and Roth, 2016). Because different mechanisms have different implications for abatement policy, it is important to disentangle them in future work. Labor market data that allow the researcher to observe hours worked by inventors could help to identify the exact mechanism behind our results. Another limitation concerns our estimates. The estimated effects of air pollution on innovation are rather conservative. We measure innovation output by the number of patents as common in the literature. However, not all innovative activity is captured in patents. For instance, our analysis does not account for the effects of air pollution on trade secrets. In addition, our back-of-the-envelope calculation did not account for the economic value of scientific output. Hence, further research should focus on the two sources of innovation that have not been covered in this chapter.

References

Abadie, Alberto, and Jann Spiess. 2021. "Robust post-matching inference." *Journal of the American Statistical Association*, 1–13.

Adalet McGowan, Müge, Dan Andrews, and Valentine Millot. 2018. "The walking dead? Zombie firms and productivity performance in OECD countries." *Economic Policy*, 33(96): 685–736.

Aghion, Philippe, and Jean Tirole. 1997. "Formal and real authority in organizations." *Journal of political economy*, 105(1): 1–29.

Aghion, Philippe, and Peter Howitt. 1990. "A model of growth through creative destruction." National Bureau of Economic Research.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and innovation: An inverted-U relationship." *The quarterly journal of economics*, 120(2): 701–728.

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard. 2012. "Credit constraints and the cyclicality of R&D investment: Evidence from France." *Journal of the European Economic Association*, 10(5): 1001–1024.

Aghion, Philippe, Richard Blundell, Rachel Griffith, Peter Howitt, and Susanne Prantl. 2009. "The effects of entry on incumbent innovation and productivity." *The Review of Economics and Statistics*, 91(1): 20–32.

Aghion, Philippe, Ufuk Akcigit, Ari Hyytinen, and Otto Toivanen. 2017. "The social origins of inventors." National Bureau of Economic Research.

Aldrich, Howard, and Ellen R Auster. 1986. "Even dwarfs started small: Liabilities of age and size and their strategic implications." *Research in organizational behavior*.

Almeida, Heitor, and Murillo Campello. 2007. "Financial constraints, asset tangibility, and corporate investment." *The Review of Financial Studies*, 20(5): 1429–1460.

Amit, Raphael, Lawrence Glosten, and Eitan Muller. 1990. "Entrepreneurial Ability, Venture Investments, and Risk Sharing." *Management Science*, 36(10): 1233–1246.

Anger, Heike. 2018. "Bilanz: 10 jahre unternehmergesellschaft." *Handelsblatt*.

Ang, James S, et al. 1991. "Small Business Uniqueness and the Theory of Financial Management." *Journal of Entrepreneurial Finance*, 1(1): 1–13.

Aragón, Fernando M., Juan Jose Miranda, and Paulina Oliva. 2017. "Particulate matter and labor supply: The role of caregiving and non-linearities." *Journal of Environmental Economics and Management*, 86: 295–309.

Arceo, Eva, Rema Hanna, and Paulina Oliva. 2016. "Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City." *The Economic Journal*, 126(591): 257–280.

Archsmith, James, Anthony Heyes, and Soodeh Saberian. 2018. "Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation." *Journal of the Association of Environmental and Resource Economists*, 5(4): 827–863.

Arrow, K. J. 1972. "Economic Welfare and the Allocation of Resources for Invention." *Readings in Industrial Economics*, 219–236.

Audretsch, David B, Werner Bönte, and Max Keilbach. 2008. "Entrepreneurship capital and its impact on knowledge diffusion and economic performance." *Journal of business venturing*, 23(6): 687–698.

Baker, George, Robert Gibbons, and Kevin J Murphy. 2002. "Relational Contracts and the Theory of the Firm." *The Quarterly Journal of Economics*, 117(1): 39–84.

Bapna, Sofia. 2019. "Complementarity of signals in early-stage equity investment decisions: Evidence from a randomized field experiment." *Management Science*, 65(2): 933–952.

Becht, Marco, Colin Mayer, and Hannes F Wagner. 2008. "Where do firms incorporate? Deregulation and the cost of entry." *Journal of Corporate Finance*, 14(3): 241–256.

Beck, Thorsten, et al. 2007. "Financing constraints of SMEs in developing countries: Evidence, determinants and solutions." 26–27.

Belenzon, Sharon, Aaron K Chatterji, and Brendan Daley. 2017. "Eponymous entrepreneurs." *American Economic Review*, 107(6): 1638–55.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen. 2019. "Who becomes an inventor in America? The importance of exposure to innovation." *The Quarterly Journal of Economics*, 134(2): 647–713.

Berger, Allen N, and Gregory F Udell. 1998. "The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle." *Journal of banking & finance*, 22(6-8): 613–673.

Berger, Allen N, and Gregory F Udell. 2002. "Small business credit availability and relationship lending: The importance of bank organisational structure." *The economic journal*, 112(477): F32–F53.

Berger, Allen N, and Gregory F Udell. 2003. "Small business and debt finance." In *Handbook of entrepreneurship research*. 299–328. Springer.

Berger, Allen N, and Gregory F Udell. 2006. "A more complete conceptual framework for SME finance." *Journal of Banking & Finance*, 30(11): 2945–2966.

Berger, Allen N, and Lamont K Black. 2011. "Bank size, lending technologies, and small business finance." *Journal of Banking & Finance*, 35(3): 724–735.

Berger, Allen N, Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein. 2005. "Does function follow organizational form? Evidence from the lending practices of large and small banks." *Journal of Financial economics*, 76(2): 237–269.

Berger, Allen N, William Goulding, and Tara Rice. 2014. "Do small businesses still prefer community banks?" *Journal of Banking & Finance*, 44: 264–278.

Besanko, David, and Anjan V Thakor. 1987*a*. "Collateral and rationing: sorting equilibria in monopolistic and competitive credit markets." *International economic review*, 671–689.

Besanko, David, and Anjan V Thakor. 1987*b*. "Competitive equilibrium in the credit market under asymmetric information." *Journal of Economic Theory*, 42(1): 167–182.

Bester, Helmut. 1985. "Screening vs. rationing in credit markets with imperfect information." *The American economic review*, 75(4): 850–855.

Bester, Helmut. 1987. "The role of collateral in credit markets with imperfect information." *European Economic Review*, 31(4): 887–899.

Bloom, Nicholas, and John Van Reenen. 2002. "Patents, real options and firm performance." *The Economic Journal*, 112(478): C97–C116.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica*, 81(4): 1347–1393.

Boot, Arnoud, Anjan Thakor, and Gregory Udell. 1991. "Secured Lending and Default Risk: Equilibrium Analysis, Policy Implications and Empirical Results." *Economic Journal*, 101(406): 458–72.

Branstetter, Lee, Francisco Lima, Lowell J Taylor, and Ana Venâncio. 2014. "Do entry regulations deter entrepreneurship and job creation? Evidence from recent reforms in Portugal." *The Economic Journal*, 124(577): 805–832.

Braun, Reiner, Horst Eidenmüller, Andreas Engert, and Lars Hornuf. 2013. "D oes Charter Competition Foster Entrepreneurship? A Difference-in-Difference Approach to European Company Law Reforms." *JCMS: Journal of Common Market Studies*, 51(3): 399–415.

Brook, Robert D, Sanjay Rajagopalan, C Arden Pope III, Jeffrey R Brook, Aruni Bhatnagar, Ana V Diez-Roux, Fernando Holguin, Yuling Hong, Russell V Luepker, Murray A Mittleman, et al. 2010. "Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association." *Circulation*, 121(21): 2331–2378.

Brown, James R, and Bruce C Petersen. 2009. "Why has the investment-cash flow sensitivity declined so sharply? Rising R&D and equity market developments." *Journal of Banking & Finance*, 33(5): 971–984.

Brown, James R, Gustav Martinsson, and Bruce C Petersen. 2012. "Do financing constraints matter for R&D?" *European Economic Review*, 56(8): 1512–1529.

Brown, James R, Steven M Fazzari, and Bruce C Petersen. 2009. "Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom." *The Journal of Finance*, 64(1): 151–185.

Bruns, Volker, Daniel V Holland, Dean A Shepherd, and Johan Wiklund. 2008. "The role of human capital in loan officers' decision policies." *Entrepreneurship Theory and Practice*, 32(3): 485–506.

Buchanan, James M, and William C Stubblebine. 1962. "Externality." In *Classic papers in natural resource economics*. 138–154. Springer.

Cassar, Gavin. 2004. "The financing of business start-ups." *Journal of business venturing*, 19(2): 261–283.

Cassar, Gavin, Christopher D Ittner, and Ken S Cavalluzzo. 2015. "Alternative information sources and information asymmetry reduction: Evidence from small business debt." *Journal of Accounting and Economics*, 59(2-3): 242–263.

Certo, S Trevis. 2003. "Influencing initial public offering investors with prestige: Signaling with board structures." *Academy of management review*, 28(3): 432–446.

Chamley, Christophe. 1983. "Entrepreneurial abilities and liabilities in a model of self-selection." *The Bell Journal of Economics*, 70–80.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. "Particulate pollution and the productivity of pear packers." *American Economic Journal: Economic Policy*, 8(3): 141–169.

Chang, Tom Y., Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2019. "The effect of pollution on worker productivity: Evidence from call center workers in China." *American Economic Journal: Applied Economics*, 11(1): 151–172.

Chan, Yuk-Shee, and Anjan V Thakor. 1987. "Collateral and competitive equilibria with moral hazard and private information." *The Journal of finance*, 42(2): 345–363.

Chua, Jess H, James J Chrisman, Franz Kellermanns, and Zhenyu Wu. 2011. "Family involvement and new venture debt financing." *Journal of business venturing*, 26(4): 472–488.

Clifford, Angela, Linda Lang, Ruoling Chen, Kaarin J Anstey, and Anthony Seaton. 2016. "Exposure to air pollution and cognitive functioning across the life course–a systematic literature review." *Environmental research*, 147: 383–398.

Coase, Ronald. 1988. "H.(1960)." The Problem of Social Cost"." *Journal of Law and Economics*, 3(1): 44.

Coate, Stephen, and Glenn C Loury. 1993. "Will affirmative-action policies eliminate negative stereotypes?" *The American Economic Review*, 1220–1240.

Cohen, Aaron J., Michael Brauer, Richard Burnett, H. Ross Anderson, Joseph Frostad, Kara Estep, Kalpana Balakrishnan, Bert Brunekreef, Lalit Dandona, Rakhi Dandona, Valery Feigin, Greg Freedman, Bryan Hubbell, Amelia Jobling, Haidong Kan, Luke Knibbs, Yang Liu, Randall Martin, Lidia Morawska, C. Arden Pope, Hwashin Shin, Kurt Straif, Gavin Shaddick, Matthew Thomas, Rita van Dingenen, Aaron van Donkelaar, Theo

Vos, Christopher J.L. Murray, and Mohammad H. Forouzanfar. 2017. "Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015." *The Lancet*, 389(10082): 1907–1918.

Cole, Rebel A, and Tatyana Sokolyk. 2018. "Debt financing, survival, and growth of start-up firms." *Journal of Corporate Finance*, 50: 609–625.

Cole, Rebel A, Lawrence G Goldberg, and Lawrence J White. 2004. "Cookie cutter vs. character: The micro structure of small business lending by large and small banks." *Journal of financial and quantitative analysis*, 39(2): 227–251.

Colombo, Massimo G, Michele Meoli, and Silvio Vismara. 2019. "Signaling in science-based IPOs: The combined effect of affiliation with prestigious universities, underwriters, and venture capitalists." *Journal of Business Venturing*, 34(1): 141–177.

Colombo, Oskar. 2021. "The use of signals in new-venture financing: A review and research agenda." *Journal of Management*, 47(1): 237–259.

Columbia University, Center for International Earth Science Information Network CIESIN. 2018. "Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11."

Conley, Timothy G. 1999. "GMM estimation with cross sectional dependence." *Journal of econometrics*, 92(1): 1–45.

Conley, Timothy G. 2010. "Spatial econometrics." In *Microeconometrics*. 303–313. Springer.

Connelly, Brian L, S Trevis Certo, R Duane Ireland, and Christopher R Reutzel. 2011. "Signaling theory: A review and assessment." *Journal of management*, 37(1): 39–67.

Conti, Annamaria, Jerry Thursby, and Marie Thursby. 2013. "Patents as signals for startup financing." *The Journal of Industrial Economics*, 61(3): 592–622.

Conti, Annamaria, Marie Thursby, and Frank T Rothaermel. 2013. "Show me the right stuff: Signals for high-tech startups." *Journal of Economics & Management Strategy*, 22(2): 341–364.

Cosh, Andy, Douglas Cumming, and Alan Hughes. 2009. "Outside entrepreneurial capital." *The Economic Journal*, 119(540): 1494–1533.

Cuneo, Philippe, and Jacques Mairesse. 1983. "Productivity and R&D at the firm level in French manufacturing." National Bureau of Economic Research.

Czarnitzki, Dirk, and Hanna Hottenrott. 2011. "R&D investment and financing constraints of small and medium-sized firms." *Small Business Economics*, 36(1): 65–83.

Czarnitzki, Dirk, and Hanna Hottenrott. 2017. "Inter-organizational collaboration and financing constraints for R&D." *Economics Letters*, 161: 15–18.

Czarnitzki, Dirk, and Julie Delanote. 2013. "Young innovative companies: the new high-growth firms?" *Industrial and Corporate change*, 22(5): 1315–1340.

Czarnitzki, Dirk, Bronwyn H Hall, and Raffaele Oriani. 2006. "The market valuation of knowledge assets in US and European firms."

Dechezleprêtre, Antoine, Nicholas Rivers, and Balazs Stadler. 2019. "The economic cost of air pollution: Evidence from Europe."

