Essays on firm innovation

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Abstract

This thesis examines the intersection of innovation, entrepreneurship and competition dynamics. Using patent data, I have very detailed information on firm technological content which allows me to understand more intricacies in firm behavior, namely the type and originality of innovation the firm is doing. My first chapter analyzes the innovation incentives exerted by the pull of potential acquirers on new start-up firms. I test the hypothesis that start-ups innovate in closer complementary areas to their potential acquirers when they expect their primary exit strategy to be a buyout. In a complementary work, I document the long run impact of the initial positions new firms choose. This study provides a measure of the push effect from having expertise built up in a technological area. It also presents some patterns that disentangle firm size and firm age on innovation choices. Finally, my third chapter analyzes the pull effect on innovation imposed by policy changes on vehicle emission limits. This study addresses the question of whether there are early mover advantages for policy makers.

Keywords: innovation, entrepreneurship, firm dynamics

Résumé

Cette thèse porte sur le comportement et les interactions des entreprises. Mes recherches examinent l'intersection de l'innovation, de l'entrepreneuriat et de la dynamique de la concurrence. En utilisant les données de brevets j'ai des informations très détaillées sur le contenu technologique de l'entreprise, ce qui me permet de comprendre davantage les subtilités du comportement de l'entreprise, à savoir le type et l'originalité de l'innovation que l'entreprise fait. Mon premier chapitre analyse les incitations à l'innovation des start-ups exercées par les perspectives de rachat par les entreprises plus anciennes. Je teste l'hypothèse selon laquelle les start-ups innovent dans des domaines plus complémentaires de leurs acquéreurs potentiels. Dans le chapitre deux, j'analyse l'impact à long terme des choix de positionnement technologique par les jeunes entreprises. Elle mesure l'inertie de ces positionnements. Elle présente également certains modèles visant à distinguer l'impact de la taille de l'entreprise et son âge sur son innovation. Enfin, le troisième chapitre analyse l'effet de changements de politiques publiques sur l'innovation, en prenant l'exemple de politiques limitant les émissions polluantes des véhicules. Je m'interroge notamment sur l'avantage comparatif qu'ont les pays à être les premiers à imposer de nouvelles normes sur les véhicules vendus sur leur territoire.

Mots clés: innovation, entrepreneuriat, dynamique des firmes

This thesis is dedicated to

my brother, Vinson,

who has been an immense inspiration to me

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Introduction

The three chapters in this thesis explore different dimensions of firm innovation. Together they aim to provide a more comprehensive understanding of how firms make their innovation choices. There is a purposeful focus on young firms and start-ups in the first two chapters to increase our understanding of the long term harms large incumbent firms may indirectly pose through their effect on start-ups. The third chapter also studies the innovation choices of a firm and in particular examines whether policy makers can give their domestic firms an innovation advantage.

My research question on large firm and start-up interaction was initially motivated by the policies made during the 2008 financial crisis and how they had an asymmetrical effect on firms. On one hand, large incumbent firms benefited from the increase in liquidity from quantitative easing. On the other hand, young and small firms were negatively affected by the changes in financial regulation which were introduced to decrease bank risk taking. At the same time, the US economy experienced a prolonged period of secular stagnation. I suspect that a part of this secular stagnation is due to the change in the way incumbent firms and startups interact and this is the motivation for chapters 1 and 2.

Large firms became an important, possibly primary, exit option for surviving start-ups during and after the crisis. I then ask the question of how the type of innovation chosen and positioning with respect to incumbent firms can affect a start-up's exit options and in particular, it's likelihood of getting bought out. Chapter 1 shows that this expectation of getting bought out does not only imply strategic behavior around the time of exit but that it affects the start-ups initial entry innovation choices as well.

Chapter 2 then examines how firms develop around their initial positions. In particular, it measures a degree of proximity between the firm's initial positions and its later innovation position over its life cycle. The result shows that proximity is higher for firms at the beginning of its life cycle and then decreases over time. This implies a degree of inertia in firm innovation choices and therefore emphasizes the importance of the initial choices made by entering firms.

In chapter 1, the main finding is that when start-ups have a higher expectation of getting bought out, they will choose to innovate closer to their potential acquirers in complementary technological fields in order to further increase their likelihood of getting bought out. As such, I show that start-ups have decreased their overall originality due to these anticipations of exit options. The long run consequences of this effect on initial choices is then investigated in chapter 2 with the goal of better understanding dynamic competition originating from young firms. Chapter 2 confirms and quantifies the intuition that firm innovation choices are path dependent. This result implies that if firms' starting innovation choices have fallen in originality, their overall contribution to innovation in the future is also lower in originality. Furthermore, if this fall in originality corresponds to an increase in proximity to complementary technology areas of the incumbent firms, then start-ups can be expected to continue developing in areas complementary to incumbent firms instead of in areas that would make them eventual competitors.

In reference to Schumpeter and the large literature that followed from his work, a major reason for incumbent firms to continue innovating is to preempt the threat of new entrants who may become future competitors. However if this perception of threat has diminished, then incumbent firms have less incentive to continuously innovate. My analysis is constrained to firm innovation responses, thus the question of whether this translates into low economic growth is not directly addressed.

Chapter 2 also documents firm innovation choices in the case of static competition. In particular, I leverage the information on technological content in patent filings to develop a proximity measure along the substitution axis and a proximity measure along the complementary axis. The proximities are then taken with respect to the firm's initial technological position to build a better understanding of what drives firms to be less inert - to make large changes to their technological position.

The results indicate that firms move further away from their initial technological position (along the substitution axis) when the concentration is higher in those technological areas. This implies a different firm reaction to competition than the traditional models that suggest an increase in innovation. By moving further away from the concentrated technological areas, the firm can relieve some of that competitive pressure. And chapter 2 shows that firms indeed do this. On the other hand, increasing innovation in its existing specialty areas is also a way to react to competition.

By looking at the change in proximity along the complementary axis, we see that it also falls as concentration increases however there is an area in the medium to high concentration levels (which may imply neck-and-neck sectors) where proximity displayed an increase. This may suggest that those firms may have something to gain by reinforcing their initial positions however also want to relieve some of the competitive pressure and therefore choose to expand in complementary fields.

Chapter 3, co-authored with Matthieu Glachant and Antoine Dechezlepretre, follows along the theme of type of innovation and explores the particular case of vehicle emissions technologies and the role of policy makers in incentivizing innovation. Emissions reduction technologies address an environmental externality that would not be incorporated into firm R&D strategies without the influence of the policy maker. As such, standards on vehicle emission are technology forcing regulations. Imposing these regulations corresponds to a cost to firms, and therefore strategic implications for policy makers become relevant in the international setting.

Chapter 3 shows that countries who implement stringent regulations early incentivize more innovation in vehicle emissions control technologies than late mover countries. An overall increase in innovation may lead to more benefits as well due to increased knowledge spillovers. However in this study, we are particularly interested in addressing whether policy makers can give their domestic firms an innovation advantage. The results show that a firm's home-country regulatory leadership increases that firm's emissions control innovation output in all the other countries the firm has a market in. The effect is insignificant and in some cases negative when the home-country is a follower. This implies that the majority of the regulation relevant innovations are made in the first few years of the regulation implementation and that countries should move early to give their domestic firms that innovation advantage.

Chapter 1

Buyouts and Start-Up Innovation Incentives

This chapter investigates how start-up innovation choices are affected by incumbent firm interactions. In particular, incumbent firms have an impact on start-up exit strategies as they can affect their expectations of getting acquired, of succeeding, or of going bankrupt. Using exogenous variation in macroeconomic and financing conditions, I infer a likelihood of getting bought out for entrants. I then estimate how an increase in the expectation of getting acquired affects the new entrant's innovation choices with respect to existing firms. I construct a novel measure of innovation proximity and show that new firms innovate "closer" to their potential acquirers.

Ce chapitre examine comment les interactions entre les start-ups et des entreprises plus anciennes influent sur les choix d'innovation des premières. Je teste l'hypothèse selon laquelle les entreprises déjà en place ont un impact sur les stratégies des start-up car elles influencent leurs anticipations de rachat, de réussite ou de faillite. En utilisant l'effet asymétrique que la crise financière de 2008 a eu sur l'accès des entreprises au financement entre les nouveaux entrants et les grandes entreprises, je calcule une probabilité de rachat pour les entrants. J'évalue ensuite comment les start-ups envisageant un rachat modifient leurs choix d'innovation en accord avec les possibles acheteurs. Je construis pour cela une nouvelle mesure de proximité de l'innovation entre les entreprises et montre que les nouvelles entreprises innovent dans des domaines technologiques proches de ceux de leurs acquéreurs potentiels.

1.1 Motivation

There is a large and growing literature on the factors that drive firm innovation. However the *type* of innovations being made by new entrant firms has been lacking in the dialogue. Whether a new firm enters with a minimally differentiated product or a radically innovative product can lead to very different trajectories for the firm and for the industry it is in. Here I will study how firm interactions affect the innovation incentives of the new entrant. Namely, I hypothesize that incumbent firms have an influence on start-up exit options, and start-ups in turn make choices to optimize their exit outcomes.

It is recognized that an exit strategy of getting acquired is increasingly being adopted by start-ups in the US.[1] In this paper I will apply the fact that acquisitions are affected by macroeconomic and financing conditions to estimate an expectation of acquisition for start-ups. I then test whether these expectations affect the start-up's choice in innovation. Using patent data, I build a measure of innovation originality as well as a measure of proximity and complementarity between firms. With data on mergers and acquisitions I identify the firms that are bought out as well as their acquirers. As such, I will provide evidence that start-ups choose to position themselves closer to their potential acquirers when they have a higher expectation of getting bought out.

Why do we care about the type of innovation that firms are doing? Figure 1.1 shows the average patenting originality of new firms in the US over time. We see patenting originality steadily increasing until 2008 and then clearly falling after. This drop off coincides with a fall in productivity in the wider economy.[2] The peak is a little bit after 2008 however R&D takes time to develop and patenting takes time to be filed so it is expected to have a lag. The literature might explain this fall in originality in different ways, for instance Bloom et al. (2017) suggests that ideas are simply getting harder to find and Akcigit et al. (2013) suggests that this is due to a fall in public funding for basic research. Specifically with respect to start-ups, Gans and Stern (2000) suggest that the effect incumbent firms have on start-up innovation choices depends on their respective

[1] For instance, the survey of 500 CEOs conducted by Inc. in 2004 found that 45 percent had thought about an exit strategy when they started their companies. A 2019 survey conducted by the Silicon Valley Bank found that over 50 percent of start-ups are specifically looking to get acquired as their primary exit strategy. See Lemley and McCreary (2021) and DeTienne (2010) for more discussion.

[2] The declining business dynamism literature dives deeper into the question of how firm entry has been affecting economic growth. See Decker et al. (2014), Decker et al. (2016) and Akcigit and Ates (2019) for an overview of the main concepts in this literature. The innovation provided by new firms is an important aspect in their valuation of entry however the type and originality of innovation is another dimension that has not yet been addressed.

bargaining powers. Similarly, Henkel et al. (2015) suggest that less competition among start-ups would lead to less novel projects on average. The decline in originality, however, coincides with the 2008 financial crisis and the fall in productivity therefore I believe the crisis has a role as well.

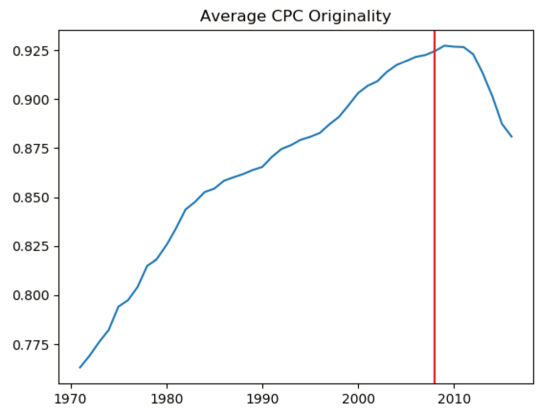


Figure 1.1: The average firm originality over time in the US
The average originality of new firms in the US. The originality measure is built following Trajtenberg et al. (1997) with full CPC technology codes. The red line is at the year 2008.

In the setting of the 2008 financial crisis and ensuing recession, there was an asymmetric effect on firm access to financing. Large incumbent firms benefited from credit easing policies while small and young firms suffered from changes to financial regulation that imposed more stringent thresholds making it harder to access financing.[3] This asymmetry created more opportunities for capital flows from large firms to young firms and therefore increased buyout expectations for start-ups. I posit that this change in buyout likelihood consequently led start-ups to react strategically in their innovation decisions to further increase their likelihood of getting bought out.

When a start-up enters, it has some degree of choice in what product it will develop, who the founders and employees are, where its funding will come from, where it will locate, where it will sell, what kind of legal status it will take on, etc.[4] The strategic component of firm entry I focus

[3]See Davis and Haltiwanger (2019), Greenstone et al. (2020), Bacchetta et al. (2019), and Ayyagari et al. (2018) for some evidence of this asymmetric financial effect.

[4]There is some literature on the initial choices of founding teams when the firm enters. Ouimet and Zarutskie (2014) look at founder characteristics such as age and Choi et al. (2019) look at the composition of founding

on is the product and corresponding technological content it enters with. What characterizes this product innovation and how does it position with respect to existing products? A new firm that enters with a highly differentiated, original, product will face less competition. However it could also take more effort and experimentation to successfully develop. The risks of failure are higher to invent an original product than one that is largely similar to existing products. Furthermore if the product is radically different, the consumer demand for the product may also be uncertain. On the other hand, if a new firm enters with a product that is complementary and more similar to existing products, it could have an easier, less risky R&D process due to knowledge spillovers. It may be able to benefit from the economies of scale of complementary products and it may increase its probability of getting bought out by potential acquirers with complementary product lines.

The choice of innovation and potential exit options are also important considerations for the start-up when they look for initial sources of capital. When an equity investor, like a venture capitalist or an angel investor invests in a start-up it wants to maximize its return on investment and getting acquired is often the preferred way to achieve this. Of course the start-ups' founders also want to maximize their payoffs with some going so far as to start a company for the sole purpose of selling it quickly - leading to the emergence of serial entrepreneurs. As large existing firms are a critical set of potential acquirers, any factors that influence them are carefully monitored. This is exemplified in a TechCrunch article in response to Elizabeth Warren's announcement of her policy on Big Tech.[5] This article argues that breaking up Big Tech companies will actually have a negative effect on start-ups because it eliminates a major exit option for their investors who will therefore be less willing to invest.

In contrast, when a bank finances a start-up with credit, it primarily cares about getting the interest and principal repaid with minimal risk. A bank does not overly consider the start-ups' exit options and does not take up a seat on the board where it can influence decision making. The financial regulatory changes in response to the crisis, however, added more controls on lending causing access to bank credit for small and new firms to become more difficult. Furthermore, house valuations fell dramatically in the crisis and Davis and Haltiwanger (2019) argue that

teams.

[5]https://techcrunch.com/2019/03/08/venture-investors-and-startup-execs-say-they-dont-need-elizabeth-warren-to-defend-them-from-big-tech/

houses are an important source of collateral for loans to entrepreneurs. While there was a decrease in access to bank financing it was offset to some extent by the flow of funds into venture capital as investors looked for alternative sources of return. As such, there was a decrease in the level of traditional bank financing yet an increase in the share of financing from equity investors like angel investors and venture capitalists for new firms.

The innovation literature distinguishes between push and pull effects on innovation. The push effect can come from knowledge spillovers or increased access to financing while the pull effect acts through the demand for innovation. There is an expansive literature on the push drivers such as knowledge spillovers explored in the networks literature, increased resources such as financing, etc. however to the best of my knowledge, the demand pull channel is less explored. It has been discussed in the trade literature as a change in demand comes from the opening up of an export market (see Aghion et al. (2019)). It also appears in the environmental economics literature as a regulation change affects the markets for certain products.[6]

While financing has traditionally been considered to have a push effect on innovation by enabling access to more resources, here I suggest it can also exert a pull - the demand for innovative technologies from potential acquirers can affect the direction of innovation firms choose.[7] This is a financial incentive directly implicating the kind of innovation a potential seller-firm is doing. Particularly in the case of equity investors or firm acquirers, there is some pressure to align firm decisions with investors' or acquirers' interests. Tian and Wang (2014) have empirically studied the impact of venture capital tolerance for failure on innovation and Nanda and Rhodes-Kropf (2013) construct a theoretical model of shareholder's failure tolerance and manager's innovation choices to align risk preferences. These are studies that align risk preferences, however there is also a case to be made for aligning technological content. For instance, Atanasova and Chemla (2020) find a familiarity bias in investment decisions made by firm defined benefit pension plans. Investors and acquiring firms exert a demand on their potential target firms' innovation positioning.

[6] See Horbach et al. (2012), Nemet (2009), Jones (2011) and Negro and Schorfheide (2004) among others.

[7] See Hall and Lerner (2010) and Kerr and Nanda (2015) for some surveys on the finance and innovation nexus. And along a similar topic, Kerr and Nanda (2009) review the literature on financing constraints and general entrepreneurship.

The M&A and innovation literature has mainly focused on the ex-post effect of a merger or acquisition on innovation.[8] Chemmanur and Tian (2018) look at the effect of Anti-Takeover Provisions and find a positive effect on amount of innovation that is particularly pronounced in competitive markets and for firms with more information asymmetry. However, the innovation measures is often a count of patents or a citation weighted count of patents and the technological position and type of innovation is overlooked. Arora et al. (2018) develop a model to explain acquisition timing and the role of investment in absorptive capacity. Bena and Li (2014) and Hussinger (2010) are the closest in content to this study. They find that technological overlap between firm pairs increases the likelihood of an M&A deal. I supplement their contribution with a tailored measure of innovation proximity that captures technological complementarity and I further filter on deal pairs that involve a potential acquirer who is a large incumbent firm and a potential seller who is a young and small firm. This provides a better analysis of the motif that start-ups are bought out for innovation acquisition purposes.

Treating the technology in patents as the main dimension of interest, I will assume that a more original patent corresponds to a more differentiated product. Using patent data from Patstat, I measure patent originality and firm differentiation in terms of technological content. I will present results from some existing patent measures and explain their different interpretations then I will introduce some new changes to the measures. Firm differentiation (intuitively the opposite of firm "proximity") is defined based on firm patent portfolios and firm originality is the patent originality averaged to the firm level.[9]

I also use Patstat to identify new entrants with the assumption that firms that develop a new product will apply for patent protection before entering the market. Therefore my entry year is the first year of patenting. If the firm were to start selling before filing the patent, it could then be subject to reverse engineering and imitation. I assume that the set of firm's that enter the market before patenting is small. To identify firms that have been bought out, I use data from Thomson SDC Platinum. I then link the patenting behavior of the target and acquirer to patent applicants in Patstat using a customized fuzzy string matching algorithm based on firm names.

[8] See Seru (2014), Sevilir and Tian (2015), Ornaghi (2009), Haucap et al. (2019), Lerner et al. (2011) among others.

[9] These measures are explained in more detail in the data section.

The empirical analysis focuses on two main variables, likelihood of buyout and innovation proximity. The analysis needs to be done with caution because I am positing that the innovation distance affects the likelihood of buyout but also that the likelihood of buyout affects the choice of innovation distance. However, this is in fact not an issue as I focus on new entrants. Before they start a research project, they do not have any apriori innovation measures. They do however have information on buyout trends, market sentiment, etc. as well as their financing options. Thus before a start-up comes into existence, its founders have beliefs on their likelihood of buyout. The hypotheses is that when the likelihood of buyout is low, new firms may believe their best option is to work on more original innovations and grow organically to eventually compete, while when the likelihood of buyout is high, new firms may be more incentivized to further increase their chances of buyout by innovating strategically closer to their potential acquirer.

As such, I ask two specific questions:

1. Can the proximity of a firm to another firm affect its likelihood of buyout?

2. Do the expectations of being bought out affect new entrants' innovation originality?

In order to first confirm that firms have a reason to believe their innovation positioning choices can affect their buyout likelihood, I build a firm pair dataset with a proximity-complementarity measure for each pair. I regress this complementary proximity measure on an indicator variable indicating whether the firm pair have had a buyout deal.

To address whether new entrants have indeed been changing their innovation behavior in response to their buyout expectations, I build another cross sectional dataset of firms in their first year of patenting. I then use a two step estimation model where I construct a measure of buyout expectations in the first step which I then use in the main regression on entrants' innovation choices. Using financing and macroeconomic variables to capture the conditions of the crisis and sector level concentration measures as controls, I extract a predicted number of buyouts by sector-year. I assume that this is a strong indicator for expectations of buyout and I use it as a proxy in the second step. With this proxy, I find that indeed a higher expectation of buyout decreases innovation originality in new entrants.

In the following section I will describe the setting of the financial crisis. Then in Section 1.3 I detail the datasets that I use and how the innovation measures were constructed. Section 1.4 then presents the empirical strategy, the main results and some robustness checks. Section 1.5 concludes.

1.2 The Setting

The Great Recession is characterized by the rupture of the subprime lending market, the use of unconventional policies and a prolonged period of low growth. I will investigate how this setting affected expectations on firm exit options. In particular, I suggest that the recessionary environment increased the chances of firm failure. However, conditional on survival, the likelihood of getting bought out increased. Buyouts involve a large sum of funds and are therefore sensitive to financing conditions. The crisis of 2008 was a shock on financial markets that spilled over to the entire economy. Normally in this situation, the Federal Reserve (Fed) would undertake expansionary monetary policy and lower the federal funds rate. However in the early 2000s, the Fed had already began decreasing the fed funds rate and there was not much room for manipulation by the time the crisis hit. As such, the Fed had to employ unconventional policies such as Quantitative Easing (QE) and forward guidance to boost the economy.

Monetary policy has traditionally had the effect of boosting household consumption by decreasing the interest rate to lower returns on savings and lower the cost of short term borrowing. QE, however, consists of large scale purchases of asset backed securities, collateralized debt obligations and other securitized instruments that put downward pressure on long term interest rates to further credit expansion. However long term debt is used for different purchases than short term debt. For households, long term debt is more likely to be used for automobile or house purchases (and student loans for students) - in general, large purchases. Yet the financial crisis was caused by easy credit for house purchases, therefore this effect was much more restrained. Although automobile loans and student loans did increase, this has arguably had a limited effect on the rest of the economy.

Instead I am putting forward that the principal effect of QE was through firms. Firms are entities that often have to make large purchases and investments that may be debt financed.[10] They have many reasons to take out long term debt such as for equipment purchases, R&D investments or simply because they have the means and the rate is low. In fact, the crisis saw a number of firms take out debt to finance dividends or stock buybacks as well as firms that took advantage of the low rates to refinance their debt.

I further suggest that the effect of the crisis on firms was asymmetric. The severity of the crisis saw a high degree of economic uncertainty and risk aversion. It also raised awareness of issues in the financial system leading to financial regulatory reforms, such as Dodd Frank and Basel III, that included stricter rules on lending and the creation of a new macroprudential regulatory agency. This made it much more difficult for potential new firms to access financing. Small and young firms without collateral and established income streams found it particularly hard to access bank financing (see Ayyagari et al. (2018)). Furthermore since small business founders often use their house as collateral to access financing and housing prices fell drastically at the start of the crisis, new firms also experienced more limited access to financing through this channel as well.[11]

Since the crisis and following years was a time of high uncertainty, firms were less likely to invest in long term risky R&D projects. It was simply easier for start-ups to work on incremental innovation if they believed they were more likely to get acquired. In addition, in a recessionary setting, it is likely that firm survival was more difficult. New firms that choose to enter are likely to act strategically so as to decrease their likelihood of failure.[12] It was also easier for large existing firms to work on incremental products however they have the added option of using that money to acquire innovations instead. Since a new R&D project requires a large upfront fixed cost with the risk of being unsuccessful, a large firm might decide to take the less risky option and diversify its investments in multiple smaller R&D firms (for instance, through corporate venture capital) or to buyout new firms after they have successfully developed an innovation.

On a whole, the shock of the crisis and following policies clearly made firms reevaluate their decision making process and how they allocate investments. I will investigate whether the trends

[10]See Eaton et al. (2016) for a discussion of the effect of the crisis on traded durable goods.
[11]See Davis and Haltiwanger (2019) and Acharya et al. (2020)
[12]See Cahn et al. (2019) for an evaluation of the effects of firm failure on the founders' future options.

in buyouts changed and how that in turn affected the innovation choices of new entrants.

1.3 The Data

My primary sources of data are Patstat for innovation measures and Thomson SDC Platinum for data on mergers and acquisitions. Below I discuss the data sources, the cleaning involved and the construction of the final datasets.

Patstat is a comprehensive database maintained by the European Patent Office (EPO) on patent applications and publications. It covers all major patent offices however I will be focusing on patents filed by companies who used an address in the United States. The database includes information on the applicants, inventors, application authority, filing dates, technology codes, whether it was granted, citations of other patents and of the non-patent literature, etc.. It also provides some constructed information such as industry codes and patent family identifiers as well as a preliminary applicant and inventor name cleaning because the information on applicants is subject to typos. Patstat also includes an educated guess on the type of applicant (ex. individual, company, university, etc.) which is what I use to primarily identify a firm (see Appendix A for more details).

A limitation of using patent data for my firm innovation measures is that I miss any firm innovation that has not been patented. The set of firms that patent is much smaller than the set of firms that do not patent. However this does not affect our results if there has not been a change in startup decisions to patent.

With a firm identified as a disambiguated company applicant, I construct its innovation measures.[13] I build a firm-level originality measure as well as a firm-pair-level proximity measure. The originality measure, already seen in Figure 1.1, was proposed by Trajtenberg et al. (1997) and is like a Herfindahl index:

$$Orig_p = 1 - \sum_{k \in \mathbb{K}} \left(\frac{Ncites_{p,k}}{Ncites_p} \right)^2$$

[13]See Appendix A for details on the applicant name cleaning and disambiguation.

where $Ncites_{p,k}$ is the number of citations in technology class k from patent p and $Ncites_p$ is the number of patent p citations. This is simply a measure of concentration of the cited patents' technology codes with the implication being that a patent with more concentrated cited technology codes is less original. Originality is a patent level measure which I then aggregate to the firm-year level by taking the average.

Firm proximity is measured with respect to a firm pair following Jaffe (1986).

$$Prox_{i,j} = \frac{\mathbf{F}_i \cdot \mathbf{F}_j'}{\sqrt{\mathbf{F}_i \cdot \mathbf{F}_i'}\sqrt{\mathbf{F}_j \cdot \mathbf{F}_j'}}$$

where $\{i, j\}$ is a firm pair and $\mathbf{F}_i = (F_{i,1}, F_{i,2}, ...F_{i,K})$ is a vector of $F_{i,k}$, defined as the percent of firm i's patents that are in technology code k.

This proximity measure is essentially an uncentered correlation measure between two firms' patent shares in the different 4-digit IPC technology classes. The Jaffe measure however calculates the proximity only when two firms' technology codes overlap. In reality, certain technologies are more connected. Bloom et al. (2013) measure this connection through technology spillovers. They build a weighting matrix, Ω, from the covariance of the firm patent shares in each technology class.

$$Prox_{i,j} = \frac{\mathbf{F}_i \cdot \boldsymbol{\Omega} \cdot \mathbf{F}_j'}{\sqrt{\mathbf{F}_i \cdot \boldsymbol{\Omega} \cdot \mathbf{F}_i'}\sqrt{\mathbf{F}_j \cdot \boldsymbol{\Omega} \cdot \mathbf{F}_j'}} \tag{1.1}$$

I build the Bloom et al. (2013) measure however I also develop a different weighting matrix from *patent* level technology codes. By building Ω from the patent level, I capture the frequency that technology code pairs appear together in a patent. This more granular distinction better captures the technology codes that are complementary to each other since all the technology codes in a given patent are necessary for the invention in that patent. Building the weighting matrix at the firm level, also captures this effect however the measure is confounded if a firm has numerous product lines that are unrelated. I therefore suggest that building Ω from the patent level better captures complementarity between technology codes.

In practice, I build these measures from the 4-digit IPC codes. Since this aggregates multiple full IPC codes, a 4-digit IPC code can, and in fact does, appear multiple times in one patent. I keep all the repeated codes in the initial calculation to preserve the weights of each code. However this gives me a resulting matrix with a very heavy diagonal. Since the values along the diagonal will get confounded with the substitution effect I remove them and normalize the matrix. My final Ω weighting matrix is a measure of complementarity between technology codes which I then use in the construction of proximity to build a measure of complementarity between firms.

I also build a patent level measure of proximity where i is a patent and j is the set of patents cited by patent i. Since the citations of a patent consist of, in theory, the existing technologies at the frontier of the field of this patent, a proximity measure between the patent and its citations is similar to a measure of originality except it accounts for overlap between the patent's technology codes and its cited patents' technology codes. Intuitively, proximity should have an inverse relationship with originality. Indeed the trends are inversed for patent level proximity and originality as seen in Figure 1.2 below.

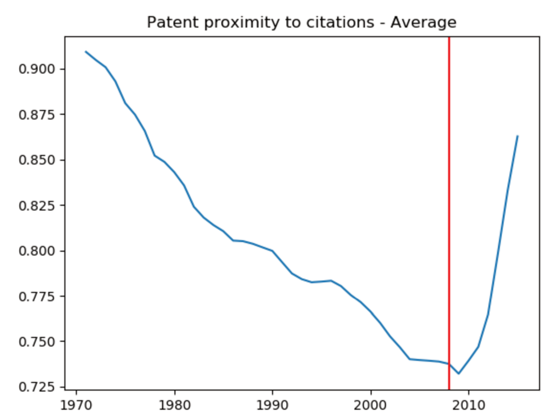


Figure 1.2: Average patent proximity to its citations in the US over time
The average patent proximity (from IPC codes) in the US. The red line is at the year 2008.

To summarize the time series trends in originality and to comment on the debate over whether entrants or incumbents are the most innovative, we can look at Figure 1.3 which plots the average originality for new firms and for twenty year old firms.[14] This shows that traditionally, new

[14]The age of the firm is inferred from the the year the firm first begins patenting. See Chapter 2 for more discussion on this assumption.

firms were more original than older firms although both have seen an upward trend. However in more recent years, new firm average originality has fallen below that of older firms and both groups are now showing a fall from their highs in the mid 2000s.

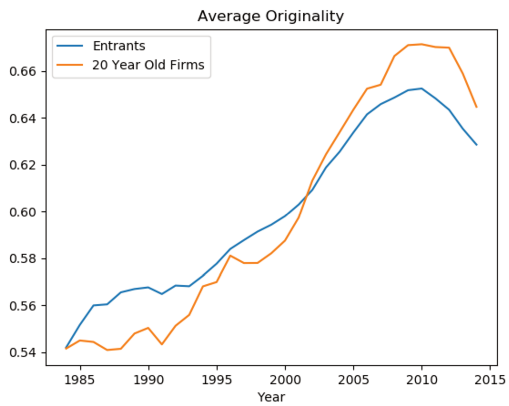


Figure 1.3: Average patent originality for incumbents and new entrants
This figure shows the five-year moving average of the mean 4-digit IPC code originality over time for new entrants and incumbent firms, where incumbent firms are defined as 20-year old firms.