De la Torre, Augusto, María Soledad Martínez Pería, and Sergio L Schmukler. 2010. "Bank involvement with SMEs: Beyond relationship lending." *Journal of Banking & Finance*, 34(9): 2280–2293.

de Rassenfosse, Gaétan, Jan Kozak, and Florian Seliger. 2019. "Geocoding of worldwide patent data." *Scientific Data*, 6(1): 260.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. "The long-run economic consequences of high- stakes examinations: Evidence from transitory variation in pollution." *American Economic Journal: Applied Economics*, 8(4): 36–65.

Eddleston, Kimberly A, Jamie J Ladge, Cheryl Mitteness, and Lakshmi Balachandra. 2016. "Do you see what I see? Signaling effects of gender and firm characteristics on financing entrepreneurial ventures." *Entrepreneurship Theory and Practice*, 40(3): 489–514.

Epure, Mircea, and Martí Guasch. 2020. "Debt signaling and outside investors in early stage firms." *Journal of Business Venturing*, 35(2): 105929.

European Commission. 2020. "Science, Research and Innovation Performance of the EU 2020."

European Environment Agency. 2020. "Air quality in Europe — 2020 report."

European Parliament and Council of the European Union. 2008. "Directive 2008/50/EC." *OJ*, L 152: 1–44.

Eurostat. 2017. "Eurostat regional yearbook 2017."

Fairlie, Robert W, and Harry A Krashinsky. 2012. "Liquidity constraints, household wealth, and entrepreneurship revisited." *Review of Income and Wealth*, 58(2): 279–306.

Fama, Eugene F. 1978. "The effects of a firm's investment and financing decisions on the welfare of its security holders." *The American Economic Review*, 68(3): 272–284.

Foreman, Tim. 2020. "*SPATIAL_HAC_IV*: Stata module to estimate an instrumental variable regression, adjusting standard errors for spatial correlation, heteroskedasticity, and autocorrelation." *Statistical Software Components, Boston College Department of Economics*.

Gambardella, Alfonso, Dietmar Harhoff, and Bart Verspagen. 2008. "The value of European patents." *European Management Review*, 5(2): 69–84.

Garratt, John Roy. 1994. "The atmospheric boundary layer." *Earth-Science Reviews*, 37(1-2): 89–134.

Gartner, William B, Casey J Frid, and John C Alexander. 2012. "Financing the emerging firm." *Small business economics*, 39(3): 745–761.

Gelaro, Ronald, Will McCarty, Max J Suárez, Ricardo Todling, Andrea Molod, Lawrence Takacs, Cynthia A Randles, Anton Darmenov, Michael G Bosilovich, Rolf Reichle, et al. 2017. "The modern-era retrospective analysis for research and applications, version 2 (MERRA-2)." *Journal of climate*, 30(14): 5419–5454.

Gelter, Martin. 2019. "Centros and defensive regulatory competition: some thoughts and a glimpse at the data." *European Business Organization Law Review*, 20(3): 467–492.

Genc, D. Deniz, Canan Yesilyurt, and Gurdal Tuncel. 2010. "Air pollution forecasting in Ankara, Turkey using air pollution index and its relation to assimilative capacity of the atmosphere." *Environmental Monitoring and Assessment*, 166(1): 11–27.

Gerner-Beuerle, Carsten, Federico M Mucciarelli, Edmund Schuster, and Mathias Siems. 2018. "Cross-border reincorporations in the European Union: the case for comprehensive harmonisation." *Journal of Corporate Law Studies*, 18(1): 1–42.

Glenn, Hubbard R, et al. 2004. "Entrepreneurship and Household Saving." *The BE Journal of Economic Analysis & Policy*, 4(1): 1–57.

Goldfinger, Charles. 1997. "Intangible economy and its implications for statistics and statisticians." *International Statistical Review*, 65(2): 191–220.

Graham, John R. 2000. "How big are the tax benefits of debt?" *The journal of finance*, 55(5): 1901–1941.

Gramsch, E, D Cáceres, P Oyola, F Reyes, Y Vásquez, MA Rubio, and G Sánchez. 2014. "Influence of surface and subsidence thermal inversion on PM2. 5 and black carbon concentration." *Atmospheric Environment*, 98: 290–298.

Griliches, Zvi. 1990. "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature*, 28(4): 1661.

Hadlock, Charles J, and Joshua R Pierce. 2010. "New evidence on measuring financial constraints: Moving beyond the KZ index." *The Review of Financial Studies*, 23(5): 1909–1940.

Hall, Bronwyn H, Adam B Jaffe, and Manuel Trajtenberg. 2001. "The NBER patent citation data file: Lessons, insights and methodological tools." National Bureau of Economic Research.

Hall, Bronwyn H, Adam Jaffe, and Manuel Trajtenberg. 2005. "Market value and patent citations." *RAND Journal of economics*, 16–38.

Hall, Bronwyn H, and Josh Lerner. 2010. "The financing of R&D and innovation." In *Handbook of the Economics of Innovation*. Vol. 1, 609–639. Elsevier.

Hall, Bronwyn H, Jacques Mairesse, and Pierre Mohnen. 2010. "Measuring the Returns to R&D." In *Handbook of the Economics of Innovation*. Vol. 2, 1033–1082. Elsevier.

Haltiwanger, John, Ron S Jarmin, and Javier Miranda. 2013. "Who creates jobs? Small versus large versus young." *Review of Economics and Statistics*, 95(2): 347–361.

Hammer, Melanie S, Aaron van Donkelaar, Chi Li, Alexei Lyapustin, Andrew M Sayer, N Christina Hsu, Robert C Levy, Michael J Garay, Olga V Kalashnikova, Ralph A Kahn, et al. 2020. "Global estimates and long-term trends of fine particulate matter concentrations (1998–2018)." *Environmental Science & Technology*, 54(13): 7879–7890.

Han, Liang, Stuart Fraser, and David J Storey. 2009. "The role of collateral in entrepreneurial finance." *Journal of Business Finance & Accounting*, 36(3-4): 424–455.

Hanna, Rema, and Paulina Oliva. 2015. "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City." *Journal of Public Economics*, 122: 68–79.

Hansen, Lars Peter. 1982. "Large sample properties of generalized method of moments estimators." *Econometrica: Journal of the Econometric Society*, 1029–1054.

Harhoff, Dietmar. 2000. "Are there financing constraints for R&D and investment in German manufacturing firms?" In *The economics and econometrics of innovation*. 399–434. Springer.

Hart, Oliver. 1995. *Firms, contracts, and financial structure.* Clarendon press.

Heblich, Stephan, Alex Trew, and Yanos Zylberberg. 2021. "East-Side Story: Historical Pollution and Persistent Neighborhood Sorting."

He, Jiaxiu, Haoming Liu, and Alberto Salvo. 2019. "Severe air pollution and labor productivity: Evidence from industrial towns in China." *American Economic Journal: Applied Economics*, 11(1): 173–201.

Hersbach, Hans, Bill Bell, Paul Berrisford, Shoji Hirahara, András Horányi, Joaquín Muñoz-Sabater, Julien Nicolas, Carole Peubey, Raluca Radu, Dinand Schepers, et al. 2020. "The ERA5 global reanalysis." *Quarterly Journal of the Royal Meteorological Society*, 146(730): 1999–2049.

Holzworth, George C. 1967. "Mixing depths, wind speeds and air pollution potential for selected locations in the United States." *Journal of applied Meteorology*, 6(6): 1039–1044.

Holzworth, George C. 1972. *Mixing heights, wind speeds, and potential for urban air pollution throughout the contiguous United States.* US Government Printing Office.

Hottenrott, Hanna, Bronwyn H Hall, and Dirk Czarnitzki. 2016. "Patents as quality signals? The implications for financing constraints on R&D." *Economics of innovation and new technology*, 25(3): 197–217.

Hou, Xuewei, Dongdong Fei, Hanqing Kang, Yinglong Zhang, and Jinhui Gao. 2018. "Seasonal statistical analysis of the impact of meteorological factors on fine particle pollution in China in 2013–2017." *Natural Hazards*, 93(2): 677–698.

Hsu, David H, and Rosemarie H Ziedonis. 2013. "Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents." *Strategic Management Journal*, 34(7): 761–781.

Hughes, Joseph P, Julapa Jagtiani, Loretta J Mester, and Choon-Geol Moon. 2019. "Does scale matter in community bank performance? Evidence obtained by applying several new measures of performance." *Journal of Banking & Finance*, 106: 471–499.

Hurst, Erik, and Annamaria Lusardi. 2004. "Liquidity constraints, household wealth, and entrepreneurship." *Journal of political Economy*, 112(2): 319–347.

IAB and ZEW. 2022. "IAB/ZEW Start-up Panel."

Islam, Mazhar, Adam Fremeth, and Alfred Marcus. 2018. "Signaling by early stage startups: US government research grants and venture capital funding." *Journal of Business Venturing*, 33(1): 35–51.

Jagtiani, Julapa, Catharine Lemieux, et al. 2016. "Small business lending after the financial crisis: A new competitive landscape for community banks." *Economic perspectives*, 40(3): 1–30.

Jimenez, Gabriel, Vicente Salas, and Jesus Saurina. 2006. "Determinants of collateral." *Journal of financial economics*, 81(2): 255–281.

Jones, Benjamin, and Lawrence Summers. 2020. "A Calculation of the Social Returns to Innovation." National Bureau of Economic Research, Cambridge, MA.

Kausar, Asad, Nemit Shroff, and Hal White. 2016. "Real effects of the audit choice." *Journal of Accounting and Economics*, 62(1): 157–181.

Khanna, Gaurav, Wenquan Liang, A Mushfiq Mobarak, and Ran Song. 2021. "The Productivity Consequences of Pollution-Induced Migration in China."

Kirmani, Amna, and Akshay R Rao. 2000. "No pain, no gain: A critical review of the literature on signaling unobservable product quality." *Journal of marketing*, 64(2): 66–79.

Klapper, Leora, Luc Laeven, and Raghuram Rajan. 2006. "Entry regulation as a barrier to entrepreneurship." *Journal of financial economics*, 82(3): 591–629.

Ko, Eun-Jeong, and Alexander McKelvie. 2018. "Signaling for more money: The roles of founders' human capital and investor prominence in resource acquisition across different stages of firm development." *Journal of Business Venturing*, 33(4): 438–454.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *The Quarterly Journal of Economics*, 132(2): 665–712.

Koolen, Cedric D, and Gadi Rothenberg. 2019. "Air pollution in Europe." *ChemSusChem*, 12(1): 164.

Künn, Steffen, Juan Palacios, and Nico Pestel. 2019. "Indoor Air Quality and Cognitive Performance."

Landier, Augustin. 2005. "Entrepreneurship and the Stigma of Failure." *Available at SSRN 850446*.

Landrigan, Philip J., Richard Fuller, Nereus J.R. Acosta, Olusoji Adeyi, Robert Arnold, Niladri (Nil) Basu, Abdoulaye Bibi Baldé, Roberto Bertollini, Stephan Bose-O'Reilly, Jo Ivey Boufford, Patrick N. Breysse, Thomas Chiles, Chulabhorn Mahidol, Awa M. Coll-Seck, Maureen L. Cropper, Julius Fobil, Valentin Fuster, Michael Greenstone, Andy Haines, David Hanrahan, David Hunter, Mukesh Khare, Alan Krupnick, Bruce Lanphear, Bindu Lohani, Keith Martin, Karen V. Mathiasen, Maureen A. McTeer, Christopher J.L. Murray, Johanita D. Ndahimananjara, Frederica Perera, Janez Potočnik, Alexander S. Preker, Jairam Ramesh, Johan Rockström, Carlos Salinas, Leona D. Samson, Karti Sandilya, Peter D. Sly, Kirk R. Smith, Achim Steiner, Richard B. Stewart, William A. Suk, Onno C.P. van Schayck, Gautam N. Yadama, Kandeh Yumkella, and Ma Zhong. 2018. "The Lancet Commission on pollution and health."

Leland, Hayne E, and David H Pyle. 1977. "Informational asymmetries, financial structure, and financial intermediation." *The journal of Finance*, 32(2): 371–387.

Levine, Ross, and Yona Rubinstein. 2017. "Smart and illicit: who becomes an entrepreneur and do they earn more?" *The Quarterly Journal of Economics*, 132(2): 963–1018.

Levin, Jonathan, et al. 2009. "The dynamics of collective reputation." *The BE Journal of Theoretical Economics*, 9(1): 1–25.

Levinson, Arik. 2012. "Valuing public goods using happiness data: The case of air quality." *Journal of Public Economics*, 96(9-10): 869–880.

Liberti, José María, and Mitchell A Petersen. 2019. "Information: Hard and soft." *Review of Corporate Finance Studies*, 8(1): 1–41.

Lichter, Andreas, Nico Pestel, and Eric Sommer. 2017. "Productivity effects of air pollution: Evidence from professional soccer." *Labour Economics*, 48: 54–66.

Lin, Wei, and Jeffrey M Wooldridge. 2019. "Testing and correcting for endogeneity in nonlinear unobserved effects models." In *Panel Data Econometrics*. 21–43. Elsevier.

Long, Clarisa. 2002. "Patent signals." *The University of Chicago Law Review*, 625–679.

Lu, Jackson G, Julia J Lee, Francesca Gino, and Adam D Galinsky. 2018. "Polluted morality: Air pollution predicts criminal activity and unethical behavior." *Psychological science*, 29(3): 340–355.

Mann, William. 2018. "Creditor rights and innovation: Evidence from patent collateral." *Journal of Financial Economics*, 130(1): 25–47.

Mathez, Antje. 2013. "Mit einem Euro zum Erfolg." *Frankfurter Rundschau*.

Matusik, Sharon F, Jennifer M George, and Michael B Heeley. 2008. "Values and judgment under uncertainty: evidence from venture capitalist assessments of founders." *Strategic Entrepreneurship Journal*, 2(2): 95–115.