The acquisitions data comes from Thomson SDC Platinum (henceforth SDC) which offers detailed deal information such as target and acquiror names, address information, immediate and ultimate parents, industry codes, deal announcement date, effective deal date, whether the firm is a financial firm, the deal value, the percent of shares acquired, the source(s) of funding, etc. I extracted the deals involving only US targets as I am primarily interested in the innovation incentives of target US firms.

To connect target firms with their innovation behavior, I merge this with Patstat. Patstat, however, does not use any official nor external firm identifier when noting applicant information. The applicant name is therefore prone to misspellings and errors even after the name cleaning done by the EPO. Without a concordance of applicants with an official data source, it is tricky to merge Patstat with any other datasets. The best we can do is to match firm names. This has been done with some other datasets such with French firms (see Aghion et al. (2019)) among others.

However, to the best of our knowledge, this is the first time this has been done with Patstat and SDC. SDC uses firm identifiers to define a firm, so their firm names are also subject to some degree of misspellings and inconsistencies. There are different issues of matching firm names and these are discussed in detail in Appendix A. Due to the typos in firm names, I develop a fuzzy string matching algorithm to account for this. A fuzzy string matching algorithm however will inherently introduce errors into the dataset. It is a tradeoff between number of missed matches versus number of wrong matches. I do various checks to remove wrong matches such as checking for common words and matching addresses, however some error will always remain.

Another important issue with name matching is that firm names can change over time. And there is no standard on what name an entity within a firm group would use. Since we use firm names as our firm identifier, we cannot follow firms with name changes over time. This source of measurement error is not an issue in the main specification as I look only at firms in the first year they patent.[15]

Starting from around 147000 merger and acquisition deals in the US between 1990 and 2016, I remove deals where the acquirer was a financial company or an employee stock buyback etc. I also require that the deal resulted in a controlling majority share and count deals that were split into block share acquisitions as one. From Patstat I have about 151000 companies who filed a patent with an address in the US. After the merge process, I end up with 24347 deals with an acquirer who has patented, 28154 deals that involved a patenting target firm and 11393 deals where both the acquirer and target firms have patented and where the acquirer firm is large and the target firm is small.[16] I filter on large and small firms to capture the motive of buying technology and innovation as opposed to other reasons such as market share. The proportion matched seems small at first but this is roughly consistent with the proportion of firms that patent globally.

To address my two questions asked earlier, I will build two datasets:

- a firm pair level dataset with innovation proximity measures between the two firms

[15] The industry specific focus at the firm pair level however could be subject to this issue. This issue will also give me more entrant firms than in reality and it might give an upwards bias to my estimates later because I expect firms to have some path dependency in their R&D behavior.

[16] A large firm is defined as a firm in the top 10 percent of the firm size distribution where size is proxied by number of patents. Likewise, a small firm is a firm in the bottom 90% of the firm size distribution.

- a firm level dataset of new entrants with innovation measures at entry

The firm pair dataset will focus on the software industry to keep the analysis tractable.[17] I construct all possible firm pairs for firms in the software sector. As I am only interested in potential firm pairs that would have one firm acquired for its innovation (as opposed to a merger of equals or acquisitions for market share reasons), I keep only the firm pairs that involve one small firm, and where the firm size ratio is under 50%. I also remove firm pairs where both firms are in the top 1% of patenters as this might not be entirely captured by the firm size ratio restriction due to the skewed distribution of the firm size distribution.

From this smaller set of firm pairs, I build their innovation proximity measures and other innovation controls such as their originality, whether they have collaborated together before, direct spillovers between the two firms and a commonality measure *Share_common* that Ornaghi (2009) suggests captures complementarity. However the *Share_common* measure does not take into account technology codes, it is simply a share of common cited patents over all cited patents. Therefore I prefer the proximity measure described in equation 1.1 to measure complementarity and I keep this *Share_common* measure as a control. In fact since this measure simply measures the share of cited patents the two firms have in common, this measure may capture substitutability more than complementarity. It is difficult to distinguish between the two and therefore I will present results with and without this measure. To measure the other spillovers, let us define P_i and P_j as the patents owned by firms i and j and B_i and B_j as the patents cited by firms i and j. The spillover controls are measured as:

$$Spill_{i,j} = \frac{||B_j \cap P_i||}{||B_j||} \tag{1.2}$$

$$Spill_{j,i} = \frac{||B_i \cap P_j||}{||B_i||} \tag{1.3}$$

$$Share\_common_{i,j} = \frac{||B_i \cap B_j||}{||B_j||} \tag{1.4}$$

The final firm pair dataset is very large and most of the firm pairs are not involved in a merger. To make this dataset tractable, I run the analysis on different random samples and the results are very stable between the different samples.

[17] I identify software firms by first identifying patents that are considered software patents following Bessen and Hunt (2007). Then I consider a firm a software firm if over 50% of its patents are software patents. Similarly, for ICT, I first identify patents that are ICT patents based on the OECD concordance with IPC codes then I consider a firm an ICT firm if over 50% of its patents are ICT patents

The new entrant, firm-level dataset is fairly straightforward to construct. I identify all the patent(s) filed in the first year of patenting for a company applicant with a US address. I use the first year and not simply the first patent because, depending on the industry, some products are composed of multiple patents. For these patents, I build their originality and patent-level proximity measures as described above, then I take an average to get the measures at the firm level.

I also include industry and year controls in this dataset. To identify the industry of the firm, I use the Nace code table in Patstat to convert to 2-digit SIC codes. The Nace code table includes a weighting of the codes the patent can be classified under which is calculated from its technology codes. I take the sum of all the patents a firm has at entry and their Nace code weightings and I consider the firm's primary industry to be the Nace code with the highest weight. Another issue with merging Patstat and SDC is that Patstat only provides NACE codes which are used primarily in Europe and SDC provides only codes used in the US, namely SIC and NAICS. I therefore had to use a concordance table to convert the applicant's NACE code to an SIC code. Since the classification between the two are quite different and uses different information content, I can only convert the NACE code to the broad 2-digit SIC codes.[18]

I also know the year the firm first applies for a patent. With this, I gather and merge data on the short and long term treasury rates, regulatory measures, house price index, the AAA and BAA spread, the implied volatility index (VIX), consumer confidence measure, stock market indices, unemployment rate, as well as other macroeconomic variables and sector measures such as the Herfindahl Index and the share of top 4 firms in a sector as defined by its 2-digit SIC code. These are controls for the financing, concentration and macroeconomic environment at the year of firm entry.

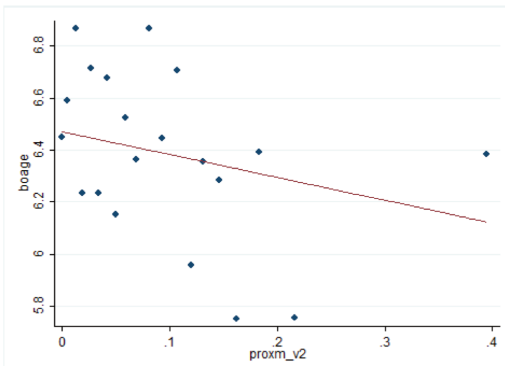
[18]The conversion table is available upon request

1.4 Empirical Strategy and Results

1.4.1 Firm pair proximity

Here we address the question of whether firm innovation positions can really affect their buyout likelihood. Figure 1.4 plots the buyout age of the target firm against its complementary proximity to the acquiring firm at buyout. The negative slope implies that firms are getting bought out faster when they are in closer proximity (more complementary) to their acquirers. The correlation is about -0.006.

Figure 1.4: Proximity with respect to firm buyout age



Binned scatter plot of firm complementary proximity at buyout vs target firm buyout age. This proximity measure is built from the set of patents the two firms have applied for up until the buyout year and uses the complementarity weighting described in the appendix. The buyout age is the difference between the buyout announcement year and the first year the target started patenting. The right most point seems to be an outlier but since this is a binned scatterplot, it aggregates multiple points. Most of the firms in this right-most group are pharmaceutical firms as their patents often consist of a similar set of technology codes.

Similarly, when we look at target firm originality we see the same result. On the left in figure 1.5, we have the maximum firm originality over its lifetime, while on the right in figure 1.6 we have the target firms' originality in the first year it enters. The effect is clearly positive for max originality but less clear for the originality of patents in the first year. The blue points represent the firm originality before 2008 and the red points represent the set after 2008. We see that the correlation becomes more positive after 2008 for firm initial originality. This implies that before 2008 new firms that entered didn't react to this strategy of closer positioning because they had less reason to believe they would be bought out. However after 2008 they begin using this strategic channel as they believe their buyout likelihood has increased and that they can further influence their chances.

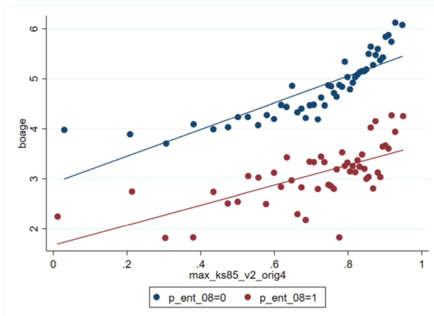


Figure 1.5: Maximum originality by firm buyout age
Binned scatter plot of firm age at buyout and the maximum firm originality achieved over its lifetime.

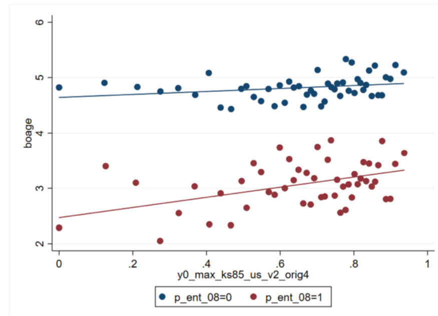


Figure 1.6: Initial firm originality by firm buyout age
Binned scatter plot of firm age at buyout and the firm originality in the first year it patents.

These figures are from the subset of deals that have been realized, we need to also consider the extensive margin and look at deals that have not happened yet. We also need to control for other factors. To do this I use the firm pair dataset described above on software firms.

To address whether firms have reason to believe their innovation positioning has an effect on their buyout likelihood, I run a logit on a firm pair cross section.

$$\mathbb{1}[\mathit{Firm\ i\ buys\ Firm\ j}] = \alpha_0 + \alpha_1 Prox^0_{i,j} + \alpha_3 Controls^0_i + \alpha_4 Controls^0_j + \alpha_5 Controls^0_{i,j} + \varepsilon_{i,j} \quad (1.5)$$

Where firm i is the set of large firms in the top 10% of the firm size distribution and firm j are the other firms (the smaller firms in the bottom 90%). The firm size distribution is defined on the number of firm patent holdings. $Controls^0_i$ include the log knowledge stock of firm i which is defined as the aggregation of firm patents constructed using the usual inventory method with a depreciation rate of 15%. In a robustness check, the firm level controls also include financial measures such as total assets, number of employees and profits.

To avoid endogeneity I fix the right hand side variables over time intervals. Ideally I would take the pre-sample average of the proximity, originality, knowledge stock and firm pair spillover controls as my regressors. This means that I assume these values remained constant over the time period in my dataset. However my time period of 2000-2016 is quite long and firms are likely to have changed quite a bit over the time period. Instead I follow Prais (1958) and build two measures of each variable with each observation equally weighted. One average is constructed from the pre-sample 10 year period and one average is from the end of sample period. The end of sample average is taken from 2009 to 2016 to avoid a potential bias from the crisis in 2008.

Table 1.1 presents the results from the firm pair logit regression from equation 1.5. We indeed see that firm complementary proximity has a positive effect on likelihood of being bought out. This is consistent with figure 1.4 where we saw that firms get bought out faster when their complementary proximity is higher. The positive estimate on proximity is robust to different controls that are added. Table 1.1 also shows that the knowledge stock of a firm has a positive effect on the likelihood of getting bought out.

	(1)	(2)	(3)	(4)	(5)
Proximity	0.9883***	0.9629***	0.9699***	0.9631***	0.9698***
	(0.0406)	(0.0420)	(0.0424)	(0.0422)	(0.0425)
Firm 1 knowledge stock	0.4724***	0.4773***	0.4765***	0.4773***	0.4765***
	(0.0148)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
Firm 2 knowledge stock	0.3020***	0.2968***	0.2967***	0.2967***	0.2967***
	(0.0530)	(0.0527)	(0.0527)	(0.0527)	(0.0527)
Firm 1 originality			-1.3630***		-1.3631***
			(0.1025)		(0.1024)
Firm 2 originality				-0.0084	0.0039
				(0.0895)	(0.0895)
Collaborated		0.4475	0.4416	0.4475	0.4415
		(0.4741)	(0.4845)	(0.4741)	(0.4845)
Spill 2		60.2270**	61.3487**	60.2442**	61.3406**
		(28.5342)	(28.4264)	(28.5343)	(28.4268)
Spill 1		-58.1090***	-58.8728***	-58.1182***	-58.8684***
		(14.9743)	(15.0223)	(14.9740)	(15.0213)
Common cites		5.2639***	5.3635***	5.2646***	5.3631***
		(1.0970)	(1.0986)	(1.0968)	(1.0984)
Number of observations	168796	168793	168793	168793	168793

Table 1.1: Firm pair regressions with the complementarity proximity measure

This table contains the firm pair regressions with proximity calculated with the complementary weighting. The observations are on the software sector as defined following Bessen and Hunt (2007). Firm 1 is defined as large firms in the top 10% of the firm size distribution and firm 2 are the set of smaller firms in the bottom 90% of the firm size distribution. Both of the knowledge stock variables are logged with an adding 0.01 to avoid losing observations. A dummy variable is also added to control for those cases where the knowledge stock is zero.

From Table 1.1 we also see that the effect of the knowledge stock of firm i is large and significantly positive. Knowledge stock can be considered a proxy for firm size, so this suggests that buyout deals are more likely to come from larger firms. The coefficient on firm j originality is consistently negative albeit insignificant. This is consistent with the hypothesis that buyouts have a negative effect on target firm originality. Column (3) shows that the buyout likelihood is negatively affected by the larger firm's originality yet positively affected by its knowledge stock. This implies that the larger firm (the potential acquiror) is more likely to acquire another firm when it has historically invested a lot in R&D yet has a low degree of originality. This contributes to the literature on the question of when an incumbent firm chooses to buy or build innovations. The coefficient on firm 2 (the smaller firm and potential target) originality is insignificant. Since we expect proximity to capture the majority of the type of innovation choices, it is not surprising that the originality of the smaller firm is insignificant. When we include the other spillover measures, we see that Spill 2, the percent of firm 2 patents that are cited by firm 1 has a positive effect on buyout likelihood. However Spill 1, the percent of firm 1 patents cited by firm 2 has a negative and significant effect on buyout likelihood. When the two firms have a higher amount of common cited patents, they also increase their likelihood of buyout.

On the other hand, when we regress the likelihood of buyout on the Jaffe proximity (which measures proximity along the substitutability axis) we see that proximity has a negative and significant coefficient (see table 1.2). This result contrasts with the findings in Bena and Li (2014) and Hussinger (2010) who find a positive effect with the Jaffe measure. This discrepancy is likely due to my specification focusing on large-small firm pairs instead of all firm pairs. Small firms that are closely positioned along the substitutability axis to large firms have to compete more directly with the large firms. A buyout along substitutable firms primarily occurs in order to gain market share and eliminate a rival. My dataset here has specifically chosen firm 2 to be small firms and thus they are unlikely to be serious rivals to the large firms right away. In this case, large firms have different strategies they can use to deal with the competition from small firms and although an acquisition is an option, here we see that it is not likely. If the firm pairs also included large-large firm pairs, it is possible that a closer proximity will increase the likelihood of an M&A deal. This however would confound the effect of proximity on acquisitions for technology or for market share. The estimates on the other measures, namely knowledge stock, originality, and spillovers remain consistent.

	(1)	(2)	(3)	(4)	(5)
Proximity	-2.3787***	-2.3825***	-2.4398***	-2.3825***	-2.4398***
	(0.0879)	(0.0882)	(0.0887)	(0.0882)	(0.0887)
Firm 1 knowledge stock	0.4408***	0.4434***	0.4379***	0.4434***	0.4379***
	(0.0126)	(0.0126)	(0.0127)	(0.0126)	(0.0127)
Firm 2 knowledge stock	0.2900***	0.2776***	0.2785***	0.2777***	0.2787***
	(0.0411)	(0.0413)	(0.0417)	(0.0413)	(0.0417)
Firm 1 originality			-1.8790***		-1.8794***
			(0.1111)		(0.1111)
Firm 2 originality				0.0154	0.0258
				(0.0938)	(0.0936)
Collaborated		1.5623***	1.5617***	1.5617***	1.5607***
		(0.4943)	(0.5060)	(0.4943)	(0.5059)
Spill 2		67.1130**	68.9348**	67.0820**	68.8833**
		(29.4007)	(29.3384)	(29.4015)	(29.3394)
Spill 1		-75.3877***	-76.3697***	-75.3653***	-76.3321***
		(12.7034)	(12.6561)	(12.7005)	(12.6503)
Common cites		9.2161***	9.3445***	9.2133***	9.3397***
		(1.5300)	(1.5255)	(1.5297)	(1.5248)
Number of observations	115506	115503	115503	115503	115503

Table 1.2: Firm pair regressions with the Jaffe proximity measure

This table contains the firm pair regressions on the software sector with the Jaffe proximity measure. Both of the knowledge stock variables are logged with an adding 0.01 to avoid losing observations. A dummy variable is also added to control for those cases where the knowledge stock is zero. Firm 1 is defined as large firms in the top 10% of the firm size distribution and firm 2 are the set of smaller firms in the bottom 90% of the firm size distribution. The observations are on the software sector as defined following Bessen and Hunt (2007).

The different result between these two tables highlight that the complementary proximity measure in table 1.1 captures a different interaction between the small firm and large firm. They are less likely to be rivals. And the complementary technologies may imply that synergies can be found with a buyout. In general, we have seen that there is some reason for a firm to expect its innovation positioning can affect its likelihood of getting bought out. A firm that is closely positioned in complementary technological areas increases its likelihood of buyout while a firm that is closely positioned in substitutable areas has a lower likelihood of getting acquired.

1.4.2 Firm entry innovation

To address my central question of how buyout beliefs affect new entrant innovation originality, I first develop a model for buyout expectations. New entrants do not expect to get acquired immediately after they enter the market. The average age of target firms when they are acquired is 9.5 years while the median is 7 years. Since my focus is on deals involving a start-up acquisition, I remove all deals with a target firm above 10 years old.[19] As such, the average buyout age is 4.7 and the median is 4. This implies that new entrants will base their entry decisions on their buyout beliefs at least a few years into the future.

There is, unfortunately, no consensus on how to model firm expectations. Landier et al. (2019) provide some discussion and experimental evidence comparing rational expectations with interpolation and extrapolation. They find that extrapolation is the most prominent while rational expectations is the least realistic. Kuchler and Zafar (2019) also find that extrapolation matches best with survey evidence. There is a discussion on models of expectations formation in macroeconomics as well. Although their models are usually focused on inflation expectations, they also find that the full information rational expectations model is often mismatched with reality.[20] There is also a financial economics and behavioral economics literature on expectations and learning with many different models put forward.[21]

Here I will build a simple reduced form expectations model based on the extrapolation concept where I define the information set of the entrant firms as a set of variables that characterize the 2008 crisis. I assume that the potential firm entrant already knows what industry it will enter in and the strategic innovation decision is made within that industry on the technological class. In particular, since I want to build an expectations measure for firms before they enter, I do not have any information on firm specific characteristics. As such, my expectations measure will be formed at the industry level. Specifically, I assume that prior to entering the market, all potential new firms within an industry have the same expectations and that their expectations are based on a common set of macroeconomic, financial, and industry specific data points.

Let $\mathcal{F}_t$ be the information set of all potential entrants at time t. This includes data such as past buyout deal details as well as historical short and long term interest rates, financial regulation changes and a house price index to proxy financing conditions plus macroeconomic measures and industry level concentration. To capture regulatory changes I use the number of restric-

[19] An older target firm also implies that the firm has an established market share and that it is more likely to be bought out for market share reasons rather than R&D reasons.

[20] See Woodford (2013), Coibion et al. (2018), Negro and Schorfheide (2004), Davila (2014), Bordalo et al. (2018), etc.

[21] See Fudenberg and Levine (2016), Heidhues et al. (2018), Gilboa et al. (2008), Gilboa (2014), Diecidue and de Ven (2008), etc.

tions in financial titles collected and parsed by RegData. The macroeconomics measures include the VIX as a volatility indicator, a measure of consumer sentiment from the OECD, the S&P 500 index as a measure of stock market sentiment, the inflation rate and the unemployment rate. As buyouts may be more likely to happen in different times in the industry life cycle, I control for this with the Herfindahl index and the share of sales by the top ten firms in each industry.

I assume that the expectations of buyout is a linear model of the number of buyouts in the same industry as the potential entrant. Let $Y_{s,t}$ be the number of buyouts in industry s in year t. What I want to predict is :

$$\mathbb{E}(Y_{s,t+\gamma}|\mathcal{F}_t;\beta^{(t,\gamma)}) \tag{1.6}$$

where γ is the number of years ahead predicted and $\beta^{(t,\gamma)}$ is the set of parameters at time t for γ years ahead. Since $\beta^{(t,\gamma)}$ is unobserved, I estimate it with the information available at t. Namely:

$$\hat{\beta}^{(t,\gamma)} = \min_{\beta}(Y_{s,t} - \mathbb{E}(Y_{s,t}|\mathcal{F}_{t-\gamma};\beta^{(t,\gamma)}))^2 \tag{1.7}$$

Assuming that $\mathbb{E}(Y_{s,t}|\mathcal{F}_{t-\gamma};\beta^{(t,\gamma)})$ is linear, equation (1.7) can be concretely rewritten as:

$$\textit{Num buyouts}_{s,t} = \beta_0^{(t,\gamma)} + \beta_f^{(t,\gamma)}\textit{Financing measures}_{t-\gamma} + \beta_m^{(t,\gamma)}\textit{Macro controls}_{t-\gamma} + \beta_s^{(t,\gamma)}\textit{Sector controls}_{s,t-\gamma} + \epsilon_{s,t}$$

Since the estimates from equation (1.7) are used in the main regression, I need a source of exogenous variation. The variables in the information set are mostly the same as the variables that I use in the main regression as controls. I gain some additional variation by including the lagged number of buyout deals in this first stage regression. The previous number of buyout deals should not have any direct effect on the entrant firm's innovation choice except through its buyout expectations. For another source of variation, I also run a robustness check where my first step estimate is calculated with an added second lag on the variables. Specifically, let $\mathcal{F}_t = \{f_t, f_{t-1}, f_{t-2}, ...\}$ where f_t is the information arriving in year t. Then my $\hat{\beta}^{t,\gamma}$ is estimated from :

$$\hat{\beta}^{(t,\gamma)} = \min_{\beta}(Y_{s,t} - \mathbb{E}[Y_{s,t}|f_{t-\gamma}, f_{t-1-\gamma};\beta^{(t,\gamma)}])^2 \tag{1.8}$$

This gives an estimate of $\hat{\beta}^{(t,\gamma)}$ which is plugged into eq (1.6) to give the predicted number of buyout deals in year $t+\gamma$. To be clear, my predicted number of buyouts at year t for year $t+\gamma$ is :

$$\widehat{Num\ buyouts}_{s,t+\gamma} = \hat{\beta}_0^{(t,\gamma)} + \hat{\beta}_f^{(t,\gamma)} Financing\ measures_t + \hat{\beta}_m^{(t,\gamma)} Macro\ controls_t + \hat{\beta}_s^{(t,\gamma)} Sector\ controls_{s,t} + \eta_{s,t}$$

This step is run multiple times with different γ lag years (ex. $0,1,...,5$). Having obtained these predicted number of buyouts, I return to the main question of how expectations affect new firm entrants' innovation originality. My main specification is:

$$Originality_{i_{s,t}} = \mathbb{E}_{s,t}[i \text{ will be bought out}] + Financing\ measures_t + Sector\ Controls_{s,t} + Macro\ Controls_t + \upsilon_i \tag{1.9}$$

Where $Originality_{i_{s,t}}$ is the average originality of the firm entrant i in industry s in the first year it enters t. Financing measures include interest rates, regulatory restrictions and the house price index and the sector and macro controls are the same as the set in the estimation of β in eq (1.8). I assume: $\mathbb{E}_{s,t}[i \text{ will be bought out}] = \phi_0 + \phi_1 \widehat{Num\ of\ buyouts}_{s,t+\gamma} + \zeta_{s,t}$

Table 1.3 presents the results from the regression as described in equation (1.7). We expect that financing conditions should be a major predictor and we indeed see that the federal funds rate (a.k.a. the overnight borrowing rate) is highly negative and significant with the effect becoming slightly less significant in higher lead years. The treasury 10 year rate is weakly negative and significant here. The financial regulatory restrictions on the other hand, have an ambiguous effect across the lead years. We expected the regulatory restrictions to have more of an effect on the young firms and we will clearly see that this is the case later. The fact that the coefficient fluctuates here implies that the negative effect of more regulatory restrictions is entangled with the positive effect of the asymmetric pass-through.

The lagged number of buyouts is the most significant predictor of future buyouts. The coefficient stays positive and significant over the different lead years I use. This implies that momentum is an important cause of buyouts. When there are more buyouts one year, there is likely to be more next year as well. The M&A literature has suggested that when a deal happens between two firms in an industry, the competition landscape changes and spurs the other firms in that industry to also do deals to remain competitive. Note that this regression is over the entire time period (1980-2016) thus the R^2 is quite high. However the predicted number of buyouts measure I use in the second stage is from rerunning the regression each year with only data up until that year. Evidently the out-of-sample fit is worse although it gets better over time as more data becomes available.

	Number of Buyouts				
	t+1	t+2	t+3	t+4	t+5
Number of Buyouts t-1	9.924e-01***	9.804e-01***	9.740e-01***	9.647e-01***	9.535e-01***
	(3.997e-02)	(5.584e-02)	(6.336e-02)	(5.781e-02)	(4.999e-02)
Fed Funds rate t-1	-4.212e+00***	-8.865e+00***	-1.282e+01***	-1.112e+01***	-7.331e+00*
	(1.224e+00)	(1.935e+00)	(2.591e+00)	(3.301e+00)	(3.756e+00)
Treasury 10yr rate t-1	6.560e+00**	6.086e+00	1.377e+01**	1.034e+01	8.125e+00
	(2.871e+00)	(4.943e+00)	(6.791e+00)	(8.580e+00)	(1.031e+01)
Regulatory Restrictions t-1	4.630e+03	-1.814e+04	-2.810e+04	-3.588e+04*	-1.659e+04
	(8.538e+03)	(1.294e+04)	(1.774e+04)	(1.928e+04)	(2.148e+04)
Concentration t-1	7.621e-01	1.744e+00**	2.614e+00**	3.629e+00***	5.021e+00***
	(6.244e-01)	(8.790e-01)	(1.040e+00)	(1.069e+00)	(1.229e+00)
House Price t-1	-8.341e-02*	-2.825e-01***	-3.180e-01***	-2.194e-01*	5.949e-02
	(4.505e-02)	(7.941e-02)	(9.440e-02)	(1.176e-01)	(1.215e-01)
Nasdaq t-1	-1.351e-02***	-2.212e-02***	-1.224e-02	8.718e-03	2.781e-02***
	(4.061e-03)	(6.867e-03)	(9.050e-03)	(7.708e-03)	(7.708e-03)
Volatility t-1	-7.227e-01***	-7.771e-01***	-9.966e-01***	-1.181e+00***	-9.280e-01*
	(1.691e-01)	(2.199e-01)	(2.834e-01)	(3.786e-01)	(5.273e-01)
Consumer Confidence t-1	5.085e+00***	5.663e+00**	-9.173e-01	-1.456e+01***	-3.107e+01***
	(1.791e+00)	(2.840e+00)	(3.752e+00)	(4.829e+00)	(5.749e+00)
Inflation t-1	6.390e-01**	4.752e-01	3.613e-01	-4.288e-01	-1.088e+00*
	(2.568e-01)	(3.549e-01)	(5.227e-01)	(5.583e-01)	(5.764e-01)
Unemployment t-1	1.306e+00	-3.181e+00*	-3.716e+00*	-2.300e+00	-4.906e-01
	(1.521e+00)	(1.810e+00)	(2.095e+00)	(2.719e+00)	(3.170e+00)
Oil Price t-1	5.402e-03	3.742e-01***	2.000e-01	-2.866e-01	-1.013e+00***
	(9.329e-02)	(1.393e-01)	(1.575e-01)	(2.169e-01)	(2.787e-01)
N	1912	1849	1779	1714	1648

Table 1.3: Regression output from the first step based on OLS

Note: All the regressor variables are lagged by one year. This is a linear regression at the sector-year level and the number of buyouts are by sector year where a sector is a 2-digit SIC code. The concentration index is the Herfindahl index and the various indices that come in daily or monthly or quarterly frequencies have been averaged to the yearly frequency. The standard errors are in the parenthesis.

Since the dependent variable in the first stage is a count of deals, I run a robustness check with a negative binomial regression with the output in Table 1.4. The results are largely consistent with the OLS regression.

Table 1.4 presents the main regression described in equation 1.9. We see clearly that the expected number of buyouts in the firms' primary sector has a negative and significant effect on its originality confirming our hypothesis that increased beliefs of buyout likelihood lead new firms to conduct less original innovation. The effect is slightly weaker as the lead years increase but this is likely due to the higher prediction error for higher lead years.