Ministry of Justice Stockholm. 1967. "Patents Act (1967:837)." Art. 95., [Last Accessed: June 15th 2018].

Mock, Sebastian. 2016. "The Mini-GMBH (Unternehmergesellschaft Haftungsbeschränkt [UG]) in Germany." *I Modelli di Impresa Societaria fra Tradizione e Innovazione nel Contesto Europeo*, 153–164.

Modigliani, Franco, and Merton H Miller. 1958. "The cost of capital, corporation finance and the theory of investment." *The American economic review*, 48(3): 261–297.

Morrison, Greg, Massimo Riccaboni, and Fabio Pammolli. 2017. "Disambiguation of patent inventors and assignees using high-resolution geolocation data." *Scientific data*, 4(1): 1–21.

Muñoz-Sabater, J. 2019. "ERA5-Land hourly data from 2001 to present."

Nauze, Andrea La, Edson R Severnini, and H John Heinz. 2021. "Air Pollution and Adult Cognition: Evidence from Brain Training."

Negro, Giacomo, Michael T Hannan, and Magali Fassiotto. 2015. "Category signaling and reputation." *Organization Science*, 26(2): 584–600.

Nelson, Richard R. 1959. "The simple economics of basic scientific research." *Journal of political economy*, 67(3): 297–306.

Nordhaus, William. 2004. "Schumpeterian Profits in the American Economy: Theory and Measurement." National Bureau of Economic Research, Cambridge, MA.

Oberdörster, Günther, Zachary Sharp, Viorel Atudorei, Alison Elder, Robert Gelein, Wolfgang Kreyling, and Christopher Cox. 2004. "Translocation of inhaled ultrafine particles to the brain." *Inhalation toxicology*, 16(6-7): 437–445.

Parker, Simon C, et al. 2018. "The Economics of Entrepreneurship." *Cambridge Books*.

Pearl, Judea. 2009. *Causality.* Cambridge university press.

Pittman, Jeffrey A, and Steve Fortin. 2004. "Auditor choice and the cost of debt capital for newly public firms." *Journal of accounting and economics*, 37(1): 113–136.

Plummer, Lawrence A, Thomas H Allison, and Brian L Connelly. 2016. "Better together? Signaling interactions in new venture pursuit of initial external capital." *Academy of Management Journal*, 59(5): 1585–1604.

Pollock, Timothy G, Guoli Chen, Eric M Jackson, and Donald C Hambrick. 2010. "How much prestige is enough? Assessing the value of multiple types of high-status affiliates for young firms." *Journal of business venturing*, 25(1): 6–23.

Power, Melinda C, Sara D Adar, Jeff D Yanosky, and Jennifer Weuve. 2016. "Exposure to air pollution as a potential contributor to cognitive function, cognitive decline, brain imaging, and dementia: a systematic review of epidemiologic research." *Neurotoxicology*, 56: 235–253.

Ravenscraft, D., and F. M. Scherer. 1982. "The lag structure of returns to research and development." *Applied Economics*, 14: 603–620.

Robb, Alicia M, and David T Robinson. 2014. "The capital structure decisions of new firms." *The Review of Financial Studies*, 27(1): 153–179.

Romer, Paul M. 1990. "Endogenous technological change." *Journal of political Economy*, 98(5, Part 2): S71–S102.

Sanders, Wm Gerard, and Steven Boivie. 2004. "Sorting things out: Valuation of new firms in uncertain markets." *Strategic Management Journal*, 25(2): 167–186.

Santos, Filipe M, and Kathleen M Eisenhardt. 2009. "Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields." *Academy of Management Journal*, 52(4): 643–671.

Scherer, F M. 1965. "Corporate inventive output, profits, and growth." *Journal of Political Economy*, 73(3): 290–297.

Schmalz, Martin C, David A Sraer, and David Thesmar. 2017. "Housing collateral and entrepreneurship." *The Journal of Finance*, 72(1): 99–132.

Schmookler, Jacob. 1966. *Invention and economic growth.* Harvard University Press.

Schoar, Antoinette. 2010. "The divide between subsistence and transformational entrepreneurship." *Innovation policy and the economy*, 10(1): 57–81.

Schumpeter, Joseph A. 1911. "The Theory of Economic Development, reprinted in 1934, trans. Redvers Opie."

Sengupta, Partha. 1998. "Corporate disclosure quality and the cost of debt." *Accounting review*, 459–474.

Solow, Robert M. 1956. "A contribution to the theory of economic growth." *The quarterly journal of economics*, 70(1): 65–94.

Spence, Michael. 1973. "Job market signaling." *Quarterly Journal of Economics*, 87(3): 355–374.

Stafford, Tess M. 2015. "Indoor air quality and academic performance." *Journal of Environmental Economics and Management*, 70: 34–50.

Stavins, Robert N. 2011. "The problem of the commons: still unsettled after 100 years." *American Economic Review*, 101(1): 81–108.

Steijvers, Tensie, and Wim Voordeckers. 2009. "Collateral and credit rationing: a review of recent empirical studies as a guide for future research." *Journal of Economic Surveys*, 23(5): 924–946.

Stein, Jeremy C. 2002. "Information production and capital allocation: Decentralized versus hierarchical firms." *The journal of finance*, 57(5): 1891–1921.

Stiglitz, Joseph E, and Andrew Weiss. 1981. "Credit rationing in markets with imperfect information." *The American economic review*, 71(3): 393–410.

Stock, James, and Motohiro Yogo. 2002. "Testing for Weak Instruments in Linear IV Regression." National Bureau of Economic Research, Inc.

Storey, David J. 1994. "The role of legal status in influencing bank financing and new firm growth." *Applied economics*, 26(2): 129–136.

Stull, Roland B. 1988. *An Introduction to Boundary Layer Meteorology.* Vol. 13, Springer Science & Business Media.

The Minister of Justice Den Haag. 1995. "the Dutch Patents Act." Art. 67., [Last Accessed: March 25th 2022].

Tirole, Jean. 1996. "A theory of collective reputations (with applications to the persistence of corruption and to firm quality)." *The Review of Economic Studies*, 63(1): 1–22.

Tobler, Waldo R. 1970. "A computer movie simulating urban growth in the Detroit region." *Economic geography*, 46(sup1): 234–240.

Torssander, Jenny, and Robert Erikson. 2009. "Stratification and Mortality—A Comparison of Education, Class, Status, and Income." *European Sociological Review*, 26(4): 465–474.

Torvik, Vetle I. 2015. "MapAffil: A bibliographic tool for mapping author affiliation strings to cities and their geocodes worldwide." Vol. 21, NIH Public Access.

Trajtenberg, Manuel. 1990. "A penny for your quotes: patent citations and the value of innovations." *The Rand journal of economics*, 172–187.

Ueda, Masako. 2004. "Banks versus venture capital: Project evaluation, screening, and expropriation." *The Journal of Finance*, 59(2): 601–621.

Underwood, Emily. 2017. "The Polluted Brain." *Science*, 355(6323): 342–345.

US EPA (US Environmental Protection Agency). 1997. "40 CFR Part 50. National Ambient Air Quality Standards for particulate matter. Final rule." *Fed Reg 62*, 38652–38460.

Vallero, Daniel. 2014. "Chapter 3 - The Science of Air Pollution." In *Fundamentals of Air Pollution (Fifth Edition)*. . Fifth Edition ed., , ed. Daniel Vallero, 43–81. Boston:Academic Press.

Van Donkelaar, Aaron, Randall V Martin, Chi Li, and Richard T Burnett. 2019. "Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors." *Environmental science & technology*, 53(5): 2595–2611.

Viehmann, Anja, Sabine Hertel, Kateryna Fuks, Lewin Eisele, Susanne Moebus, Stefan Möhlenkamp, Michael Nonnemacher, Hermann Jakobs, Raimund Erbel, Karl-Heinz Jöckel, et al. 2015. "Long-term residential exposure to urban air pollution, and repeated measures of systemic blood markers of inflammation and coagulation." *Occupational and environmental medicine*, 72(9): 656–663.

Villanueva, Jaume, Andrew H Van de Ven, and Harry J Sapienza. 2012. "Resource mobilization in entrepreneurial firms." *Journal of Business Venturing*, 27(1): 19–30.

WHO. 2016. *Ambient air pollution: a global assessment of exposure and burden of disease.* World Health Organization.

Wiklund, Johan, Ted Baker, and Dean Shepherd. 2010. "The age-effect of financial indicators as buffers against the liability of newness." *Journal of business venturing*, 25(4): 423–437.

Wooldridge, Jeffrey M. 1999. "Distribution-free estimation of some nonlinear panel data models." *Journal of Econometrics*, 90(1): 77–97.

World Bank. 2020. *Doing Business 2020.* Washington DC:World Bank Publications.

Xu, Gang, Limin Jiao, Boen Zhang, Suli Zhao, Man Yuan, Yanyan Gu, Jiafeng Liu, Xin Tang, et al. 2017. "Spatial and temporal variability of the PM2. 5/PM10 ratio in Wuhan, Central China." *Aerosol and Air Quality Research*, 17(3): 741–751.

Yang, Siluo, Dietmar Wolfram, and Feifei Wang. 2017. "The relationship between the author byline and contribution lists: a comparison of three general medical journals." *Scientometrics*, 110(3): 1273–1296.

Zacchia, Paolo. 2018. "Benefiting colleagues but not the city: Localized effects from the relocation of superstar inventors." *Research Policy*, 47(5): 992–1005.

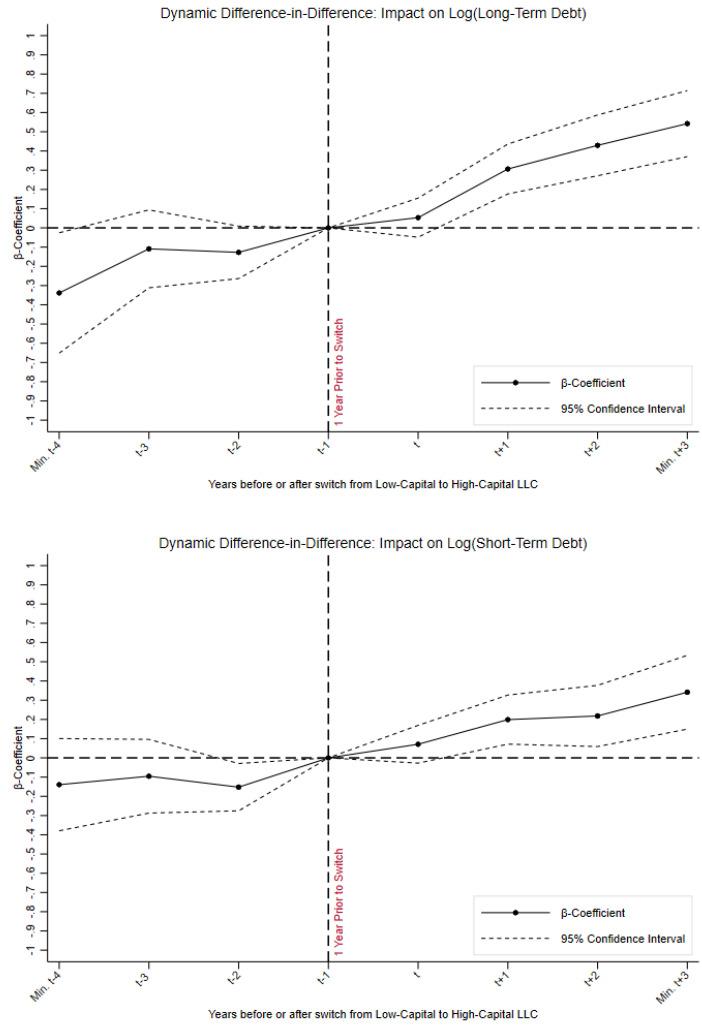
Zivin, Joshua Graff, and Matthew Neidell. 2012. "The impact of pollution on worker productivity." *American Economic Review*, 102(7): 3652–3673.

Zivin, Joshua Graff, and Matthew Neidell. 2018. "Air pollution's hidden impacts." *Science*, 359(6371): 39–40.

Appendices

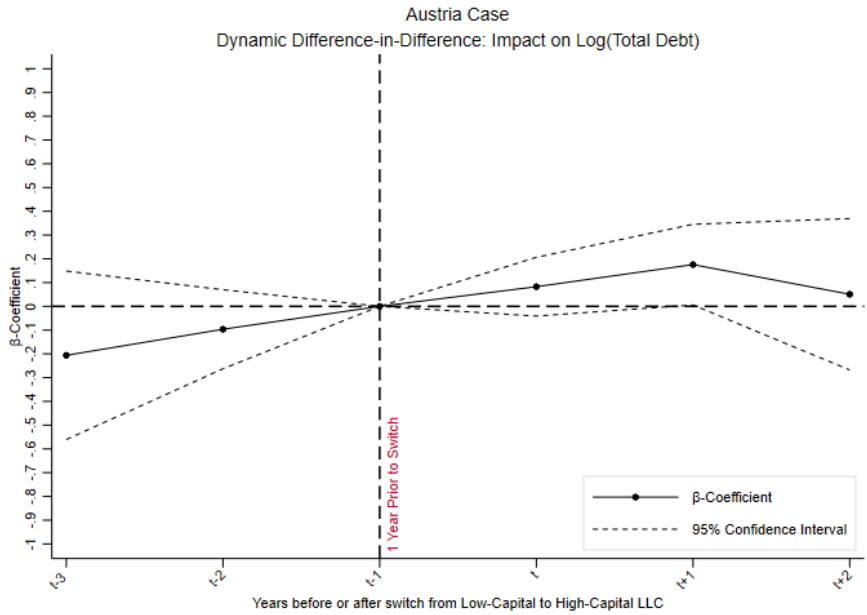
A Chapter 1

Figure A1



This figure presents the results of the dynamic difference-in-differences regression of long-term- (graph on the top) and short-term-debt (graph on the bottom) over time since change of legal form. The control group are high-capital LLCs. Dotted lines represent 95% confidence intervals.