	Number of Buyouts				
	t+1	t+2	t+3	t+4	t+5
Number of Buyouts t-1	6.635e-03***	6.599e-03***	6.577e-03***	6.595e-03***	6.573e-03***
	(5.060e-04)	(5.330e-04)	(5.510e-04)	(5.760e-04)	(5.950e-04)
Fed Funds rate t-1	-3.060e-02	-7.932e-02***	-1.001e-01***	-8.369e-02***	-5.748e-02**
	(2.020e-02)	(2.160e-02)	(2.550e-02)	(2.730e-02)	(2.700e-02)
Treasury 10yr rate t-1	4.300e-02	5.380e-02	8.310e-02	5.440e-02	4.450E-02
	(4.490e-02)	(4.760e-02)	(5.430e-02)	(5.980e-02)	(6.270e-02)
Regulatory Restrictions t-1	-1.790e+01	-2.635e+02**	-4.222e+02***	-2.975e+02**	6.360e+00
	(1.100e+02)	(1.240e+02)	(1.310e+02)	(1.370e+02)	(1.520e+02)
Concentration t-1	9.299e-02***	9.338e-02***	9.271e-02***	9.240e-02***	9.347e-02***
	(6.120e-03)	(6.710e-03)	(7.110e-03)	(7.660e-03)	(8.420e-03)
House Price t-1	-1.620e-03**	-3.004e-03***	-3.233e-03***	-2.092e-03**	-2.370E-05
	(7.250e-04)	(8.230e-04)	(8.710e-04)	(8.990e-04)	(9.930e-04)
Nasdaq t-1	-1.854e-04***	-1.693e-04***	-1.670e-05	1.450e-04***	2.934e-04***
	(3.770e-05)	(4.620e-05)	(5.180e-05)	(5.500e-05)	(5.700e-05)
Volatility t-1	-6.749e-03**	-7.565e-03**	-9.916e-03***	-1.041e-02***	-7.791e-03*
	(2.690e-03)	(2.980e-03)	(3.160e-03)	(3.520e-03)	(4.160e-03)
Consumer confidence t-1	7.844e-02**	5.700e-02	-2.410e-02	-1.593e-01***	-3.037e-01***
	(3.320e-02)	(3.780e-02)	(4.000e-02)	(4.340e-02)	(4.520e-02)
Inflation t-1	1.089e-02***	6.069e-03*	1.770e-03	-3.790e-03	-8.679e-03**
	(3.390e-03)	(3.500e-03)	(3.800e-03)	(4.150e-03)	(4.120e-03)
Unemployment t-1	-2.010e-02	-5.394e-02**	-5.031e-02*	-3.510e-02	-2.540e-02
	(2.590e-02)	(2.670e-02)	(2.820e-02)	(2.960e-02)	(3.170e-02)
Oil Price t-1	-9.770e-04	1.530e-03	-1.070e-03	-5.425e-03**	-9.286e-03***
	(1.650e-03)	(2.160e-03)	(2.230e-03)	(2.500e-03)	(2.740e-03)
N	1.912e+03	1.849e+03	1.779e+03	1.714e+03	1.648e+03

Table 1.4: Regression output from the first step based on a negative binomial model

Note that all the regressor variables are lagged by one year. This is a negative binomial regression at the sector-year level and the number of buyouts are by sector year where a sector is a 2-digit SIC code. The concentration index is the Herfindahl index and the various indices that come in daily or monthly or quarterly frequencies have been averaged to the yearly frequency. The standard errors are in the parenthesis.

We also see that the fed funds rate, a principle measure of start-up access to financing, has a negative effect on innovation originality as expected. A higher interest rate means it is more costly to borrow and therefore makes R&D more difficult.The 10 year Treasury rate is also consistently negative albeit insignificant. Similarly more financial regulatory restrictions have a negative and significant effect on new firm innovation. Although the financial regulatory restrictions are only applied directly to financial intermediaries, we see evidence here that it is passed on to their borrowers as well.

Finally, the house price index is also a measure of young firm access to financing. Here we see that the coefficient on the house price index is positive which is inline with the intuition that higher house prices mean more collateral value which allows more access to debt capital and hence leads to more original innovation. The interest rates, regulatory restrictions and house price index have a push effect on innovation that I expect would also increase the rate of patenting while the buyout expectations measure captures the pull effect described earlier.

	Firm Entry Originality				
E[Num Buyouts$_{t+1}$]	-2.512e-05***				
	(1.064e-05)				
E[Num Buyouts$_{t+2}$]		-1.137e-05***			
		(3.985e-06)			
E[Num Buyouts$_{t+3}$]			-1.248e-05**		
			(4.979e-06)		
E[Num Buyouts$_{t+4}$]				-1.142e-05*	
				(6.661e-06)	
E[Num Buyouts$_{t+5}$]					3.120e-06
					(3.147e-06)
Fed Funds Rate	-2.762e-03***	-2.667e-03***	-2.947e-03***	-3.088e-03***	-2.710e-03***
	(8.035e-04)	(8.055e-04)	(8.048e-04)	(8.247e-04)	(8.106e-04)
Treasury 10 year rate	-4.503e-04	-1.804e-03	-8.723e-04	-3.355e-05	-1.066e-03
	(1.977e-03)	(1.984e-03)	(1.962e-03)	(2.057e-03)	(1.962e-03)
Regulatory Restrictions	-1.270e-06***	-1.365e-06***	-1.367e-06***	-1.235e-06***	-1.276e-06***
	(2.266e-07)	(2.308e-07)	(2.321e-07)	(2.262e-07)	(2.289e-07)
House Price Index	2.799e-04***	2.867e-04***	2.731e-04***	2.859e-04***	3.148e-04***
	(4.030e-05)	(3.931e-05)	(4.098e-05)	(4.093e-05)	(3.907e-05)
Nasdaq Avg	-4.190e-06**	-2.567e-06	-3.027e-06*	-2.590e-06	-1.609e-07
	(2.136e-06)	(1.703e-06)	(1.799e-06)	(1.852e-06)	(1.784e-06)
Volatility Avg	1.563e-04	1.788e-04	4.480e-05	-4.492e-06	1.496e-04
	(1.549e-04)	(1.552e-04)	(1.608e-04)	(1.818e-04)	(1.548e-04)
Consumer Confidence Avg	-4.360e-04	-2.686e-04	-2.166e-04	-1.491e-03	-2.038e-03
	(1.617e-03)	(1.593e-03)	(1.626e-03)	(1.493e-03)	(1.479e-03)
Inflation Index	6.065e-04***	4.231e-04**	4.889e-04**	5.159e-04**	3.001e-04
	(2.222e-04)	(1.948e-04)	(2.007e-04)	(2.175e-04)	(1.992e-04)
Unemployment Rate	-1.621e-03*	-1.083e-03	-1.044e-03	-1.530e-03	-8.274e-04
	(9.844e-04)	(9.674e-04)	(9.682e-04)	(9.936e-04)	(1.023e-03)
Oil Price	-1.749e-04*	-9.943e-05	-5.724e-05	-1.335e-04	-1.240e-04
	(9.912e-05)	(9.940e-05)	(1.037e-04)	(9.820e-05)	(9.949e-05)
N	154955	154955	154955	154955	154955

Table 1.5: Baseline regressions results

Stage 2 regression on 4-digit firm originality in the first year it patents. Also included in the regressors are 2-digit SIC controls as well as controls for whether the firm is in the ICT or software sector. Standard errors are clustered on 2-digit SIC sectors. Expected number of buyouts are measured in the first stage as described above. All time-varying RHS variables are lagged one year.

1.4.3 Robustness Check

Table 1.6 is a robustness check of the main result with the alternative proximity measure. Here the dependent variable is replaced by a measure built using the same methodology as proximity between firms. In this case, it is proximity between the technology codes in the firm's patents vs the cited patents. We expect proximity to have an inverse effect as compared to originality and indeed in Table 1.6 the sign of the coefficient on buyout expectations is now positive. Different constructions of the dependent variable are also tested and available in Appendix B. The results are generally very consistent.

	Firm Entry Proximity				
E[Num Buyouts t + 1]	1.709e-05***				
	(5.280e-06)				
E[Num Buyouts t + 2]		1.914e-05***			
		(2.589e-06)			
E[Num Buyouts t + 3]			1.005e-05***		
			(3.191e-06)		
E[Num Buyouts t + 4]				8.484e-06**	
				(3.688e-06)	
E[Num Buyouts t + 5]					1.491e-05***
					(4.013e-06)
Fed Funds Rate t - 1	7.317e-03***	7.265e-03***	7.356e-03***	7.315e-03***	7.396e-03***
	(8.568e-04)	(8.405e-04)	(8.468e-04)	(8.541e-04)	(8.636e-04)
Treasury 10yr Rate t - 1	-7.510e-03**	-6.919e-03**	-7.562e-03**	-7.677e-03**	-7.406e-03**
	(2.741e-03)	(2.724e-03)	(2.720e-03)	(2.710e-03)	(2.757e-03)
Regulatory Restrictions t - 1	4.242e-06***	4.283e-06***	4.271e-06***	4.247e-06***	4.193e-06***
	(3.075e-07)	(3.055e-07)	(3.049e-07)	(3.064e-07)	(3.084e-07)
House Price t - 1	-1.785e-04***	-1.791e-04***	-1.724e-04***	-1.715e-04***	-1.730e-04***
	(4.657e-05)	(4.527e-05)	(4.431e-05)	(4.405e-05)	(4.509e-05)
Oil Price t - 1	7.666e-04***	7.263e-04***	7.406e-04***	7.641e-04***	7.789e-04***
	(1.047e-04)	(1.043e-04)	(1.075e-04)	(1.044e-04)	(1.025e-04)
Nasdaq t - 1	5.175e-06***	5.314e-06***	5.228e-06***	5.324e-06***	5.423e-06***
	(8.026e-07)	(7.679e-07)	(8.113e-07)	(8.121e-07)	(7.271e-07)
Volatility t - 1	5.593e-04**	5.237e-04**	5.956e-04***	6.159e-04***	5.536e-04**
	(1.975e-04)	(1.937e-04)	(1.861e-04)	(1.809e-04)	(1.982e-04)
Consumer Confidence t - 1	6.763e-03***	6.052e-03***	6.680e-03***	7.068e-03***	6.888e-03***
	(2.014e-03)	(1.904e-03)	(1.948e-03)	(1.848e-03)	(1.876e-03)
Inflation t - 1	-1.163e-03***	-1.118e-03***	-1.165e-03***	-1.189e-03***	-1.180e-03***
	(2.077e-04)	(2.011e-04)	(2.010e-04)	(1.959e-04)	(2.047e-04)
Unemployment Rate t - 1	1.037e-02***	1.011e-02***	1.028e-02***	1.046e-02***	1.069e-02***
	(1.333e-03)	(1.346e-03)	(1.369e-03)	(1.386e-03)	(1.385e-03)
Sector controls	yes	yes	yes	yes	yes
N	125389	125389	125389	125389	125389

Table 1.6: Robustness check using the alternative patent proximity measure

Stage 2 regression on firm entry proximity in the first year it patents with 2-digit SIC controls as well as controls for whether the firm is in the ICT or software sector. The proximity measure is akin to an uncentered correlation measure of the technology codes in the patents held by the firm and the technology codes of the patents cited by the firm. Standard errors are clustered on 2-digit SIC sectors. Expected number of buyouts are measured in the first stage as described above. All time-varying RHS variables are lagged one year.

An alternative theory for why we might be seeing a drop in originality is that perhaps I am capturing some spurious effect due to changes in firm patenting strategies. There is some anecdotal evidence that some firms are choosing to protect their inventions by filing more patents of a smaller scope. This arguably increases the chances of at least one patent being granted. For instance, young firms that are looking for bank financing might choose to file more patents of smaller scope since patents can be used as collateral. Since the Trajtenberg et al. (1997) originality measure is built at the patent level and then averaged to the firm level, this possibility would bias my results. In order to adjust for this, I simply build an additional originality

	Firm entry proximity				
	(1)	(2)	(3)	(4)	(5)
E[Num Deals$_{t+1}$]	2.57e-05***				
	(7.74e-06)				
E[Num Deals$_{t+2}$]		2.20e-05***			
		(3.00e-06)			
E[Num Deals$_{t+3}$]			2.36e-05***		
			(3.77e-06)		
E[Num Deals$_{t+4}$]				1.23e-05**	
				(4.92e-06)	
E[Num Deals$_{t+5}$]					5.49e-06**
					(2.37e-06)
Fed Funds Rate	6.56e-03***	6.33e-03***	6.87e-03***	6.92e-03***	6.79e-03***
	(5.92e-04)	(5.93e-04)	(5.94e-04)	(6.012e-04)	(5.97e-04)
Treasury 10y rate	-5.59e-03***	-3.50e-03**	-5.29e-03***	-6.06e-03***	-4.99e-03***
	(1.41e-03)	(1.40e-03)	(1.39e-03)	(1.45e-03)	(1.39e-03)
Regulatory Restrictions	3.90e-06***	4.11e-06***	4.11e-06***	3.86e-06***	3.80e-06***
	(1.56e-07)	(1.59e-07)	(1.60e-07)	(1.55e-07)	(1.58e-07)
House Price Index	-1.93e-04***	-1.80e-04***	-1.55e-04***	-1.98e-04***	-2.14e-04***
	(2.95e-05)	(2.86e-05)	(3.02e-05)	(2.98e-05)	(2.83e-05)
Nasdaq Avg	6.61e-04***	6.35e-06***	7.14e-06***	4.98e-06***	4.58e-06***
	(1.56e-06)	(1.25e-06)	(1.33e-06)	(1.37e-06)	(1.31e-06)
Volatility Avg	3.34e-04***	2.89e-04**	5.44e-04***	5.09e-04***	3.30e-04***
	(1.12e-04)	(1.12e-04)	(1.17e-04)	(1.31e-04)	(1.12e-04)
Consumer Confidence Avg	4.59e-03***	2.94e-03**	2.94e-03**	5.69e-03***	5.92e-03***
	(1.18e-03)	(1.17e-03)	(1.20e-03)	(1.10e-03)	(1.09e-03)
Inflation Index	-1.11e-03***	-9.83e-04***	-1.10e-03***	-1.02e-03***	-9.14e-04***
	(1.61e-04)	(1.40e-04)	(1.45e-04)	(1.56e-04)	(1.42e-04)
Unemployment Rate	8.87e-03***	8.24e-03***	8.18e-03***	8.79e-03***	8.94e-03***
	(7.34e-04)	(7.17e-04)	(7.17e-04)	(7.33e-04)	(7.56e-04)
Oil Price	7.10e-04***	5.95e-04***	5.17e-04***	6.66e-04***	6.99e-04***
	(7.45e-05)	(7.41e-05)	(7.72e-05)	(7.35e-05)	(7.43e-05)
N	151714	1517154	1517154	1517154	1517154

	Firm level entry originality				
	(1)	(2)	(3)	(4)	(5)
E[Num Deals t+1]	-5.93e-05***				
	(1.01e-05)				
E[Num Deals t+2]		-1.32e-05***			
		(3.76e-06)			
E[Num Deals t+3]			-1.89e-05***		
			(4.73e-06)		
E[Num Deals t+4]				-2.98e-05***	
				(6.30e-06)	
E[Num Deals t+5]					-1.69e-06
					(2.96e-06)
Fed Funds Rate	-1.95e-03**	-1.90e-03**	-2.29e-03***	-2.88e-03***	-2.15e-03***
	(7.59e-04)	(7.60e-04)	(7.60e-04)	(7.84e-04)	(7.651e-04)
Treasury 10 y rate	-1.03e-03	-3.36e-03*	-2.22e-03	3.08e-04	-2.41e-03
	(1.85e-03)	(1.86e-03)	(1.84e-03)	(1.93e-03)	(1.84e-03)
Regulatory Restrictions	-1.08e-06***	-1.15e-06***	-1.20e-06***	-1.01e-06***	-9.85e-07***
	(2.09e-07)	(2.13e-07)	(2.15e-07)	(2.09e-07)	(2.12e-07)
House Price Index	1.16e-04***	1.60e-04***	1.31e04***	1.22e-04***	1.83e-04***
	(3.81e-05)	(3.72e-05)	(3.88e-05)	(3.87e-05)	(3.69e-05)
Nasdaq Avg	-6.54e-06***	-5.84e-07	-1.82e-06	-2.93e-06*	9.09e-07
	(2.03e-06)	(1.61e-06)	(1.71e-06)	(1.75e-06)	(1.69e-06)
Volatility Avg	-2.73e-05	-8.79e-06	-2.06e-04	-4.65e-04***	-3.91e-05
	(1.47e-04)	(1.47e-04)	(1.52e-04)	(1.72e-04)	(1.47e-04)
Consumer Confidence Avg	2.29e-03	6.32e-04	1.26e-03	-2.70e-04	-1.26e-03
	(1.54e-03)	(1.51e-03)	(1.54e-03)	(1.42e-03)	(1.40e-03)
Inflation Index	1.02e-03***	4.85e-04***	6.12e-04***	8.53e-04***	4.26e-04**
	(2.10e-04)	(1.84e-04)	(1.90e-04)	(2.06e-04)	(1.88e-04)
Unemployment Rate	-3.03e-03***	-1.82e-03**	-1.75e-03*	-2.97e-03***	-2.10e-03**
	(9.35e-04)	(9.19e-04)	(9.19e-04)	(9.44e-04)	(9.70e-04)
Oil Price	-2.50e-04***	-1.19e-04	-4.20e-05	-1.55e-04*	-1.77e-04*
	(9.43e-05)	(9.44e-05)	(9.85e-05)	(9.33e-05)	(9.45e-05)
N	143915	143915	143915	143915	143915

measure at the firm level directly instead of at the patent-level firm. This means I aggregate all the firms patents in its first year and get the set of technology codes of the backwards citations, then I build the originality with the same formula as before. In this way, I group all the patents and their technology codes into a given firm-year so this measure should not be affected by the changes in patenting strategies just described. Tables 1.7 and 1.8 are the results for firm-level originality and firm-level proximity and again we find similar results.