Figure A2



This figure presents the results of the dynamic difference-in-differences regression of total debt over time since increase in minimum capital of Austrian low-capital LLCs. The control group are Austrian LLCs that have permanently higher capital. Dotted lines represent 95% confidence intervals.

Table A1: Variable Description

Variable	Descritpion	Datasource
Low-Capital LLC	Dummy set to one if firm operates under the legal form with low capital requirements (i.e. UG in Germany or Low Capital GmbH in Austria)	Orbis
Total Debt	Non-Current Liabilities + Current Liabilities	Orbis
Log(Total Debt)	Log of Total Debt	Orbis
Access to Long-Term Debt	Dummy set to one if long term debt > 0	Orbis
Long-Term Debt	Long term debt in euro, conditional of having debt	Orbis
Log(Long-Term Debt)	Log of Long-Term Debt	Orbis
Access to Short-Term Debt	Dummy set to one if Current Liabilities > 0	Orbis
Short-Term Debt	Total of Current Liabilities in euro, conditional of having debt	Orbis
Log(Short-Term Debt)	Log of Long-Term Debt	Orbis
Access to Bank Loans (survey)	Dummy set to one if investments have been financed by bank loans	IAB/ZEW Startup Panel
% Inv. Financed by Ext. Funds	Percentage of investments that are financed by external funding	IAB/ZEW Startup Panel
Financing Constraints	Financing difficulties due to (any) external investors	IAB/ZEW Startup Panel
Bank Financing Constraints	Financing difficulties due to banks	IAB/ZEW Startup Panel
No Funds Needed	Dummy set to one if firm does not need external finance	IAB/ZEW Startup Panel
Share Relationship Banks	Dummy set to 1 if the weighted share of small relationship banks for a NUTS-2 region is higher than or equal to 75 percent	Orbis
Trade Credit	Firm's value of inventory divided by total assets	Orbis
Foreign Owner (IV)	Dummy set to one if founder has foreign nationality	IAB/ZEW Startup Panel
Post Switch	Dummy set to one if a low-capital LLC has turned into a high-capital LLC	Orbis
Capital	Issued Share capital (Authorized capital)	Orbis
Accumulated Profit/Loss	All Shareholders funds not linked with the Issued capital such as Reserve capital, Undistributed profit	Orbis
Size	Natural log of Tangible fixed assets + 1	Orbis
Age	Years since founding date	Orbis
Tangible Assets	Tangible fixed assets / total assets	Orbis
Patent Stock	Depreciated (annual rate of 15 percent) stock of patents	Orbis IP
Investments	Investment volume in euro	IAB/ZEW Startup Panel
R&D Expenses	R&D expenditures in euro	IAB/ZEW Startup Panel
Export	Turnover due to export in euro	IAB/ZEW Startup Panel
Employees at Start-Up	Enterprise's employees at founding date	IAB/ZEW Startup Panel
Founders	Number of founders	IAB/ZEW Startup Panel
Family Members	Number of family members working in the enterprise at founding date	IAB/ZEW Startup Panel
Gender	Dummy set to one if female is part of the founding team	IAB/ZEW Startup Panel
Previous Enterprise	Dummy set to on if (one of the) founder(s) has founded an enterprise before	IAB/ZEW Startup Panel
Prior Experience	Industry experience in years (for teams: founder with the longest experience)	IAB/ZEW Startup Panel
Motive: Self-Employment	Dummy set to one if founding motive = self-determined working	IAB/ZEW Startup Panel
Motive: Business Idea	Dummy set to one if founding motive = realisation of certain business idea	IAB/ZEW Startup Panel
Motive: No Emp. Opp.	Dummy set to one if founding motive = improper employment opportunities	IAB/ZEW Startup Panel
Motive: Unemployment	Dummy set to one if founding motive = Escape from unemployment	IAB/ZEW Startup Panel
Motive: Better Earnings	Dummy set to one if founding motive = Encouragement by former employer	IAB/ZEW Startup Panel
Prior: Self-Employed	Dummy set to one if employment situation immediately before founding = Self-employed	IAB/ZEW Startup Panel
Prior: Employed (Private)	Dummy set to one if employment situation immediately before founding = private employed	IAB/ZEW Startup Panel
Prior: Employed (Public)	Dummy set to one if employment situation immediately before founding = public employed	IAB/ZEW Startup Panel
Prior: Unemployed	Dummy set to one if employment situation immediately before founding = unemployed	IAB/ZEW Startup Panel
Prior: Inactive	Dummy set to one if employment situation immediately before founding = inactive	IAB/ZEW Startup Panel
Edu: No Degree / High School	Dummy set to one if highest qualification of the founders = No Degree / Technical High School	IAB/ZEW Startup Panel
Edu: Bachelor	Dummy set to one if highest qualification of the founders = Professional bachelor / Official training	IAB/ZEW Startup Panel
Edu: University	Dummy set to one if highest qualification of the founders = University degree	IAB/ZEW Startup Panel

This table shows all variables and respective data sources used for the empirical analysis.

Table A2: Newly established firms in Germany and Austria over time

	Germany		Austria
Foundation Year	# Newly registered High-Capital LLCs (GmbH)	# Newly registered High- and Low-Capital LLCs (GmbH and UG)	# High-Capital LLCs (GmbH)
2003	31,394	31,394	6,047
2004	33,400	33,400	7,504
2005	35.509	35.509	8,994
2006	38,398	38,398	8,699
2007	38,563	38,563	9,249
2008	34,653	36,672	8,542
2009	32,547	43,901	7,598
2010	31,139	41,820	7,710
Yearly average # Newly Registered Firms during Pre-MoMiG period (03-07):	35,453	35,453	8,099
Yearly average # Newly Registered Firms during Post-MoMiG year (08-10):	32,780	40,798	7,950
Average % change Pre vs. Post:	-7.54%	15,08%	-1.84%

This table presents the number of newly established LLCs within Germany and Austria over time. Data comes from historical records of the Orbis Database. High-capital LLCs are companies with the legal form GmbH. Low-capital LLCs are companies with the legal form UG.

Table A3: Data Cleaning - German Sample

Cleaning Steps	Number firms	Number observations
Raw Data	204,312	702,246
Remove financial companies		-52,500
Clean Capital variable		-15,253
Drop large firms		-34,833
Drop missing and implausible observations		-40,071
Final sample	170,480	559,588

This table describes the cleaning procedure. The raw data includes all unconsolidated balance sheet data for all German low- and high-capital LLCs (i.e. UGs and GmbHs) that were incorporated between 2008 and 2017, which are included in the Historical Orbis Database (Database version February 2019). We cleaned the data by removing financial firms. We also cleaned the capital data by removing high-capital LLCs that had values below the minimum that should be available. We only included small companies in the data as defined by the German Accounting Implication Act (BilRUG). As a final cleaning step, we removed firms with missing data on Capital, a small number of doubles in the data, and firms that reported a zero or negative number on total assets.

Table A4: Descriptive Statistics: DiD

Panel A: Treated and control observations

	Permanent High-Capital LLC		Firms that switch from Low- to High-Capital LLC	
	N: 473,523		N: 8,525	
	Mean	Std. Dev.	Mean	Std. Dev.
$Low-Capital\,LLC$	0.000	0.000	0.455	0.498
$Total\,Debt_{(\times 1000)}$	281.521	443.842	189.173	298.538
$Log(Total\,Debt)$	10.984	2.356	11.027	1.870
$Access\,to\,Long-Term\,Debt$	0.626	0.484	0.650	0.477
$Long-Term\,Debt_{(\times 1000)}$	245.150	395.624	142.181	248.950
$Log(Long-Term\,Debt)$	10.870	2.363	10.624	1.942
$Access\,to\,Short-Term\,Debt$	0.541	0.498	0.586	0.493
$Short-Term\,Debt_{(\times 1000)}$	100.877	241.349	75.618	184.878
$Log(Short-Term\,Debt)$	10.548	2.378	10.441	2.017
$Capital_{(\times 1000)}$	28.795	24.204	14.704	14.277
$Accumulated\,Profit/Loss_{(\times 1000)}$	57.794	194.167	60.884	148.697
$Total\,Assets_{(\times 1000)}$	408.390	607.861	285.157	419.189
$Size$	8.796	3.727	9.028	2.839
Age	2.436	1.839	2.723	1.869
$Tangible\,Assets$	0.176	0.219	0.184	0.206
$Patent\,Stock$	0.030	0.493	0.028	0.334

Panel B: Treated firms before and after switch

	Low-Capital LLC (pre switch)		High-Capital LLC (post switch)	
	N: 3,881		N: 4,644	
	Mean	Std. Dev.	Mean	Std. Dev.
$Low-Capital\,LLC$	1	0	0	0
$Total\,Debt_{(\times 1000)}$	105.123	186.500	260.079	352.132
$Log(Total\,Debt)$	10.377	1.915	11.566	1.647
$Access\,to\,Long-Term\,Debt$	0.568	0.495	0.715	0.451
$Long-Term\,Debt_{(\times 1000)}$	78.024	153.123	183.546	287.170
$Log(Long-Term\,Debt)$	9.983	1.967	11.038	1.809
$Access\,to\,Short-Term\,Debt$	0.597	0.491	0.578	0.494
$Short-Term\,Debt_{(\times 1000)}$	46.873	128.438	99.745	218.525
$Log(Short-Term\,Debt)$	9.886	2.039	10.922	1.869
$Capital_{(\times 1000)}$	2.136	3.308	25.123	11.145
$Accumulated\,Profit/Loss_{(\times 1000)}$	32.812	94.482	84.649	179.008
$Total\,Assets_{(\times 1000)}$	150.107	260.090	395.406	486.754
$Size$	8.279	2.944	9.544	2.644
Age	1.418	1.226	3.814	1.594
$Tangible\,Assets$	0.184	0.210	0.184	0.204
$Patent\,Stock$	0.018	0.275	0.037	0.377

Panel A provides descriptive statistics for firms that switched legal forms from a low-capital LLC to a high-capital LLC in our sample period, as well as for a Permanent high-capital LLCs (i.e. firms that opted for the legal form high-capital LLC (GmbH) at startup). Panel B provides statistics about the observations in either the pre and post switch period. Corresponding variable definitions can be found in Table A1. All monetary values are in euro.

Table A5: OLS: Survey Sample with same outcome variables used for the Full Sample

	Log(Total Debt)		Access to Long-Term Debt		Log(Long-Term Debt)		Access to Short-Term Debt		Log(Short-Term Debt)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Low – Capital LLC	-2.046***	-0.831***	-0.105***	-0.041	-2.187***	-1.108***	-0.067**	-0.022	-1.717***	-0.685***
	(0.100)	(0.081)	(0.026)	(0.030)	(0.136)	(0.133)	(0.027)	(0.032)	(0.123)	(0.120)
Capital		0.001*		0.000		0.001		-0.000		0.002***
		(0.001)		(0.000)		(0.001)		(0.000)		(0.001)
Accumulated Profit/Loss		-0.000***		-0.000**		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Size		0.405***		0.025***		0.366***		0.015***		0.385***
		(0.016)		(0.004)		(0.024)		(0.004)		(0.021)
Age		0.149***		0.024		0.145**		-0.033*		0.026
		(0.046)		(0.015)		(0.066)		(0.018)		(0.074)
Tangible Assets		-2.176***		0.197***		-0.997***		-0.154***		-2.996***
		(0.128)		(0.034)		(0.173)		(0.046)		(0.180)
Patent Stock		0.138***		-0.005		0.180***		0.009		0.060*
		(0.023)		(0.008)		(0.034)		(0.007)		(0.031)
Additional Firm Controls	No	No	No	No	No	No	No	No	No	No
Founder Controls	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,368	8,719	9,298	8,669	6,813	6,446	9,403	8,723	5,658	5,328
R-squared	0.291	0.522	0.057	0.094	0.208	0.346	0.032	0.041	0.201	0.347

This table presents estimates from regressions of financing constraint measures on legal form choice. Variable definitions are presented in Table A1. In this setup, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A6: OLS: Survey Sample with full controls I