	Firm Entry Average Firm-level Originality				
E[Num Buyouts$_{t+1}$]	-5.930e-05***				
	(1.008e-05)				
E[Num Buyouts$_{t+2}$]		-1.323e-05***			
		(3.759e-06)			
E[Num Buyouts$_{t+3}$]			-1.893e-05***		
			(4.725e-06)		
E[Num Buyouts$_{t+4}$]				-2.983e-05***	
				(6.296e-06)	
E[Num Buyouts$_{t+5}$]					-1.693e-06
					(2.956e-06)
Fed Funds Rate	-1.947e-03**	-1.897e-03**	-2.285e-03***	-2.882e-03***	-2.147e-03***
	(7.585e-04)	(7.602e-04)	(7.599e-04)	(7.784e-04)	(7.651e-04)
Treasury 10 year rate	-1.032e-03	-3.355e-03*	-2.216e-03	3.077e-04	-2.407e-03
	(1.851e-03)	(1.855e-03)	(1.836e-03)	(1.927e-03)	(1.836e-03)
Num Regulatory Restrictions	-1.077e-06***	-1.152e-06***	-1.202e-06***	-1.008e-06***	-9.853e-07***
	(2.094e-07)	(2.134e-07)	(2.148e-07)	(2.091e-07)	(2.117e-07)
House Price Index	1.163e-04***	1.600e-04***	1.312e-04***	1.223e-04***	1.825e-04***
	(3.809e-05)	(3.716e-05)	(3.881e-05)	(3.869e-05)	(3.691e-05)
Nasdaq Avg	-6.536e-06***	-5.843e-07	-1.823e-06	-2.928e-06*	9.094e-07
	(2.030e-06)	(1.610e-06)	(1.705e-06)	(1.754e-06)	(1.685e-06)
Volatility Avg	-2.730e-05	-8.790e-06	-2.064e-04	-4.654e-04***	-3.908e-05
	(1.466e-04)	(1.469e-04)	(1.521e-04)	(1.720e-04)	(1.465e-04)
Consumer Confidence Avg	2.293e-03	6.316e-04	1.259e-03	-2.695e-04	-1.263e-03
	(1.538e-03)	(1.511e-03)	(1.544e-03)	(1.416e-03)	(1.403e-03)
Inflation Index	1.022e-03***	4.853e-04***	6.124e-04***	8.527e-04***	4.258e-04**
	(2.104e-04)	(1.839e-04)	(1.897e-04)	(2.055e-04)	(1.880e-04)
Unemployment Rate	-3.031e-03***	-1.815e-03**	-1.746e-03*	-2.965e-03***	-2.099e-03**
	(9.349e-04)	(9.187e-04)	(9.192e-04)	(9.435e-04)	(9.699e-04)
Oil Price	-2.504e-04***	-1.185e-04	-4.195e-05	-1.546e-04*	-1.766e-04*
	(9.425e-05)	(9.443e-05)	(9.852e-05)	(9.334e-05)	(9.447e-05)
N	143915	143915	143915	143915	143915

Table 1.7: Robustness check using the firm-level originality measure

Stage 2 regression on 4-digit mean firm US patenting firm level originality in the first year it patents. Also included in the regressors are 2-digit SIC controls as well as controls for whether the firm is in the ICT or software sector. Standard errors are clustered on 2-digit SIC sectors. The expected number of deals are . All time-varying RHS variables are lagged one year.

	Firm Entry Average Firm-level Proximity				
E[Num Buyouts$_{t+1}$]	8.187e-05***				
	(1.154e-05)				
E[Num Buyouts$_{t+2}$]		1.672e-05***			
		(4.259e-06)			
E[Num Buyouts$_{t+3}$]			1.266e-05**		
			(5.445e-06)		
E[Num Buyouts$_{t+4}$]				8.124e-06	
				(7.081e-06)	
E[Num Deals$_{t+5}$]					-9.189e-06***
					(3.368e-06)
Fed Funds Rate	2.485e-03***	2.436e-03***	2.794e-03***	2.863e-03***	2.354e-03***
	(8.771e-04)	(8.782e-04)	(8.797e-04)	(8.908e-04)	(8.802e-04)
Treasury 10 year rate	-1.157e-03	1.943e-03	6.419e-04	7.097e-05	8.483e-04
	(2.073e-03)	(2.077e-03)	(2.057e-03)	(2.155e-03)	(2.055e-03)
Num Regulatory Restrictions	-1.363e-06***	-1.279e-06***	-1.334e-06***	-1.467e-06***	-1.356e-06***
	(2.495e-07)	(2.538e-07)	(2.557e-07)	(2.490e-07)	(2.530e-07)
House Price Index	-2.343e-04***	-2.983e-04***	-2.946e-04***	-3.143e-04***	-3.475e-04***
	(4.406e-05)	(4.269e-05)	(4.476e-05)	(4.442e-05)	(4.222e-05)
Nasdaq Avg	6.504e-06***	-1.938e-06	-2.230e-06	-3.178e-06	-6.643e-06***
	(2.282e-06)	(1.787e-06)	(1.913e-06)	(1.970e-06)	(1.894e-06)
Volatility Avg	-1.606e-04	-1.856e-04	-3.662e-05	-3.330e-05	-1.368e-04
	(1.657e-04)	(1.660e-04)	(1.724e-04)	(1.930e-04)	(1.659e-04)
Consumer Confidence Avg	-8.782e-03***	-6.264e-03***	-5.542e-03***	-4.108e-03**	-3.452e-03**
	(1.731e-03)	(1.702e-03)	(1.754e-03)	(1.596e-03)	(1.583e-03)
Inflation Index	-1.621e-04	5.896e-04***	5.567e-04***	5.781e-04**	8.353e-04***
	(2.366e-04)	(2.050e-04)	(2.124e-04)	(2.305e-04)	(2.090e-04)
Unemployment Rate	4.989e-05	-1.615e-03	-1.612e-03	-1.224e-03	-2.453e-03**
	(1.095e-03)	(1.074e-03)	(1.075e-03)	(1.099e-03)	(1.125e-03)
Oil Price	-2.297e-05	-1.989e-04*	-2.221e-04*	-1.419e-04	-1.838e-04*
	(1.091e-04)	(1.093e-04)	(1.145e-04)	(1.081e-04)	(1.096e-04)
is ICT	-1.066e-02***	-1.066e-02***	-1.062e-02***	-1.062e-02***	-1.063e-02***
	(1.858e-03)	(1.858e-03)	(1.858e-03)	(1.858e-03)	(1.858e-03)
is Software	8.419e-03**	8.463e-03**	8.505e-03**	8.577e-03**	8.534e-03**
	(3.727e-03)	(3.727e-03)	(3.728e-03)	(3.728e-03)	(3.728e-03)
N	147553	147553	147553	147553	147553

Table 1.8: Robustness check using the alternative proximity measure built at the firm-level

Stage 2 regression on 4-digit mean firm US patenting firm level patenting proximity to citations in the first year it patents. Also included in the regressors are 2-digit SIC controls. Standard errors are clustered on 2-digit SIC sectors. The expected number of deals are . All time-varying RHS variables are lagged one year.

1.5 Concluding remarks

We have seen that firm originality has been decreasing since 2008 and that young firms have become less original with respect to older firms. We have also established that the proximity of a firm to its potential acquirer has a positive effect on its likelihood of buyout and that indeed the expectations of being bought out have a robust negative effect on firm entry originality.

The innovation literature considers new firms to be an important source of radical innovation however this paper shows that due to changes in financing conditions, through buyout expectations, new firms are doing less original innovation. This study has been focused on innovation measures built with technology codes to quantify an innovation position. In chapter 2, I will do a complimentary study on the effect of initial conditions, namely innovation position, on future firm development.

This study has also shed light on how startup innovation choices are affected by their exit options. I suggested that getting bought out has increasingly become a chief exit option since the financial crisis and this has consequently affected their initial entry innovation strategies. Namely, if a start-up believes that getting bought out is its primary exit option, then it will rationally choose to further increase its likelihood of getting bought out by innovating in closer complementary proximity to their potential acquirer.

The bigger picture is to consider the consequences of more consolidation and less original firms. If the objective of new firms is increasingly to be bought out then there will be less competition in the future, implying a stagnating economy. We did in fact see a prolonged and persistent period of low growth after the financial crisis and this paper suggests that changing firm innovation incentives due to firm interactions may be one mechanism.

In addition to proposing a part of the reason for declining business dynamism, our analysis also has implications for policy makers. The increase in alternative funds for new firms may offset some of the direct effect on entry however it may be skewing the innovation incentives on the new entrants that leave a longer term effect.

This paper also provides a new perspective on the push and pull effects of financing on innovation. Traditionally finance has been considered to have a push effect on innovation however here I suggest it can also have an indirect pull effect. Namely when the medium of financing is equity, there are a mix of motives for the firm and the investors. In the case of buyouts, the source of funds is the acquiring firm and that firm has a demand for certain kinds of technology and innovations. This demand from firms for types of innovation is what influences the initial decisions made by startups.

A Name matching process

The names we start off with are applicant names from Patstat that have already been cleaned (the variable psn_name), and target and acquiror names from Thomson SDC Platinum. Names in Patstat are particularly difficult to work with as there is no regularization nor tracking over time or between patent offices, they are not verified with official databases and they are prone to misspellings.

The names matching consists of first dealing the the name misspellings and disambiguation, then running a fuzzy string matching algorithm on the cleanned names, and then filtering out mismatches where names are short or consist of common words.

The name cleaning and disambiguation consists of:

- first converting all letters to uppercase,
- then dealing with symbols. Almost all are removed and replaced with a space. Except, we replace & with "AND" and $ with "S"
- then we group single letter words in the name together. This could be relevant for initials or country codes or incorporation status, etc.
- then we remove a list of words that do not define the company. To be clear, these are: CORPORATION, COMPANY, COMPANIES, COMP, CORP, INCORPORATED, INTERNATIONAL, HOLDING, SYSTEM(S), PRODUCT(S), KABUSHIKI KAISHA, THE, INC, SAS, GMBHDE, GMBH, MBH, LTDA, LTD, SRL, SARL, SA, SPA, SE, ABP, AB, BV, NV, PTE, PTY, LLC, PLC, AG, KG, OY, SL, AS.
- finally we build a dictionary for certain words that appear with different spellings but refer to the same thing. This also includes firms that are often referred to be their abbreviations. For example: IBM -¿ International Business Machines, 3M -¿ Minnesota Mining and Manufacturing, BMW -¿ Bayerische Motoren Werke, as well as Mgmt -¿ Management, Tech -¿ Technology, etc.

We do this initial cleaning with both Patstat applicant PSN names and SDC target and acquiror names.

Then we start the name matching. We assume that company names in SDC are more reliable and therefore base our definition of a *name* match as a threshold percentage of word matches in the SDC name. We ran this twice, once with a requirement that all words match and once with a requirement that 60 percent of the words match. To minimize potential false positives, we show only results from the requirement that all words match.

The algorithm then iterates the list of SDC names and compares with each PSN name. This comparison is done by splitting the name into a list of words then comparing each word for a match.

A *word* match is calculated from the levenshtein distance and the restriction is variable depending on the length of the word. If the word has less than or equal to 5 characters, we require an exact match. If there are between 6 and 9 characters and the levenshtein distance is less than or equal to 1, we consider that a match. Finally, if the word is over 9 characters, we say it is a match if the levenshtein distance is less than or equal to 2.

At this point we have a set of potential matches however there are a few checks to be made. Some company names use generic words and make a minor change (e.g. SOLUTIONS vs. eSOLUTIONS). "eSolutions" will match with any company name that has the word "solutions" in it and since it is a common word, there may be many mismatches. To check for common words, we build a list of common words from Patstat names by simply spliting the Patstat name into words and counting the occurance of each word. We consider common words to be words that are counted at least 100 times and are at least five characters long. We then run through the potential name matches and check if the SDC name contains a common word substring. If so, then we require that the matching name has a word that matches exactly with this.

Another source of error in our potential matches are in the length of names. After our cleaning step, we have a few SDC names that are only one word. As Patstat has a lot of applicants and many with long names, we get many erroneous matches for short SDC names. One check we do is to identify the one word SDC firm names and require that the matching name be at most 2 words with the one that doesn't match being a maximum of 3 letters. Another check we do is on both short names and common words. If the SDC firm name is less than or equal to 3 words and at least one is a common word, then we require an exact match on the uncommon word.

This is the extent of our name matching right now. To complete the merge between the two databases, we use additional data on zip code, state code, and country code to supplement the matching when available.

Patstat has address data on applicants however SDC only goes down to the granularity of zip code and the zip code field is poorly populated in Patstat. Sometimes it appears in the address field and needs to be parsed. To do so, I use the usaddress python package to extract the zip codes and state codes when available. The zip code and state code data in both Patstat and SDC are still relatively poorly populated but for the firms that we do have information for, we use as a filter to check for an address match.