	Log(Total Debt)	Access to Long-Term Debt	Log(Long-Term Debt)	Access to Short-Term Debt
	(1)	(2)	(3)	(4)
Low – Capital LLC	-0.664***	-0.022	-0.956***	-0.062
	(0.098)	(0.039)	(0.183)	(0.043)
Capital	0.002***	-0.000	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Accumulated Profit/Loss	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.354***	0.026***	0.324***	0.018***
	(0.025)	(0.005)	(0.038)	(0.006)
Age	0.068	0.028	0.026	-0.045*
	(0.061)	(0.021)	(0.098)	(0.025)
Tangible Assets	-1.799***	0.163***	-0.672***	-0.160***
	(0.169)	(0.047)	(0.248)	(0.062)
Patent Stock	0.117**	0.002	0.213***	-0.000
	(0.046)	(0.011)	(0.075)	(0.013)
Investments	0.008*	0.002	-0.003	-0.001
	(0.004)	(0.002)	(0.007)	(0.002)
R&D Expenses	0.011**	-0.001	0.007	0.000
	(0.005)	(0.002)	(0.009)	(0.002)
Export	0.021***	-0.000	0.014*	-0.002
	(0.005)	(0.002)	(0.008)	(0.002)
Employees at Start-Up	0.215***	0.015	0.189**	0.013
	(0.055)	(0.020)	(0.096)	(0.023)
Founders	0.153***	0.026**	0.140***	0.005
	(0.033)	(0.011)	(0.054)	(0.014)
Family Members	-0.139*	0.002	-0.030	-0.034
	(0.078)	(0.024)	(0.098)	(0.030)
Gender	-0.151**	-0.017	-0.048	0.000
	(0.075)	(0.027)	(0.112)	(0.032)
Previous Enterprise	0.009	0.019	-0.114	0.046*
	(0.065)	(0.024)	(0.098)	(0.027)
Prior Experience	0.001	0.000	0.004	-0.000
	(0.003)	(0.001)	(0.004)	(0.001)
Motive: Business Idea	0.011	-0.017	0.196**	0.014
	(0.060)	(0.022)	(0.096)	(0.024)
Motive: No Emp. Opp.	0.080	-0.041	0.077	0.048
	(0.104)	(0.037)	(0.162)	(0.043)
Motive: Unemployment	-0.187	0.018	-0.283	-0.062
	(0.156)	(0.053)	(0.195)	(0.076)
Motive: Better Earnings	0.349***	-0.099*	0.071	0.003
	(0.118)	(0.055)	(0.263)	(0.058)
Prior: Self-Employed	-0.045	-0.040	0.001	-0.056
	(0.088)	(0.031)	(0.134)	(0.038)
Prior: Employed (Private)	0.064	0.031	0.071	-0.043
	(0.081)	(0.029)	(0.131)	(0.035)
Prior: Employed (Public)	-0.135	-0.032	-0.197	0.072
	(0.144)	(0.045)	(0.209)	(0.047)
Prior: Unemployed	-0.170	0.029	-0.054	-0.019
	(0.111)	(0.040)	(0.167)	(0.051)
Prior: Inactive	-0.279**	-0.050	-0.196	-0.030
	(0.133)	(0.049)	(0.220)	(0.053)
Edu: High School	-0.170**	0.035	-0.301***	-0.013
	(0.071)	(0.025)	(0.114)	(0.027)
Edu: Bachelor	-0.137*	0.059**	-0.327**	-0.012
	(0.077)	(0.027)	(0.129)	(0.031)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,584	3,561	2,672	3,583
R-squared	0.536	0.116	0.347	0.053

This table presents estimates from regressions of financing constraint measures on legal form choice. Variable definitions are presented in Table A1. In this setup, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A7: OLS: Survey Sample with full controls II

	Log(Short-Term Debt)	Financing Constraints	Bank Financing Constraints	No Funds Needed
	(1)	(2)	(3)	(4)
Low – Capital LLC	-0.407***	0.054*	0.058*	-0.041
	(0.143)	(0.032)	(0.030)	(0.029)
Capital	0.002***	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	-0.000***	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.351***	-0.001	0.003	-0.003
	(0.033)	(0.004)	(0.004)	(0.004)
Age	-0.018	-0.086***	-0.083***	0.081***
	(0.097)	(0.018)	(0.017)	(0.019)
Tangible Assets	-2.773***	0.089*	0.050	-0.126***
	(0.248)	(0.047)	(0.045)	(0.047)
Patent Stock	0.018	0.005	-0.013	-0.034**
	(0.068)	(0.011)	(0.008)	(0.014)
Investments	0.006	-0.001	-0.001	-0.001
	(0.007)	(0.001)	(0.001)	(0.002)
R&D Expenses	0.017**	0.005***	0.003**	-0.006***
	(0.008)	(0.002)	(0.001)	(0.002)
Export	0.027***	0.002*	0.003**	0.001
	(0.007)	(0.001)	(0.001)	(0.001)
Employees at Start-Up	0.209**	0.005	0.009	-0.003
	(0.083)	(0.017)	(0.016)	(0.016)
Founders	0.123***	-0.004	-0.008	0.005
	(0.044)	(0.009)	(0.008)	(0.009)
Family Members	-0.013	0.006	-0.007	0.021
	(0.110)	(0.022)	(0.020)	(0.023)
Gender	-0.217*	-0.010	-0.003	0.036*
	(0.121)	(0.022)	(0.020)	(0.022)
Previous Enterprise	0.141	0.041**	0.039**	-0.045**
	(0.106)	(0.018)	(0.017)	(0.017)
Prior Experience	0.001	-0.002**	-0.002**	0.002***
	(0.004)	(0.001)	(0.001)	(0.001)
Motive: Business Idea	-0.105	0.020	0.008	-0.018
	(0.088)	(0.017)	(0.016)	(0.017)
Motive: No Emp. Opp.	0.091	0.053*	0.050*	-0.003
	(0.159)	(0.030)	(0.028)	(0.031)
Motive: Unemployment	-0.264	0.054	0.076*	-0.038
	(0.326)	(0.045)	(0.044)	(0.043)
Motive: Better Earnings	0.582***	-0.015	-0.002	0.049
	(0.185)	(0.044)	(0.043)	(0.045)
Prior: Self-Employed	-0.209	0.025	0.013	-0.020
	(0.133)	(0.024)	(0.023)	(0.025)
Prior: Employed (Private)	-0.154	-0.029	-0.026	0.009
	(0.128)	(0.024)	(0.023)	(0.025)
Prior: Employed (Public)	-0.464**	-0.064**	-0.065**	0.021
	(0.235)	(0.032)	(0.027)	(0.035)
Prior: Unemployed	-0.346*	0.045	0.027	-0.024
	(0.199)	(0.037)	(0.036)	(0.035)
Prior: Inactive	-0.448**	0.034	0.018	-0.058
	(0.187)	(0.039)	(0.035)	(0.037)
Edu: High School	-0.029	-0.017	-0.015	-0.002
	(0.107)	(0.020)	(0.018)	(0.019)
Edu: Bachelor	0.060	-0.008	0.010	0.017
	(0.107)	(0.023)	(0.022)	(0.022)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,209	3,575	3,575	3,575
R-squared	0.371	0.094	0.083	0.436

This table presents estimates from regressions of financing constraint measures on legal form choice. Variable definitions are presented in Table A1. In this setup, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A8: OLS: Alternative Measures from Survey Data

	Access to Bank Loans (survey data)			% Inv. Financed by Ext. Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
Low – Capital LLC	-0.169***	-0.085**	-0.081**	-0.059**	-0.119***	-0.089***
	(0.030)	(0.036)	(0.041)	(0.027)	(0.026)	(0.028)
Capital		-0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Accumulated Profit/Loss		0.000***	0.000**		-0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Size		0.038***	0.029***		-0.011**	-0.030***
		(0.005)	(0.005)		(0.005)	(0.006)
Age		0.093***	0.164***		-0.222***	-0.204***
		(0.027)	(0.029)		(0.018)	(0.020)
Tangible Assets		0.031	-0.039		0.455***	0.475***
		(0.062)	(0.064)		(0.048)	(0.051)
Patent Stock		-0.008	-0.016		0.051***	0.049***
		(0.009)	(0.013)		(0.011)	(0.014)
Investments			0.021***			0.067***
			(0.003)			(0.008)
R&D Expenses			-0.006**			0.005***
			(0.003)			(0.002)
Export			-0.005*			-0.005***
			(0.003)			(0.002)
Employees at Start – Up			0.058**			-0.008
			(0.028)			(0.018)
Founders			0.023			-0.006
			(0.015)			(0.010)
Family Members			-0.015			0.027
			(0.037)			(0.022)
Gender			-0.015			-0.025
			(0.038)			(0.023)
Previous Enterprise			-0.038			-0.001
			(0.032)			(0.021)
Prior Experience			-0.001			0.000
			(0.001)			(0.001)
Motive : Business Idea			0.019			0.067***
			(0.030)			(0.018)
Motive : No Emp. Opp.			0.064			-0.010
			(0.056)			(0.030)
Motive : Unemployment			0.051			0.050
			(0.091)			(0.062)
Motive : Better Earnings			0.026			0.008
			(0.079)			(0.052)
Prior : Self – Employed			-0.046			0.026
			(0.043)			(0.029)
Prior : Employed (Private)			0.011			0.039
			(0.039)			(0.028)
Prior : Employed (Public)			-0.006			0.009
			(0.065)			(0.040)
Prior : Unemployed			-0.039			0.052
			(0.054)			(0.038)
Prior : Inactive			-0.016			0.069*
			(0.060)			(0.042)
Edu : High School			0.004			-0.036*
			(0.033)			(0.021)
Edu : Bachelor			-0.035			-0.020
			(0.036)			(0.023)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,023	1,880	1,499	3,353	3,187	2,543
R-squared	0.114	0.173	0.230	0.105	0.230	0.296

This table presents estimates from regressions of debt and financing constraint measures on legal form choice. Variable definitions are presented in Table A1. In this setup, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A9: OLS Survey Sample: Relationship vs. Transactional Banks

	Log(Total Debt)	Financing Constraints	Bank Financing Constraints	No Funds Needed
	(1)	(2)	(3)	(4)
Low – Capital LLC × Share Rel. Banks	-0.379**	0.143**	0.099	-0.135**
	(0.167)	(0.072)	(0.069)	(0.066)
Low – Capital LLC	-0.481***	0.020	0.036	0.000
	(0.121)	(0.035)	(0.032)	(0.031)
Capital	0.003***	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	-0.000*	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.336***	0.001	0.006	-0.004
	(0.025)	(0.005)	(0.004)	(0.004)
Age	0.050	-0.072***	-0.069***	0.051**
	(0.062)	(0.019)	(0.017)	(0.020)
Tangible Assets	-1.636***	0.059	0.007	-0.100**
	(0.175)	(0.049)	(0.047)	(0.048)
Patent Stock	0.201***	0.002	-0.022*	-0.042**
	(0.053)	(0.017)	(0.013)	(0.020)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Relationship Bank Regions FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,154	3,147	3,147	3,147
R-squared	0.529	0.138	0.127	0.483

This table presents estimates from regressions of debt and financing constraint measures on legal form choice. Variable definitions are presented in Table A1 in the Appendix. We use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A10: OLS: Trade Credit Dependence

Panel A: Full Sample			
	Log(Total Debt)	Log(Long-Term Debt)	Log(Short-Term Debt)
	(1)	(2)	(3)
Low – Capital LLC × Trade Credit	-0.137***	-0.070**	-0.205***
	(0.024)	(0.034)	(0.033) 7)
Low – Capital LLC	-0.605***	-0.728***	-0.515***
	(0.027)	(0.039)	(0.038)
Trade Credit	0.099***	0.045***	0.164***
	(0.011)	(0.015)	(0.016)
Capital	0.006***	0.006***	0.005***
	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Size	0.335***	0.275***	0.323***
	(0.002)	(0.003)	(0.003)
Age	0.126***	0.043***	0.136***
	(0.008)	(0.011)	(0.012)
Tangible Assets	-1.858***	-0.771***	-2.579***
	(0.020)	(0.027)	(0.028)
Patent Stock	0.033	0.042	0.016
	(0.024)	(0.031)	(0.015)
Additional Firm Controls	No	No	No
Founder Controls	No	No	No
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	384,655	257,656	227,375
R-squared	0.487	0.296	0.343

Panel B: Survey Sample				
	Log(Total Debt)	Financing Constraints	Bank Financing Constraints	No Funds Needed
	(1)	(2)	(3)	(4)
Low – Capital LLC × Trade Credit	-0.065	0.024	0.004	0.007
	(0.209)	(0.077)	(0.075)	(0.067)
Low – Capital LLC	-0.600**	0.030	0.054	-0.048
	(0.240)	(0.082)	(0.080)	(0.074)
Trade Credit	-0.021	-0.012	-0.011	0.041
	(0.085)	(0.032)	(0.029)	(0.030)
Capital	0.002***	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Accumulated Profit/Loss	-0.000***	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.353***	-0.001	0.003	-0.003
	(0.025)	(0.004)	(0.004)	(0.004)
Age	0.068	-0.086***	-0.083***	0.082***
	(0.061)	(0.018)	(0.017)	(0.019)
Tangible Assets	-1.798***	0.088*	0.050	-0.126***
	(0.169)	(0.047)	(0.045)	(0.047)
Patent Stock	0.117**	0.005	-0.013	-0.034**
	(0.046)	(0.011)	(0.008)	(0.014)
Additional Firm Controls	Yes	Yes	Yes	Yes
Founder Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,584	3,575	3,575	3,575
R-squared	0.536	0.095	0.083	0.437

This table presents estimates from regressions of debt and financing constraint measures on legal form choice. Variable definitions are presented in Table A1. In Panel A, we use data from the full sample, which is retrieved from the Orbis Historical Database. In Panel B, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A11: Foreign Ownership and external Financing

	Log(Total Debt)
Foreign Owner	-0.082
	(0.135)
Low – Capital LLC	-0.659***
	(0.099)
Capital	0.002***
	(0.001)
Accumulated Profit/Loss	0.000***
	(0.000)
Size	0.353***
	(0.025)
Age	0.068
	(0.061)
Tangible Assets	-1.795***
	(0.170)
Patent Stock	0.117**
	(0.046)
Additional Firm Controls	Yes
Founder Controls	Yes
Year FE	Yes
Industry FE	Yes
Observations	3,584
R-squared	0.536

This table presents estimates from regressions of debt and log debt on foreign ownership. Variable definitions are presented in Table A1. In this setup, we use data from the survey sample, which is retrieved from the IAB/ZEW Start-up Panel. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A12: Regression Discontiniuity Design: Survey Sample

Panel A: Full sample						
Range at Cut-off Point:	(-12,500; +12,500)		(-5,000; +5,000)		(-2,500; +2,500)	
	Log(Total Debt)		Log(Total Debt)		Log(Total Debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
RD estimate	1.435***	1.382***	1.071***	1.331***	1.298**	1.592***
	(0.286)	(0.284)	(0.387)	(0.339)	(0.662)	(0.288)
Controls	No	Yes	No	Yes	No	Yes
Observations	29,973	24,353	19,062	15,271	17,678	14,154

Panel B: Survey sample

Range at Cut-off Point:	(-12,500; +12,500)		(-12,500; +12,500)		(-12,500; +12,500)		(-12,500; +12,500)	
	Log(Total Debt)		Financing Constraints		Bank Financing Constraints		No Funds Needed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD estimate	2.104***	-3.040	-0.473**	-0.341	-2.512***	-2.641***	1.364***	1.498*
	(0.696)	(3.477)	(0.229)	(0.322)	(0.224)	(0.359)	(0.461)	(0.833)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	897	357	468	356	468	356	468	356

This table presents the results for the RDD estimates using different boundaries around the threshold of 25,000 that defines high- and low-capital LLCs in Germany. Firms in our sample that have less (more) than 25,000 in equity capital are low-capital LLCs (high-capital LLCs). Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively

Table A13: Descriptive Statistics: Austrian Sample

	Low-Capital LLC (pre switch)		High-Capital LLC (post switch)	
	N: 920		N: 945	
	Mean	Std. Dev.	Mean	Std. Dev.
$Low-Capital\,LLC$	1	0	0	0
$Total\,Debt_{(\times 1000)}$	192.636	455.596	384.618	639.912
$Log(Total\,Debt)$	10.485	2.148	11.647	1.786
$Access\,to\,Long-Term\,Debt$	0.950	0.218	0.977	0.150
$Long-Term\,Debt_{(\times 1000)}$	196.580	462.805	374.474	635.952
$Log(Long-Term\,Debt)$	10.393	2.315	11.495	1.946
$Capital_{(\times 1000)}$	7.500	2.758	32.860	13.136
$Accumulated\,Profit/Loss_{(\times 1000)}$	3.851	108.561	28.152	218.480
$Size$	8.121	4.024	9.027	3.789
Age	0.614	0.772	1.956	0.858
$Tangible\,Assets$	0.250	0.294	0.256	0.300

This table presents summary statistics for Austrian low- and high-capital LLCs. Corresponding variable definitions can be found in Table A1. All monetary values are in euro.

Table A14: Regression Discontiniuity Design: Austria

Range at Cut-off Point:	(-17,500; +17,500)		(-12,500; +12,500)		(-5,000; +5,000)	
	Log(Total Debt)		Log(Total Debt)		Log(Total Debt)	
	(1)	(2)	(3)	(4)	(5)	(6)
RD estimate	0.012	0.264***	-0.151	0.174	-0.034	0.631
	(0.084)	(0.070)	(0.246)	(0.200)	(0.493)	(0.450)
Controls	No	Yes	No	Yes	No	Yes
Observations	44,796	30,995	26,587	18,825	15,177	10,699

This table presents the results for the RDD estimates using different boundaries around the threshold of 17,500 that defines placebo high- and placebo low-capital LLCs in Austria. Firms in our sample that have less (more) than 17,500 in equity capital are placebo low-capital LLCs (placebo high-capital LLCs). Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

Table A15: Difference-in-Difference Regression: Austria

	Log(Total Debt)	Access to Long-Term Debt	Log(Long-Term Debt)
	(1)	(2)	(3)
$Post Switch \times Low-Capital LLC$	0.017	0.015*	0.064
	(0.090)	(0.009)	(0.103)
Capital	0.484*	-0.078***	0.435
	(0.274)	(0.028)	(0.286)
Accumulated Profit/Loss	-0.070***	-0.000	-0.107***
	(0.008)	(0.001)	(0.009)
Size	0.172***	0.003***	0.176***
	(0.006)	(0.001)	(0.007)
Age	0.894***	0.001	0.788***
	(0.044)	(0.005)	(0.051)
Tangible Assets	-0.292***	0.004	-0.220***
	(0.068)	(0.006)	(0.074)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	41,807	42,418	41,678
R-squared	0.887	0.586	0.872

This table presents the results for difference-in-differences regressions of debt. The Austrian treated group are firms that switched legal forms from a placebo low-capital LLC to a placebo high-capital LLC in our sample period. The control group are permanent high-capital LLCs (i.e. firms that opted for paid-in capital of 17,500 euro at startup). Variable definitions are presented in Table A1. We use data from Orbis Historical Database. Standard errors are reported in parentheses and clustered at the firm level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

B Chapter 2

Table B1: Summary statistics for patent-pledging Dutch firms

	Pre-pledge					Post-pledge till t=4				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	199	4116.55	4579.17	0.18	20247.23	276	4864.92	8534.10	8.24	79489.00
Equity	199	2031.51	3190.27	0.00	16733.63	276	1979.23	3625.46	0.00	22379.90
Employees	199	35.77	48.72	1.00	239.00	276	30.87	47.43	1.00	300.00
Age	199	17.69	18.25	1.00	99.00	276	20.09	19.75	1.00	103.00
Patentstock	199	1.69	2.01	0.00	18.21	276	1.57	1.83	0.04	15.48
Forward Cites	199	0.22	0.30	0.00	2.15	276	0.22	0.31	0.00	2.15
# Patents	199	3.78	4.98	0.00	46.00	276	4.53	6.11	1.00	46.00
# Pledged patents	199	0.00	0.00	0.00	0.00	89	2.26	2.34	1.00	17.00
N	199					276				

All monetary values are in Thd. Euros.

Table B2: Summary statistics for patent-pledging Swedish firms

	Pre-pledge					Post-pledge till t=4				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	241	6303.78	13409.71	2.93	94418.00	401	6973.39	18888.17	3.03	133773.00
Equity	241	5659.17	15345.72	0.00	121260.00	401	4361.43	11113.04	0.00	80792.09
Employees	241	74.53	186.29	0.00	1114.00	401	60.65	167.02	0.00	1342.00
Age	241	16.16	16.59	1.00	78.00	401	16.91	15.92	1.00	81.00
Patentstock	241	2.91	4.38	0.00	27.60	401	2.68	4.79	0.05	33.46
Forward Cites	241	0.39	0.40	0.00	2.19	401	0.37	0.38	0.00	2.23
# Patents	241	6.47	10.43	0.00	47.00	401	6.67	11.29	1.00	67.00
# Pledged patents	241	0.00	0.00	0.00	0.00	126	3.53	6.21	1.00	43.00
N	241					401				

All monetary values are in Thd. Euros.

Figure B1: Coefficient plots for the dynamic difference-in-difference estimation using the Dutch sample

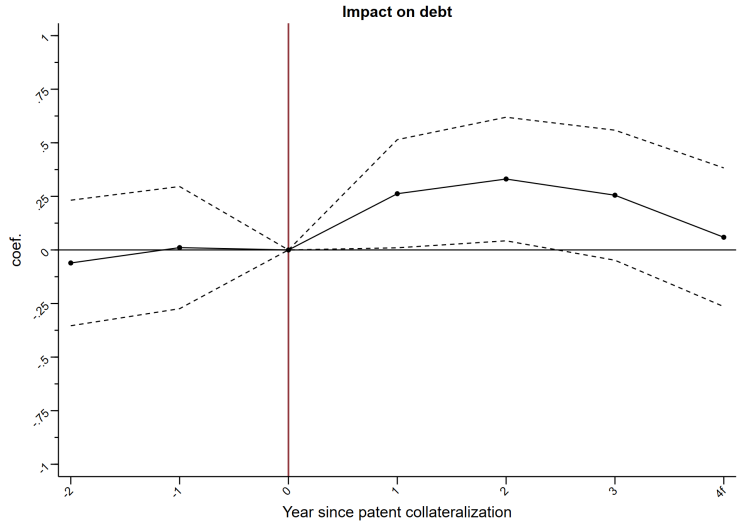


Figure B2: Coefficient plots for the dynamic difference-in-difference estimation using the Swedish sample

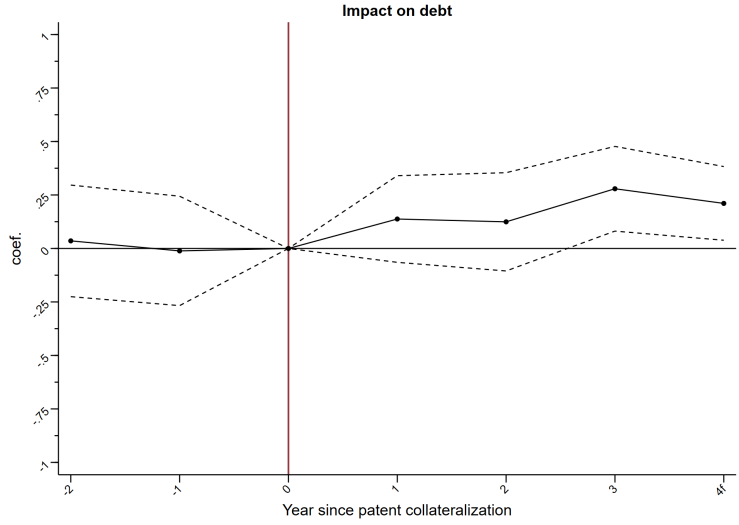


Table B3: Summary statistics for the Dutch placebo sample

	Patent pledging firms					Non-pledging firms				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	1731	7940.23	14764.48	0.16	116128.38	99287	4498.24	13510.72	0.10	160524.00
Equity	1731	4329.86	8416.49	0.00	68734.73	99287	4259.89	19074.73	0.00	405889.00
Employees	1155	92.74	169.85	1.00	1393.00	61087	62.25	255.55	1.00	40045.00
Age	1731	22.84	23.28	0.00	116.00	99287	22.16	22.90	0.00	314.00
Patentstock	1731	2.19	2.98	0.00	24.78	99287	1.13	12.13	0.00	1035.30
Forward Cites	1731	0.24	0.31	0.00	2.15	99287	0.17	0.40	0.00	13.37
N	1731					99287				

The sample includes 9064 non-pledging firms and 191 patent pledging firms with randomly assigned pledging events observed between 1994 and 2018. True pledging events have been replace by fake pledging events in periods prior the actual patent pledging event. Periods after the patent pledging events of patent pledging firms have been dropped. All monetary values are in Thd. Euros.

Table B4: Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in the Netherlands

	Diff-in-Diff	
Dep. Variable:	Log(Debt)	Log(Debt)
post_pledge	-0.072	-0.10
	(0.087)	(0.085)
Log(Equity)		-0.015***
		(0.0013)
Log(Employees)		0.25***
		(0.0081)
Log(Patent_Stock)		0.26***
		(0.015)
Log(Forward_Cites)		0.29***
		(0.064)
Year FE	YES	YES
Firm FE	YES	YES
F	0.69	313.9
R-squared	0.86	0.87
N	56148	56148

This table presents the results for the difference-in-difference regression estimating the impact of fake patent pledging events on firms' debt level. egression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B5: Summary statistics for the Swedish placebo sample

	Patent pledging firms					Non-pledging firms				
	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
Debt	410	10432.37	30002.43	1.60	203694.00	88952	5071.65	17566.38	0.87	204978.81
Equity	425	12868.55	36311.79	-120.00	364397.19	97825	5220.08	22824.25	-129.52	372612.00
Employees	413	179.35	589.17	0.00	4929.00	91193	63.60	330.17	0.00	40567.00
Age	441	15.44	18.23	0.00	100.00	98866	21.58	19.36	0.00	120.00
Patentstock	441	4.02	11.31	0.00	125.27	98866	1.31	6.83	0.00	410.56
Forward Cites	441	0.36	0.37	0.00	2.19	98866	0.19	0.38	0.00	14.31
N	441					98866				

The sample 7500 non-pledging firms and 123 patent pledging firms with randomly assigned pledging events observed between 1997 and 2018. True pledging events have been replace by fake pledging events in periods prior the actual patent pledging event. Periods after the patent pledging events of patent pledging firms have been dropped. All monetary values are in Thd. Euros.

Table B6: Difference-in-difference regression estimating the impact of a fake pledging events in pre-treatment periods on debt level in Sweden

	Diff-in-Diff	
Dep. Variable:	Log(Debt)	Log(Debt)
post_pledge	-0.15*	-0.11
	(0.087)	(0.076)
Log(*Equity*)		0.011***
		(0.0023)
Log(*Employees*)		0.65***
		(0.011)
Log(*Patent_Stock*)		0.22***
		(0.012)
Log(*Forward_Cites*)		0.16***
		(0.047)
Year FE	YES	YES
Firm FE	YES	YES
F	2.84	1031.9
R-squared	0.88	0.91
N	75492	75492

This table presents the results for the difference-in-difference regression estimating the impact of fake patent pledging events on firms' debt level. egression accounts for sampling weights. Robust standard errors are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C Chapter 3