B Additional Results

	Firm Entry Originality				
E[Num Deals$_{t+1}$]	-2.943e-05***				
	(5.533e-06)				
E[Num Deals$_{t+2}$]		-9.770e-06***			
		(1.954e-06)			
E[Num Deals$_{t+3}$]			-1.313e-05***		
			(2.439e-06)		
E[Num Deals$_{t+4}$]				-1.634e-05***	
				(3.400e-06)	
E[Num Deals$_{t+5}$]					-4.830e-06***
					(1.521e-06)
Fed Funds Rate	-2.771e-03***	-2.706e-03***	-2.973e-03***	-3.225e-03***	-2.986e-03***
	(3.963e-04)	(3.978e-04)	(3.964e-04)	(4.113e-04)	(4.010e-04)
Treasury 10 year rate	2.391e-03**	1.021e-03	1.857e-03*	3.126e-03***	1.684e-03*
	(1.022e-03)	(1.030e-03)	(1.015e-03)	(1.072e-03)	(1.015e-03)
Regulatory Restrictions	-1.768e-06***	-1.838e-06***	-1.865e-06***	-1.724e-06***	-1.670e-06***
	(1.184e-07)	(1.206e-07)	(1.211e-07)	(1.180e-07)	(1.190e-07)
House Price Index	3.175e-05	4.764e-05**	2.893e-05	3.349e-05	5.907e-05***
	(2.061e-05)	(1.986e-05)	(2.060e-05)	(2.087e-05)	(1.978e-05)
Nasdaq Avg	-4.978e-06***	-2.476e-06***	-3.273e-06***	-3.436e-06***	-2.291e-06**
	(1.107e-06)	(8.612e-07)	(9.047e-07)	(9.394e-07)	(8.952e-07)
Volatility Avg	-2.413e-04***	-2.226e-04***	-3.589e-04***	-4.709e-04***	-2.362e-04***
	(7.851e-05)	(7.871e-05)	(8.114e-05)	(9.336e-05)	(7.838e-05)
Consumer Confidence Avg	-1.749e-04	-5.332e-04	-1.620e-04	-1.345e-03*	-1.747e-03**
	(8.148e-04)	(8.036e-04)	(8.176e-04)	(7.473e-04)	(7.394e-04)
Inflation Index	1.038e-03***	7.913e-04***	8.756e-04***	9.687e-04***	7.939e-04***
	(1.161e-04)	(1.001e-04)	(1.028e-04)	(1.133e-04)	(1.029e-04)
Unemployment Rate	-3.592e-03***	-2.967e-03***	-2.914e-03***	-3.570e-03***	-3.518e-03***
	(4.859e-04)	(4.753e-04)	(4.758e-04)	(4.927e-04)	(5.062e-04)
Oil Price	-3.234e-04***	-2.464e-04***	-1.943e-04***	-2.724e-04***	-3.043e-04***
	(4.850e-05)	(4.880e-05)	(5.083e-05)	(4.795e-05)	(4.873e-05)
is ICT	3.177e-02***	3.178e-02***	3.177e-02***	3.178e-02***	3.175e-02***
	(7.285e-04)	(7.283e-04)	(7.283e-04)	(7.283e-04)	(7.282e-04)
is Software	-3.325e-03**	-3.308e-03**	-3.294e-03**	-3.369e-03**	-3.404e-03**
	(1.534e-03)	(1.534e-03)	(1.534e-03)	(1.534e-03)	(1.534e-03)
N	154955	154955	154955	154955	154955

Table 1.9: Robustness check using the N-digit originality measure

Stage 2 regression on n-digit firm originality in the first year it patents. Also included in the regressors are 2-digit SIC controls. Standard errors are clustered on 2-digit SIC sectors. Expected number of buyouts are measured in the first stage as described above. All time-varying RHS variables are lagged one year.

	Firm Entry Max Originality				
E[Num Deals_{t+1}]	-2.368e-05**				
	(1.066e-05)				
E[Num Deals_{t+2}]		-9.719e-06**			
		(3.992e-06)			
E[Num Deals_{t+3}]			-9.715e-06*		
			(4.984e-06)		
E[Num Deals_{t+4}]				-8.700e-06	
				(6.678e-06)	
E[Num Deals_{t+5}]					2.471e-06
					(3.151e-06)
Fed Funds Rate	-2.490e-03***	-2.414e-03***	-2.643e-03***	-2.748e-03***	-2.457e-03***
	(8.030e-04)	(8.051e-04)	(8.043e-04)	(8.247e-04)	(8.102e-04)
Treasury 10 year rate	-1.508e-03	-2.733e-03	-1.950e-03	-1.314e-03	-2.101e-03
	(1.978e-03)	(1.986e-03)	(1.964e-03)	(2.060e-03)	(1.964e-03)
Regulatory Restrictions	-1.137e-06***	-1.214e-06***	-1.206e-06***	-1.103e-06***	-1.135e-06***
	(2.258e-07)	(2.301e-07)	(2.315e-07)	(2.255e-07)	(2.281e-07)
House Price Index	2.926e-04***	3.017e-04***	2.928e-04***	3.032e-04***	3.254e-04***
	(4.031e-05)	(3.930e-05)	(4.098e-05)	(4.094e-05)	(3.907e-05)
Nasdaq Avg	-3.345e-06	-1.597e-06	-1.831e-06	-1.463e-06	4.111e-07
	(2.143e-06)	(1.705e-06)	(1.802e-06)	(1.856e-06)	(1.788e-06)
Volatility Avg	2.854e-04*	3.045e-04**	1.983e-04	1.626e-04	2.798e-04*
	(1.550e-04)	(1.553e-04)	(1.610e-04)	(1.821e-04)	(1.550e-04)
Consumer Confidence Avg	5.685e-04	5.481e-04	4.629e-04	-5.365e-04	-9.566e-04
	(1.619e-03)	(1.595e-03)	(1.628e-03)	(1.495e-03)	(1.481e-03)
Inflation Index	4.222e-04*	2.363e-04	2.816e-04	2.998e-04	1.340e-04
	(2.227e-04)	(1.951e-04)	(2.010e-04)	(2.178e-04)	(1.995e-04)
Unemployment Rate	-1.106e-03	-5.923e-04	-5.669e-04	-9.390e-04	-3.942e-04
	(9.843e-04)	(9.671e-04)	(9.679e-04)	(9.935e-04)	(1.023e-03)
Oil Price	-1.021e-04	-3.362e-05	-3.828e-06	-6.331e-05	-5.562e-05
	(9.903e-05)	(9.928e-05)	(1.036e-04)	(9.809e-05)	(9.937e-05)
is ICT	6.936e-02***	6.937e-02***	6.935e-02***	6.935e-02***	6.935e-02***
	(1.653e-03)	(1.653e-03)	(1.653e-03)	(1.653e-03)	(1.653e-03)
is Software	-3.189e-02***	-3.186e-02***	-3.187e-02***	-3.193e-02***	-3.192e-02***
	(3.402e-03)	(3.402e-03)	(3.402e-03)	(3.402e-03)	(3.403e-03)
N	154955	154955	154955	154955	154955

Table 1.10: Robustness check using the maximum 4-digit IPC code firm originality

Stage 2 regression on 4-digit max firm originality in the first year it patents. Also included in the regressors are 2-digit SIC controls. Standard errors are clustered on 2-digit SIC sectors. Expected number of buyouts are measured in the first stage as described above. All time-varying RHS variables are lagged one year.

	Firm Entry Max Originality				
E[Num Deals$_{t+1}$]	-2.771e-05***				
	(5.421e-06)				
E[Num Deals$_{t+2}$]		-8.364e-06***			
		(1.908e-06)			
E[Num Deals$_{t+3}$]			-1.094e-05***		
			(2.377e-06)		
E[Num Deals$_{t+4}$]				-1.468e-05***	
				(3.330e-06)	
E[Num Deals$_{t+5}$]					-4.601e-06***
					(1.485e-06)
Fed Funds Rate	-2.525e-03***	-2.474e-03***	-2.699e-03***	-2.935e-03***	-2.729e-03***
	(3.849e-04)	(3.863e-04)	(3.850e-04)	(4.004e-04)	(3.899e-04)
Treasury 10 year rate	1.917e-03*	6.832e-04	1.394e-03	2.547e-03**	1.253e-03
	(9.969e-04)	(1.003e-03)	(9.890e-04)	(1.046e-03)	(9.899e-04)
Regulatory Restrictions	-1.561e-06***	-1.618e-06***	-1.638e-06***	-1.521e-06***	-1.468e-06***
	(1.125e-07)	(1.146e-07)	(1.151e-07)	(1.121e-07)	(1.131e-07)
House Price Index	4.432e-05**	6.096e-05***	4.583e-05**	4.742e-05**	6.995e-05***
	(2.006e-05)	(1.934e-05)	(2.006e-05)	(2.035e-05)	(1.928e-05)
Nasdaq Avg	-4.284e-06***	-1.809e-06**	-2.441e-06***	-2.731e-06***	-1.768e-06**
	(1.083e-06)	(8.400e-07)	(8.822e-07)	(9.179e-07)	(8.741e-07)
Volatility Avg	-1.663e-04**	-1.505e-04*	-2.645e-04***	-3.726e-04***	-1.615e-04**
	(7.674e-05)	(7.694e-05)	(7.928e-05)	(9.138e-05)	(7.659e-05)
Consumer Confidence Avg	2.494e-04	-2.086e-04	6.765e-05	-8.784e-04	-1.228e-03*
	(7.961e-04)	(7.838e-04)	(7.971e-04)	(7.294e-04)	(7.213e-04)
Inflation Index	9.123e-04***	6.742e-04***	7.429e-04***	8.363e-04***	6.832e-04***
	(1.138e-04)	(9.802e-05)	(1.006e-04)	(1.110e-04)	(1.008e-04)
Unemployment Rate	-3.185e-03***	-2.601e-03***	-2.558e-03***	-3.140e-03***	-3.120e-03***
	(4.711e-04)	(4.604e-04)	(4.609e-04)	(4.779e-04)	(4.914e-04)
Oil Price	-2.876e-04***	-2.180e-04***	-1.754e-04***	-2.399e-04***	-2.698e-04***
	(4.679e-05)	(4.704e-05)	(4.900e-05)	(4.623e-05)	(4.699e-05)
is ICT	3.103e-02***	3.104e-02***	3.103e-02***	3.103e-02***	3.101e-02***
	(6.888e-04)	(6.887e-04)	(6.887e-04)	(6.887e-04)	(6.886e-04)
is Software	-4.291e-03***	-4.280e-03***	-4.270e-03***	-4.332e-03***	-4.365e-03***
	(1.445e-03)	(1.445e-03)	(1.446e-03)	(1.446e-03)	(1.446e-03)
N	154955	154955	154955	154955	154955

Table 1.11: Robustness check using the maximum n-digit IPC code firm originality.

Stage 2 regression on n-digit max firm originality in the first year it patents. Also included in the regressors are 2-digit SIC controls. Standard errors are clustered on 2-digit SIC sectors. Expected number of buyouts are measured in the first stage as described above. All time-varying RHS variables are lagged one year.

Chapter 2

Firm R&D Inertia

This chapter will document patterns of technological position over the firm life cycle. Using patent data, I build a measure to compare the similarity between an innovative firm's technological contents over time with its technological position when it enters. I find that new entrants are likely to continue patenting in areas similar to their initial invention for multiple years – they exhibit inertia. I then describe how the degree of inertia is affected by initial conditions. I also explore the firm size distribution and technological sector concentration and discuss how the innovation strategies may differ based on degree of competition.

Dans ce chapitre, j'étudie l'évolution de la position technologique de l'entreprise au cours de son cycle de vie. A l'aide de données de brevets, je construis une mesure pour comparer le contenu technologique d'une entreprise innovante au fil du temps et son positionnement technologique vis-à-vis de ses concurrents lors de son entrée sur le marché. Je trouve que les nouveaux entrants sont susceptibles de continuer à innover pendent plusieurs années dans des domaines similaires à leur invention initiale. Ils font preuve d'inertie. Je décris ensuite comment le degré d'inertie est affecté par ce positionnement initiale. J'utilise enfin la distribution hétérogène de la taille des entreprises et de la concentration du secteur technologique afin d'analyser en quoi les stratégies d'innovation diffèrent selon l'intensité de la concurrence dans le secteur.

2.1 Introduction

This paper aims to provide a better understanding of how the technological content of firms evolves over the firm life cycle. Firms are usually characterized by their product and any effects associated with technological changes tend to be grouped into the marginal costs of the product or translated as an increase in quality or product variety. However, as a firm grows its product line, it also admits a parallel process where it builds up a technological position with associated human and physical capital. Intuitively, this build up of expertise in a technological area will influence the future decisions the firm makes. In fact, one can expect that any decisions firms make will have some persistent effects.

Here I will explore the extent to which these inertial tendencies exist in the development of a firm's technological position, which is what I call R&D inertia. I focus in particular on the early stages of a new entrant's life cycle to test for the impact of initial conditions and choices made by the entrant, namely its initial originality and whether it has past patenting experience. Using patent data I measure the proximity of the entrant's technological position to its entry position and estimate the persistence of this measure over firm age. I also address the effects of firm size on the firm's technological choices which leads into a discussion on the effects of competition. Both potential implications for dynamic competition and innovation strategies to escape competition are discussed. The overall objective of this study is to better understand how new entrants develop, how the initial conditions affect their development and how they interact with the other firms in their industry.

What I call the technological content of the firm is simply the part of the know-how and capital that is involved in the production and R&D projects in the firm. The position is inferred from the composition of people with different expertise and specialized investments that the firm has made. Technology can enter during the production process of the product or it can consist of a part of the product. Even though the technological content is intrinsically linked with a firm's products. The position of a firm in product space (which the literature often studies with industry classifications) cannot be directly translated into a position in technological space. This is because products are usually characterized by the elements that consumers value and this does not necessarily align with the sophistication of the technological input used to develop and produce the product. Bloom et al. (2013) further discuss the differences between these spaces.

Nonetheless there are cases where patents can be directly connected to products. For instance, one will sometimes find a product with a label that says ‘patent pending’. Virtual patent markings introduced in the US in 2011 also specify the patents used in products directly. See Argente et al. (2020) for an in depth study of the association between patents and products.

My main hypothesis is that firms should exhibit a tendency to grow around the initial position it takes on. This could be due to frictions or sunk costs. Frictions can come in numerous forms, for example, labor contracts might have costs associated with firing employees. In addition, the hiring process can be long and constitute a type of sunk cost. Another sunk cost can simply be an investment in equipment to build the product or the effort put into establishing a network of suppliers. Contracts with external entities are a source of friction as well.

The different fixed costs and frictions entrench the firm in its initial position. Without considering consumers’ demand imposed on the product, the different ways the firm has invested in developing its first product will naturally impose a direction for future R&D. This is what I want to document. The concept that firm technological development is path dependent is intuitively accepted however it has not been studied explicitly empirically for the broader economy.

I will attempt to capture this inert quality to firm technological life cycles through patent data. Patents are a type of innovation output that allow me to solely focus on the technological content of firms. A patent application is filed to protect a new technological finding. Although it is written up to define the technological content, different firms and people may write about the same thing in different ways. In order to classify filings more systematically, technology codes were introduced to label them. I exploit these technology codes to understand a firm’s technological position. To measure a firm’s degree of inertia I construct the proximity measure developed in Jaffe (1987) over the firm life cycle instead of between two firms. This measure compares the technology codes of a firm’s new patent filings each year with the patents that were filed in its first year. A high proximity implies that the firm has not moved much from its initial position which I interpret as a measure of inertia.

My first central finding is that we clearly see firms patenting closer to their initial position in the beginning of their life cycle and that this measure declines over the firm's life cycle. This is robust to different time periods and different measures of constructing the proximity measures.

It is then interesting to consider what initial conditions can affect a firm's inertia. Chapter 1 suggested that entrants have become less original in their innovations. Hence, I explore the consequences of the initial originality on the future technological development of the entrant. How does their initial originality affect the technological proximity of future patents? Furthermore, do firms that start with a low initial originality continue to file patents that are low in originality? One might assume that a firm will want to move away from a low originality innovation, however I find evidence that the low originality entrants will on average actually double down on their position and patent in closer proximity than a firm who enters with a high originality. This corresponds with a slow increase in the originality of the firm over time.

Another firm initial condition that has recently been explored in the literature is the founding team and their associated characteristics such as skill and experience (see Choi et al. (2019) and Gompers et al. (2010)). I address this by identifying entrants with team members that have previous experience patenting. With patent data, I can identify the inventors and applicants of the patents and deduct to some degree of accuracy who the initial researchers/engineers are. Moreover, I can find the patenting history of the inventors listed and determine whether they have prior experience patenting. Leveraging this data, I identify whether a new firm entrant has at least one inventor on the team who has experience.

Then, I address whether firm size has an effect on inertia and innovation strategies. The literature has largely conflated young firms with small firms and large firms with old firms. Although many young firms are small and many old firms are large, not all young firms are small and not all old firms are large. Schumpeter was one of the first economists to explore this topic and his ideas are still referenced in the economics literature. His early work developed the theory centered around young and small firms as the innovative disruptors through creative destruction. However, there is room for debate given that his later work suggests that larger firms are the main innovators in an economy due to their access to more resources. Here I attempt to disentangle the age and size effects to get a clearer picture. I find that large firms are more inert. And that they surprisingly remain at a higher degree of inertia than the smaller firms even among old firms. This suggests that to grow in size, their R&D efforts were more focused around their initial position than smaller firms. However, this does not translate directly into a conclusion on originality. I find that firm maximum originality is lower for large firms however it is higher when we look at average originality.