Figure C1: Thermal Inversion

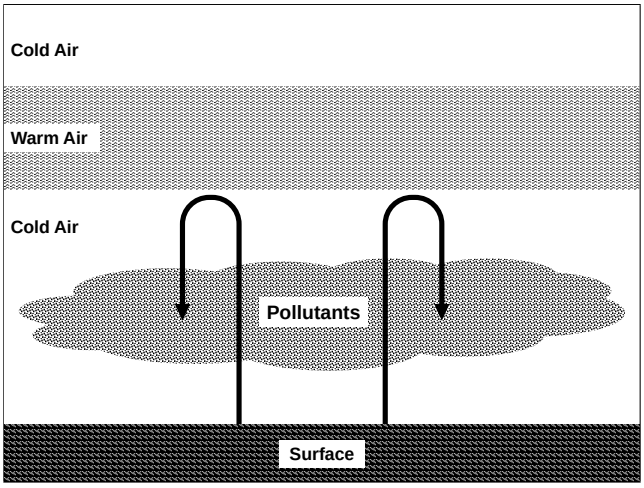


Figure C2: Ventilation Coefficient

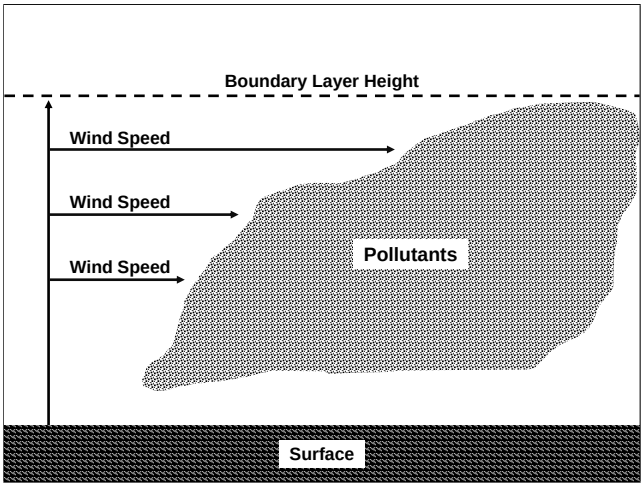


Figure C3: Annual average number of patent filings per NUTS-3 region

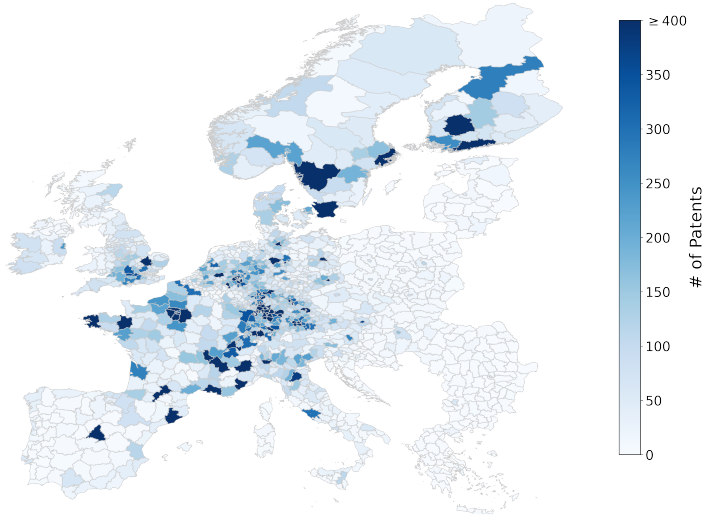


Figure C4: Annual average $PM_{2.5}$ level per NUTS-3 region

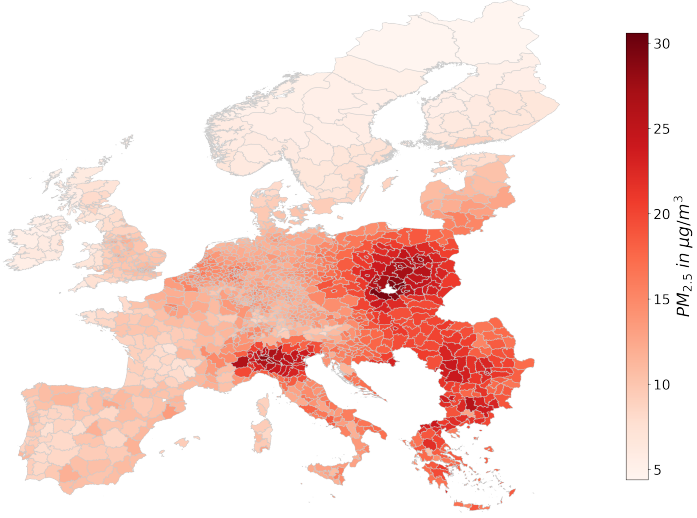


Figure C5: Dropped NUTS-3 regions with total number of patent filings equal or below the 5th percentile

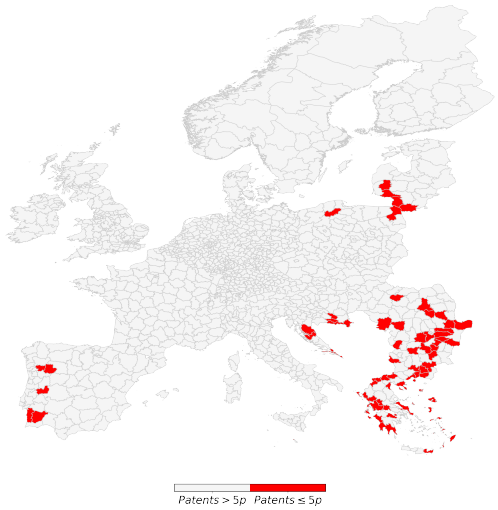


Table C1: Summary for the predicted $PM_{2.5}$ concentrations for the regressions shown in Table 3.2

	N	Mean	Std. Dev.	Min	50th	Max
Predicted $PM_{2.5}$ with TI	12924	13.75	0.33	13.20	13.71	15.04
Predicted $PM_{2.5}$ with VC	12924	13.75	0.09	13.57	13.73	14.98
Predicted $PM_{2.5}$ with both IV's	12924	13.75	0.34	13.07	13.72	15.51

Predicted $PM_{2.5}$ with TI refers to the predicted $PM_{2.5}$ concentration of regressing $PM_{2.5}$ on Thermal Inversions (Table 3.2 third column) by setting controls to mean.
Predicted $PM_{2.5}$ with VC refers to predicted $PM_{2.5}$ concentration of regressing $PM_{2.5}$ on Ventilation Capability (Table 3.2 fifth column) by setting controls to mean.
Predicted $PM_{2.5}$ with both IVs refers to predicted $PM_{2.5}$ concentration of regressing $PM_{2.5}$ on Thermal Inversions and Ventilation Capability (Table 3.2 seventh column) by setting controls to mean.

Table C2: Poisson fixed effects regression

	Poisson	Poisson CF
Dep. Variable:	Nb. Patents	Nb. Patents
$PM2.5$	-0.0077**	-0.071***
	(0.0036)	(0.027)
$\hat{v}$		0.064**
		(0.027)
NUTS-3 FE	YES	YES
Country-Year FE	YES	YES
Log likelihood	-56582.7	
Pseudo R2	0.96	
Replications		500
Clusters	1196	1365
N	13599	16380

This table presents the results for the poisson fixed effects regression. Estimates are obtained for a sample including all NUTS-3 regions. The first column shows the results for poisson fixed effects regression without accounting for endogeneity of $PM2.5$. The second column shows the poisson fixed effects results using control function approach by including first-stage residuals $\hat{v}$. We do not include surface pressure as control variable since it is collinear with the fixed effects in the poisson regression. However, further robustness test show that surface pressure do not have a significant impact on first stage-results and, thus, should not matter for the final results. The standard errors reported in parentheses and are fully robust. For the poisson regression with the control function approach, standard errors are obtained by bootstrapping the 1356 NUTS-3 regions using 500 bootstrap replications.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Accounting for spatial and serial correlation

	Clustered SE	*SE – Assumption 1*	*SE – Assumption 2*
Dep. Variable:	Log(Patents)	Log(Patents)	Log(Patents)
PM2.5	-0.087**	-0.087**	-0.087**
	(0.036)	(0.044)	(0.042)
NUTS-3 FE	YES	YES	YES
Country-Year FE	YES	YES	YES
Controls	YES	YES	YES
N	13671	13671	13671

Estimations conducted for a conservative sample including all NUTS-3 regions. Column 1 shows second-stage baseline results with SE clustered at NUTS-3 in accordance with results in Table C5. Column 2 and 3 show second-stage results with spatial heteroskedasticity and autocorrelation consistent SE in line with Conley (1999, 2010). Assumption 1 (2) assumes a spatial correlation range of 500 (1000) kilometers and a serial correlation range of 5 (10) years. Conley standard errors are computed using the Stata code provided by (Foreman, 2020).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C4: Different thresholds for a low VC

	Low VC ≤ p10		*Low VC ≤ p15*		*Low VC ≤ p20*		*Low VC ≤ p25*	
Dep. Variable:	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*
PM2.5	-0.10**		-0.088**		-0.10***		-0.054*	
	(0.047)		(0.043)		(0.036)		(0.028)	
Share Inversions		3.70***		3.67***		3.66***		3.70***
		(0.52)		(0.51)		(0.51)		(0.51)
Share p10 ≥ VC		90.6						
		(82.0)						
Share p15 ≥ VC				181.1***				
				(53.4)				
Share p20 ≥ VC						255.6***		
						(39.5)		
Share p25 ≥ VC								279.7***
								(31.5)
NUTS-3 FE	YES		YES		YES		YES	
Country-Year FE	YES		YES		YES		YES	
Controls	YES		YES		YES		YES	
KP F-stat.	26.5		31.5		44.9		63.3	
Hansen J stat. P-Val	0.15		0.81		0.78		0.27	
N	12924	12924	12924	12924	12924	12924	12924	12924

Standard errors are reported in parentheses and clustered at the NUTS-3 level.
SE clustered at NUTS-3
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C5: Different thresholds for dropping low patenting NUTS-3 regions

	No trimming		Trim NUTS-3 at 5%		Trim NUTS-3 at 10%		Trim NUTS-3 at 15%	
Dep. Variable:	Log(Patents)	*PM*2.5	Log(Patents)	*PM*2.5	Log(Patents)	*PM*2.5	Log(Patents)	*PM*2.5
*PM*2.5	-0.087**		-0.099***		-0.14***		-0.14***	
	(0.036)		(0.036)		(0.037)		(0.036)	
Share Inversions		3.78***		3.65***		3.27***		3.24***
		(0.50)		(0.51)		(0.50)		(0.52)
Share low VC		227.2***		253.7***		258.6***		259.5***
		(40.3)		(39.5)		(40.6)		(41.8)
NUTS-3 FE	YES		YES		YES		YES	
Country-Year FE	YES		YES		YES		YES	
Controls	YES		YES		YES		YES	
KP F-stat.	42.5		44.9		39.0		37.1	
Hansen J stat. P-Val	0.50		0.82		0.70		0.96	
N	13671	13671	12984	12984	12267	12267	11699	11699

SE clustered at NUTS-3
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C6: Different sample periods

Dep. Variable:	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)
*PM*2.5	-0.10***	-0.097***	-0.16***	-0.16***	-0.14***
	(0.036)	(0.034)	(0.055)	(0.047)	(0.046)
Period	2001-2012	2001-2011	2001-2010	2001-2009	2001-2008
NUTS-3 FE	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES
KP F-stat.	44.9	46.5	18.3	23.0	24.9
Hansen J stat. P-Val	0.78	0.65	0.21	0.79	0.51
N	12924	11778	10659	9565	8475

SE clustered at NUTS-3
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C7: Patenting and weather controls

Dep. Variable:	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)	Log(Patents)
Log(Pop)	0.15	0.29	0.16	0.16	0.16	0.25
	(0.27)	(0.25)	(0.27)	(0.27)	(0.27)	(0.26)
Surface Pressure	-0.00020					-0.000044
	(0.00080)					(0.00100)
$Surface\ Pressure^2$	4.0e-10					-5.9e-10
	(4.0e-09)					(5.2e-09)
Relative humidity		0.27				0.031
		(3.20)				(3.31)
$Relative\ humidity^2$		0.027				0.23
		(2.26)				(2.34)
Temperature			0.018			-0.19
			(0.91)			(1.13)
$Temperature^2$			0.0000082			0.00040
			(0.0016)			(0.0020)
Precipitation				35.3		50.1
				(63.8)		(70.2)
$Precipitation^2$				-2336.3		-6023.3
				(17437.3)		(18345.3)
Wind speed					-0.0022	-0.035
					(0.10)	(0.11)
$Wind\ speed^2$					-0.014	-0.015
					(0.014)	(0.014)
NUTS-3 FE	YES	YES	YES	YES	YES	YES
Country-Year FE	YES	YES	YES	YES	YES	YES
F-stat.	0.42	0.68	0.64	0.49	1.45	1.15
R-sq	0.96	0.96	0.96	0.96	0.96	0.96
N	13270	13399	13270	13270	13270	13152

SE clustered at NUTS-3
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C8: Patenting and air pollution with individual weather controls

Dep. Variable:	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*	Log(Patents)	*PM2.5*
PM2.5	-0.0735**		-0.0844***		-0.0759**		-0.0844***		-0.0766**		-0.0868***		-0.10***	
	(0.030)		(0.035)		(0.031)		(0.036)		(0.031)		(0.030)		(0.036)	
Share Inversions		4.05***		4.03***		4.16***		3.56***		3.97***		4.06***		3.66***
		(0.49)		(0.49)		(0.51)		(0.50)		(0.49)		(0.49)		(0.51)
Share low VC		300.6***		224.0***		295.4***		256.0***		301.4***		326.5***		255.6***
		(39.2)		(38.1)		(39.1)		(38.8)		(39.2)		(41.3)		(39.5)
Log(Pop)	0.32	0.74	0.34	0.83	0.32	0.75	0.33	0.75	0.33	0.77	0.33	0.72	0.36	0.88
	(0.26)	(0.79)	(0.26)	(0.79)	(0.26)	(0.79)	(0.26)	(0.78)	(0.26)	(0.79)	(0.26)	(0.79)	(0.26)	(0.78)
Surface Pressure			0.0014	0.020***									0.0022	0.024***
			(0.0011)	(0.0033)									(0.0014)	(0.0041)
Surface Pressure^2			-5.0e-09	-0.000000077***									-8.9e-09	-0.000000092***
			(4.9e-09)	(0.000000017)									(6.8e-09)	(0.000000021)
Relative humidity					1.53	22.4**							-0.57	2.49
					(3.51)	(9.19)							(3.49)	(9.57)
Relative humidity^2					-0.89	-17.8**							0.46	-5.30
					(2.48)	(6.58)							(2.46)	(6.78)
Temperature							0.56	5.30					-0.39	-5.06
							(1.06)	(3.60)					(1.37)	(4.50)
Temperature^2							-0.0010	-0.010					0.00063	0.0081
							(0.0019)	(0.0064)					(0.0024)	(0.0080)
Precipitation									1.27	-236.2			-0.86	-159.6
									(69.0)	(201.4)			(75.5)	(217.9)
Precipitation^2									1342.61	165018.1***			20722.2	208616.1***
									(1962.31)	(50695.6)			(21520.4)	(51402.27)
Wind speed											-0.0095	0.15	0.035	0.71*
											(0.13)	(0.38)	(0.13)	(0.43)
Wind speed^2											-0.014	0.035	-0.012	0.070
											(0.019)	(0.053)	(0.020)	(0.065)
NUTS-3 FE	YES		YES		YES		YES		YES		YES		YES	
Country-Year FE	YES		YES		YES		YES		YES		YES		YES	
KP F-stat.	60.9		49.5		57.8		45.3		59.9		62.5		44.9	
Hansen J stat. PVal	0.84		0.91		0.77		0.88		0.81		0.86		0.78	
N	12924	12924	12924	12924	12924	12924	12924	12924	12924	12924	12924	12924	12924	12924

SE clustered at NUTS-3

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C6: Coefficient plot of robustness results.

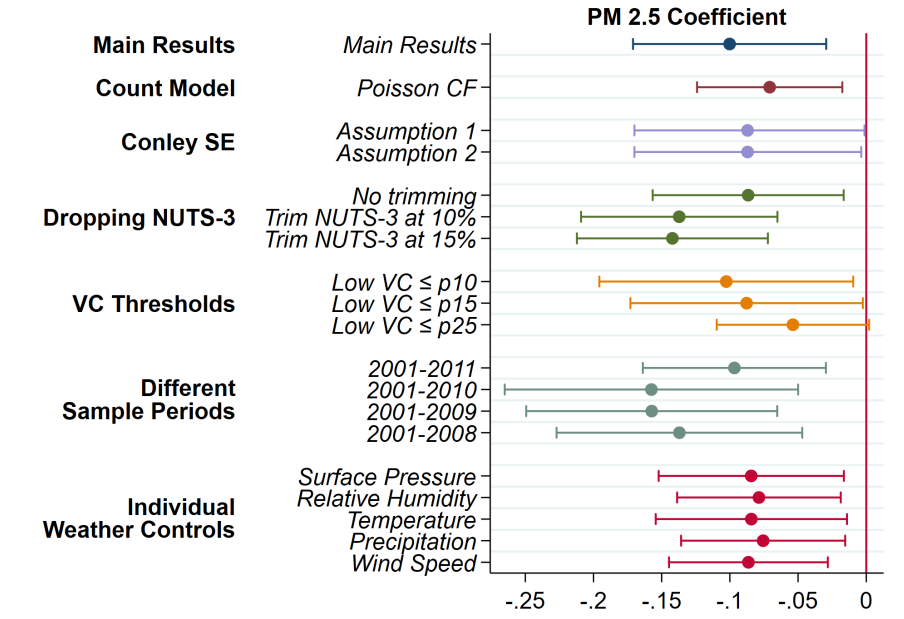


Figure C7: Annual average $PM_{2.5}$ concentration by Urban-Rural classification

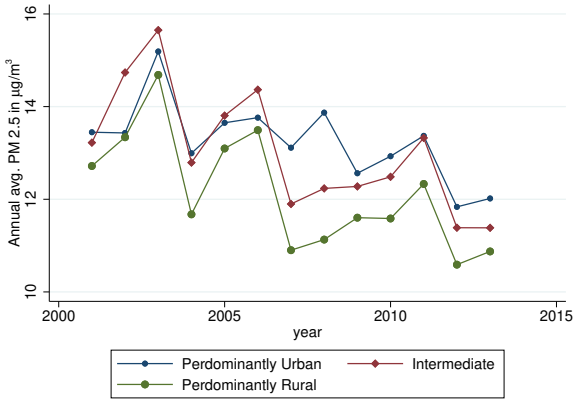
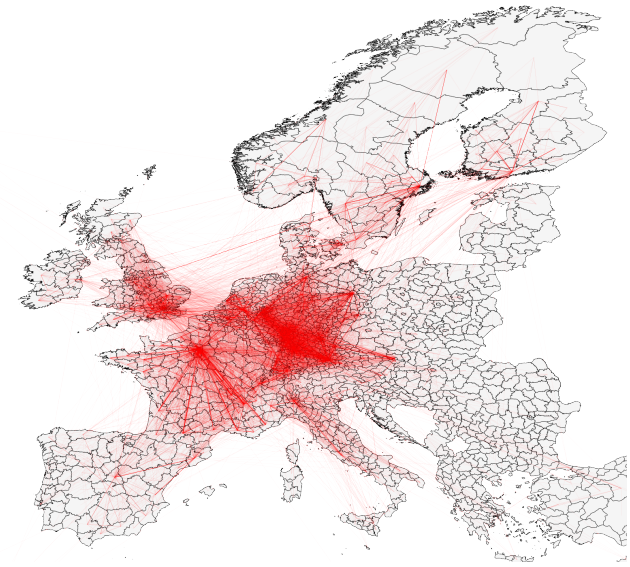


Table C9: Supplementary summary statistics

	N	Mean	Std. Dev.	10th	50th	90th
Nb. migrating inventors	16380	1.92	5.50	0	0	5
Nb. (patents) migrating inventors	16380	7.66	29.76	0	0	19
Nb. immigrating inventors	16380	2.07	5.70	0	0	5
Nb. (patents) immigrating inventors	16380	8.13	29.90	0	0	20
Nb. of publications	16380	151.70	433.72	0	9	431
Nb. of deaths	14296	3696.36	3787.99	936	2695	7210
Death rate (%)	13898	1.04	0.20	0.81	1.02	1.29
N	16380					

Summary statistics of 1365 NUTS-regions for 30 countries observed over the period 2001 - 2012. Our data includes all EU member states (+ United Kingdom) and EFTA countries. Iceland and Cyprus are not included because both countries are outside the geographical boundaries of our dataset. In contrast to the sample of our baseline results (Table 3.1), we do not drop NUTS-3 regions equal or below the 5th percentile of the distribution for total number of patent filings.

Figure C8: Inventors relocating between NUTS-3 regions for the sample period 2001-2012



Weight of line indicate relocation frequency.

Figure C9: Inventors relocating between NUTS-3 and regions outside Europe for the sample period 2001-2012.

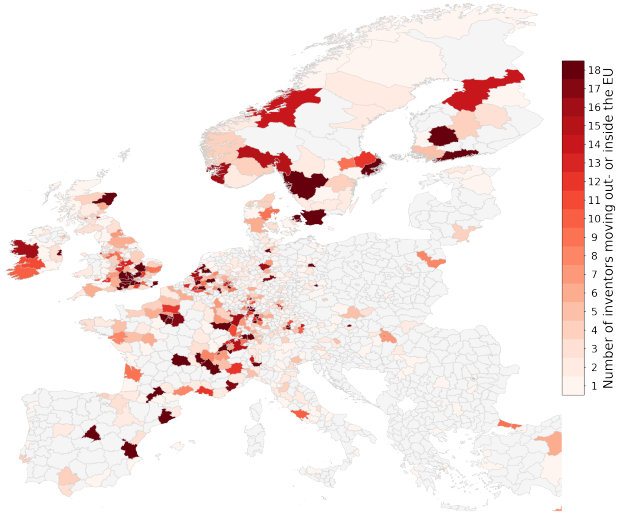


Table C10: Migrating inventors and air pollution for a restricted sample where the relocation year of an inventor can be well defined

	OLS	IV		OLS	IV	
Dep. Variable:	Log(Migr. Inv.)	Log(Migr. Inv.)	$PM2.5_{t-1}$	Log(Migr. Inv. Patents)	Log(Migr. Inv. Patents)	$PM2.5$
$PM2.5$	-0.011***	-0.0015		-0.020***	0.027	
	(0.0034)	(0.042)		(0.0068)	(0.084)	
Share Inversions			3.78***			3.78***
			(0.50)			(0.50)
Share low VC			227.2***			227.2***
			(40.3)			(40.3)
NUTS-3 FE	YES	YES		YES	YES	
Country-Year FE	YES	YES		YES	YES	
Controls	YES	YES		YES	YES	
KP F-stat.		42.5			42.5	
Hansen J stat. P-Val		0.27			0.27	
N	13671	13671	13671	13671	13671	13671

This table presents the results of regressing $PM_{2.5}$ concentration on the total number ($Log(Migr.Inv.)$) and patent weighted number of migrating inventors ($Log(Migr.Inv.Patents)$) out of NUTS-3 regions for a restricted sample where the relocation year of an inventor can be well defined. $Log(Migr.Inv.Patents)$ weights the number of migrating inventors by the number of patents inventors filed within 5 year before the relocation. The first column shows results for the OLS estimation by simply regressing the total number of migrating inventors on $PM_{2.5}$ concentration. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. The fourth column shows the OLS results for the patent weighted measure of the number of migrating inventors. The last two columns show results for same outcome variable by instrumenting $PM_{2.5}$ concentration. $Share of Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share of low VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C11: Immigrating inventors and air pollution

	OLS	IV		OLS	IV	
Dep. Variable:	Log(Immigr. Inv.)	Log(Immigr. Inv.)	$PM2.5$	Log(Immigr. Inv. Patents)	Log(Immigr. Inv. Patents)	$PM2.5$
$PM2.5$	-0.0059	-0.010		-0.0055	-0.056	
	(0.0039)	(0.043)		(0.0068)	(0.079)	
Share Inversions			3.78***			3.78***
			(0.50)			(0.50)
Share low VC			227.2***			227.2***
			(40.3)			(40.3)
NUTS-3 FE	YES	YES		YES	YES	
Country-Year FE	YES	YES		YES	YES	
Controls	YES	YES		YES	YES	
KP F-stat.		42.5			42.5	
Hansen J stat. P-Val		0.56			0.85	
N	13671	13671	13671	13671	13671	13671

This table presents the results of regressing $PM_{2.5}$ concentration on the total number ($Log(Immigr.Inv.)$) and patent weighted number of immigrating inventors ($Log(Immigr.Inv.Patents)$) to NUTS-3 regions. $Log(Immigr.Inv.Patents)$ weights the number of immigrating inventors by the number of patents inventors filed within 5 year before the relocation. The first column shows results for the OLS estimation by simply regressing the total number of immigrating inventors on $PM_{2.5}$ concentration. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. The fourth column shows the OLS results for the patent weighted measure of the number of immigrating inventors. The last two columns show results for same outcome variable by instrumenting $PM_{2.5}$ concentration. $Share of Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share of low VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C12: Immigrating inventors and air pollution for a restricted sample where the relocation year of an inventor can be well defined

	OLS	IV		OLS	IV	
Dep. Variable:	Log(Immigr. Inv.)	Log(Immigr. Inv.)	$PM2.5_{t-1}$	Log(Immigr. Inv. Patents)	Log(Immigr. Inv. Patents)	$PM2.5$
$PM2.5$	-0.0078**	-0.028		-0.010	-0.056	
	(0.0036)	(0.041)		(0.0069)	(0.079)	
Share Inversions			3.78***			3.78***
			(0.50)			(0.50)
Share low VC			227.2***			227.2***
			(40.3)			(40.3)
NUTS-3 FE	YES	YES		YES	YES	
Country-Year FE	YES	YES		YES	YES	
Controls	YES	YES		YES	YES	
KP F-stat.		42.5			42.5	
Hansen J stat. P-Val		0.64			0.85	
N	13671	13671	13671	13671	13671	13671

This table presents the results of regressing $PM_{2.5}$ concentration on the total number ($Log(Immigr.Inv.)$) and patent weighted number of immigrating inventors ($Log(Immigr.Inv.Patents)$) to NUTS-3 regions for a restricted sample where the relocation year of an inventor can be well defined. $Log(Immigr.Inv.Patents)$ weights the number of immigrating inventors by the number of patents inventors filed within 5 year before the relocation. The first column shows results for the OLS estimation by simply regressing the total number of immigrating inventors on $PM_{2.5}$ concentration. The second and third columns show the second- and first-stage results by instrumenting $PM_{2.5}$ with thermal inversion and ventilation capability. The fourth column shows the OLS results for the patent weighted measure of the number of immigrating inventors. The last two columns show results for same outcome variable by instrumenting $PM_{2.5}$ concentration. $Share of Inversions$ measures the number of days in which thermal inversions occur normalized by the total number of days per year. $Share of low VC$ measures the annual average length of consecutive days with a low ventilation coefficient normalized by the total number of days per year. We define a low ventilation coefficient as any daily average ventilation coefficient that is equal or below the $20th$ percentile of the distribution of daily average ventilation coefficients within a NUTS-3 region. Standard errors are reported in parentheses and clustered at the NUTS-3 level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1 Data cleaning inventor relocation

Morrison, Riccaboni and Pammolli (2017) provide a disambiguation of patent inventors. We assigning NUTS-3 regions to corresponding goecodes of inventor addresses. Following, we trace relocation of inventors based on changes in NUTS-3 codes of patents inventors' filed in chronological order. Any address outside NUTS-3 regions are treated equally as "outside Europe" because we are not interested in movements between regions outside Europe. In some cases the history of filed patents stating the addresses for the individual inventor does not provide a clear relocation pattern. Specifically, the history of patents for an individual inventor shows frequent alternation between two or more NUTS-3 region within a short period. Such pattern are unlikely to reflect true relocations of inventors. One reason might be that inventors alternate between office and residence addresses for the patents they had filed. This issue is described in detail by Zacchia (2018) using the same dataset to trace the relocation of inventors. We follow his procedure to clean the data for unreasonable relocation patterns by assigning inventors to NUTS-3 regions in the following way:

1. We split the patent history of each inventor into temporal intervals, which are delimited by the years when a different NUTS-3 occurs for the first time

2. To each of these intervals we assign a unique NUTS-3 region by choosing the one that is observed most frequently

3. Ties are resolved conservatively in favor of the city that occurred earlier in the inventor's patent history

Doctoral dissertations from the Faculty of Economics and Business, see:
http://www.kuleuven.ac.be/doctoraatsverdediging/archief.htm.

Faculty of Economics and Business

Department of Management, Strategy and Innovation

Naamsestraat 69
3000 LEUVEN, België
felix.bracht@kuleuven.be
www.kuleuven.be