A better understanding of how firms evolve in terms of their technological content will also help us understand the industry dynamics. The innovation output from technological choices can affect firm growth in many ways. By studying the firm life cycle, we also get a better understanding of how young and old firms compete and contribute to the economy differently through their technological positioning. In particular, do older firms have reason to consider new entrants as future competition? Which new firms are the threats?

The literature on competition in economics has long theorized that a motivating incentive for incumbents to innovate is to insulate against the threat of new entrants. This question motivates my analysis to examine technological sector concentration at the time a firm enters. Like industries, I show that technological fields have their own life cycle dynamics and I suggest that they are also subject to competition. For instance, this would explain why some firms choose not to patent their inventions and keep them as trade secrets.

The evolution of a firm's technological position will also help me better understand competitive dynamics overall. We can reasonably assume that firms that are further apart in technology space are competing less with each other. This has been expounded on in depth in the literature on monopolistic competition in product space (see Hotelling, Salop, and subsequent papers. It is also recognized in the antitrust literature, Shapiro (2012)) however I suggest it is also true for technology space. A difference is that the reaction to competition in product space often means reducing the price on the product - in technology space, I expect it to take another form. It might be to file a patent faster in order to expropriate some space from the competitor, or it may mean changing the technological position to have less competition.

I find that young firms in highly concentrated industries are the least inert. Their innovation strategy when facing tough competition from the leader firms is to differentiate away from their initial position. On the other hand, the young firms in the neck-and-neck, medium concentrated, sectors are the most inert. They react to the competition they face by strengthening their initial position. Looking at innovation in terms of technological content allows us to disentangle these two types of innovation strategy which would not have been possible with the traditional count of patents.

Overall, the existence of firm inertia means each decision in R&D has lasting consequences. This implies that initial conditions are especially important for dictating the technical trajectory. By following firms over their life cycle we also get to see how their patenting behavior changes over time. This sheds light on the different roles of young and old firms in the economy and how they affect and react to competitive dynamics.

The rest of the chapter proceeds as follows. Section 2.2 provides a literature review on the studies concerned with firm path dependency as well as a discussion of the literature on competition dynamics. Section 2.3 describes the dataset and sample construction choices. Section 2.4 discusses my econometric approach while Section 2.5 presents the main results. Section 2.6 concludes.

2.2 Literature Review

The concept of firm inertia has not entered the mainstream economics discussion, however it has been examined in the organization and strategic management literature. Here I will briefly review that literature. Nonetheless, there are few studies that directly address inertia, instead the discussion has primarily turned to the concept of balancing exploration and exploitation within organizations. This in turn resembles some concepts in the innovation literature such as incremental versus radical innovation and product versus process innovation which I will also briefly summarize. Finally, the directed technical change literature also provides some insights into how R&D decisions are made.

Hannan and Freeman (1984), influenced by ecological theories of natural selection, pose the question of what favors the selection (a.k.a. survival) of firms. They argue that stability in products, processes and policies favor selection and that therefore “high levels of structural inertia in organizations can be explained by selection in ecological-evolutionary processes.” However they also discuss the consequences of excessive inertia. In particular, they note how the investments made in specific types of physical and human capital alongside the public appeal garnered for a specific product or service greatly limits the firm's options for transformation.

Casamatta and Guembel (2010) is a more recent paper that builds on the notion discussed in Hannan and Freeman (1984). They propose that manager incentives are a cause of inertia. With a theoretical model, Casamatta and Guembel (2010) show that when managers are concerned about their legacy, they can entrench a firm on one path and generate inertia. Tripsas and Gavetti (2000) also posit that managers affect the firm's inertia. They look specifically at the case of Polaroid and how manager capabilities affect firm search and learning processes. Another study that addresses firm inertia is Ruckes and Rønde (2015). They regard inertia as the result of a moral hazard problem due to the sunk cost of finding a first successful innovation. Developing a two period theoretical model, they find that inertia increases firm profits in stable environments while it decreases profits in volatile environments; a stable environment is defined as having a high probability that the optimal project is the same in both time periods.

The organization literature expounds on the effects of inertia on learning through exploration or exploitation. March (1991) is a pioneering paper on this paradigm of organizational learning. He posits that the difference between exploration and exploitation can primarily be characterized by the degree of uncertainty of the returns and that this uncertainty exists due to a greater distance in time and space between the locus of learning and the locus for the realization of returns'. In effect, I estimate this distance with the proximity measure I will describe in Section 2.3. My measure compares the distance of a firm's first year technological content - which is the location previous returns were being realized - with a future year's innovation output - the locus of learning. March concludes that a balance is needed in organizations as too much exploitation leads to inertia while too much exploration drives out efficiencies and prevents economies of scale.

There is a vast literature on the exploration and exploitation dichotomy, albeit a lot is quite qualitative (see Levinthal and March (1993), Sorensen and Stuart (2000), Smith and Tushman (2005), Gupta et al. (2006), among others). Lavie et al. (2010), Beckman et al. (2004), Lavie and Rosenkopf (2006) and Rothaermel and Deeds (2004) study these forms of organizational learning in the context of external alliances. Benner and Tushman (2003) investigate the role of managerial processes. Sadler (2017) uses a network structure to model the collective choice to explore or exploit. He finds different incentives depending on whether the network has a more centralized or decentralized structure.

While exploration and exploitation must be balanced for firm performance, Uotila et al. (2009) suggest that the optimal proportions of the two are highly subject to environmental conditions. Tushman and O'Reilly (1996) and O'Reilly and Tushman (2008) put forth the concept of strategic ambidexterity as a way to balance the two. They define strategic ambidexterity as: the ability of a firm to conduct exploration and exploitation at the same time. They highlight the role of management structures and consider ambidexterity to be a capability to be learned. He and Wong (2004) test the impact of ambidexterity on sales growth rates and find a positive association.

Another form of organizational learning that can potentially provide a balance between exploration and exploitation is experimentation. Koning et al. (2020) empirically analyze the effects of A/B testing in the digital industry. They find that testing increases page views and product features. However they also find partial evidence that start-ups fail faster with A/B testing while large firms scale faster. This seems to imply that testing is a tool to identify misallocation. Thomke (2001) describes the fall in costs of experimentation derived from new technologies such as fast prototyping, computer simulations, etc. He suggests that these new developments make experimentation a viable form of organizational learning now.

Finally, the broadest definition of exploration and exploitation can involve learning about many different types of information. In Zhou and Wu (2010), they focus only on the technological dimension. They find that greater technological capability affects exploitation positively whereas it has an inverted-U shaped relationship with exploration. Their reasoning centers around the trade off between absorptive capacity and structural inertia.[1] They regard absorptive capacity as an element that drives exploration by increasing the firm's receptiveness to new information. Although I focus on confirming firm inertia and the consequences of it, I do not explore the role of absorptive capacity in exiting it. Nevertheless, I will look at the role of previous experience

[1] Absorptive capacity is a term coined by Cohen and Levinthal (1990) which refers to the ability of a firm to integrate external information. One major constituent of this ability is captured in the existing technological stock.This is the motivation for many papers in innovation to include a knowledge stock measure in their models.

patenting in the firm's founding team, with the suggestion that previous experience may be a weak indicator of more absorptive capacity.

Many of the studies on exploration versus exploitation have similar counterparts in the product and process innovation literature or the incremental and radical innovation literature. Notably, Manso (2011) uses the exploration and exploitation paradigm to develop a model of the incentives for radical innovation. His results emphasize the importance of tolerance for early failure and is based on the presumption that more radical innovation is needed. A number of papers empirically test his results including Aghion et al. (2013) and Tian and Wang (2014).

Other papers that discuss incremental and radical innovation include Chandy and Tellis (2000) who discuss the effects of firm size starting from an assumption that large firms do not do much radical innovation. They explain the incentives for incremental versus radical innovation in terms of the product S-curve. Ettlie et al. (1984) considers the firm structure, identifying its role in determining whether a firm does more radical or incremental innovation. They suggest that in order to produce a radical innovation, the firm should be uniquely structured for it while increment innovations can result from more traditional structures. This also connects with the firm size dimension as they investigate the food processing industry and find that incremental innovation tends to be found in large firms while radical innovations are found in smaller specialists.

Zhou and Li (2012) explore how the existing knowledge stock interacts with different knowledge integration mechanisms, namely internal knowledge sharing vs external knowledge acquisition) and how that affects radical innovation. Using survey data they find that a firm with a broad knowledge stock is more likely to produce radical innovation from internal knowledge sharing while a firm with more depth in their knowledge stock is more likely to integrate external knowledge to produce radical innovation. This addresses a similar question as Zhou and Wu (2010) with the added dimension of breadth and depth of knowledge stock.

Finally, there is a vast literature that makes a distinction between product and process innovation. This dichotomy matches well with economic models given that a product innovation can be introduced as a higher value or quality product or as a new product line (see Klette and Kortum

(2004)), while a process innovation is likely to be captured in the marginal cost parameter.

Product and process innovation can be considered through the lens of inertia in product space. New products resulting from product innovation can then generate incentives to conduct process innovations. For instance, Utterbeck and Abernathy (1978), who also discuss firm exploration and exploitation, consider the technological life cycle and suggest that product innovations have a higher payoff at the starting of the technological sector life cycle while process innovation payoffs increase later in the life cycle. This, they suggest, is due to the increased importance in reducing costs and larger economies of scale.

Some more evidence for this connection can be found in Damanpour and Gopalakrishnan (2001) who find that product innovations are adopted faster than process innovations and that the adoption of product innovations is associated with more process innovation. Similarly Cohen and Klepper (1996) suggest costs are a chief reason for process innovation. Instead of firm age however, they consider firm size and they suggest that process innovations contribute less to firm growth. However their model finds that large firms have an advantage in process R&D because they have a larger output over which they distribute the R&D costs.

A new product essentially imposes a known demand on process innovation where as the demand for product innovations is less certain. Therefore when a firm has a large demand for its products, the decision to focus on process innovations to take advantage of economies of scale can be optimal. I will provide evidence for a similar life cycle effect however I instead consider complementarities instead of processes. Complementarities are also a way to take advantage of economies of scale from prior inventions.

Finally, the directed technological change literature considers the complementarities between innovation technologies and other production inputs such as labor and capital.[2] This literature mostly treats R&D as process innovations and translates it into a productivity measure on inputs. The theory then says that innovation decisions are made with respect to the balance of the inputs and their relative costs.

[2]See Acemoglu (2002), Dosi (1982) and Aghion et al. (2016) among others

2.3 Data Description

I identify firms' technological content by the patents they file. Although many firms do not patent, I would suggest that for the purposes of studying mainly the technological dimension, patenting firms are the ones of primary interest. To be precise, I use the 2017 spring vintage of the Patstat database provided by the European Patent Office (EPO) for the entirety of my analysis. This database has a very detailed and broad coverage of patent publications information. To avoid open economy influences and avoid differences between different countries intellectual property policies, I focus my analysis on the United States.

When a technological invention is made by a firm it can choose to either patent it, publish it with a scientific journal or keep the invention internal as a trade secret. Scientific articles, however, do not protect the invention in any way. They are more a tool to gain in reputation among the scientific community. Trade secrets on the other hand, are hard to keep. Many inventions lose their secrecy once they are introduced into a product since many products may simply be taken apart to learn the technologies (a.k.a. reverse engineering). Hence patents are a viable option and arguably the best. There may also be firms that do R&D but do not produce a technological innovation, for instance, firms that study the impact of color on appetite, may be considered to do research however their finding does not necessarily contribute to a technological field. I expect these firms to be similarly affected by inertia however they may be arguably less entrenched by physical capital but perhaps more by human capital.

The Patstat database has very good coverage of granted patents in the US. Since a patent filing is made at a patent office in order to be evaluated for grant this data is nearly population data however the data becomes less reliable if we go too far back when the filings were not digitized.[3] On the other hand, patent data can also be subject to a truncation issue. Patent applications take time to be added into the database. Patent grants are a particular issue because patents often take many years to be evaluated before a grant decision is made. Furthermore, this grant lag is quite variable. To avoid these issues I choose my dataset with a time buffer, namely I use only patents filed between 1980 and 2014.

[3] There are digitization efforts that have been done to improve data quality in earlier years. See Akcigit et al. (2018) for example

In order to study the firm life cycle and effects of inertia, I need to restrict the sample to firms that patent at least twice. Furthermore a number of patents are in fact not associated with a technology code. Since my objective is to measure the technological content of firms, I keep only firms with patents that have associated technology codes. The US patent office uses a classification different from the ones used by the international community and namely different from the one used by the EPO. The EPO uses the International Patent Classification (IPC) established by the Strasbourg Agreement in 1971 and overseen by the World Intellectual Property Organization.[4] My final dataset covers 88511 firms.

Although patent applications do not change, their technology classification codes may change. The technology codes were introduced by the patent offices to sort documents and facilitate search. As new technological sectors emerge, the patents get rearranged into those sectors. While the manual process before the digitization of the patent offices classified patents under a single technological code, digitization now allows patents to be classified under different technology codes. As I am primarily interested in the technological content of firms; which I infer from the patent classification codes, my measures are subject to change as classification codes change.

2.3.1 Construction of main measures

The primary objective of this study is to compare the composition of firm technology over its life cycle. In particular, to measure the inertia of initial decisions, I will compare a firm's technological content to its technological position in the first year it patented. To do this, I refer to Jaffe (1987) for a proximity measure that can measure the technological distance between two patent portfolios. I will construct this measure with 4 digit IPC codes as is common in the literature when building measures with technology codes. The Jaffe measure is essentially an uncentered correlation. As such, if the definition of the technology codes is too narrow, the measure may return many zeros. In 2013 Bloom, Schankerman and Van Reenen developed a variation on this proximity measure where they introduced a weighting matrix between the technology codes in order to capture spillovers between technology codes. They build the weighting matrix by calculating the correlation between patent classes that are filed together within a firm.

[4] There might be some patents lost in the concordance between the USPC and the IPC. In 2013 the USPTO jointly developed a classification system with the EPO called the Cooperative Patent Classification (CPC) system. The CPC code is likely a better match however it is quite new and it may be subject to a break due to the changes in technology class definitions. Therefore I focus my analysis on the patents that have IPC codes.

I modify this measure in a way that I suggests better captures complementarity between patent classes. The Bloom et al. weights are constructed by grouping the technology codes at the firm level. This could be mixing the technology codes that are complementary to each other with the technology codes that are filed in different products within a firm. Some firms, such as conglomerates, have many product lines with little connection to each other. It could be argued that most product lines within a firm are likely to be complementary products and therefore technology codes between the two are likely complementary. However this mixes complementarity in the product space with complementarity in the technology space. Their measure also confuses the complementarity versus substitution effects by keeping the values along the diagonal. Here I construct a slightly different weighting matrix where the correlation is built at the patent level. The majority of patents are classified under multiple technology codes and it is the combination of these technology codes that capture the content of the patent. This implies that these technology codes are complementary in this patent. Therefore, to get a more precise measure of complementarity, I build the weights based on the set of technology codes at the patent level. In addition, to ensure that I am only measuring complementarity and not substitution effects, I remove the values along the diagonal. Ideally I would construct this weighting matrix at the full digit level of the technology codes however when I am dealing with patent level matrices, this is simply not feasible. Therefore I build the measure with IPC codes at the 4 digit level. Unfortunately when I remove measures along the diagonal, I am also removing different full-digit technology codes that might otherwise have been complementary. It is difficult to say whether two full technology codes are more complementary or more substitutable if they are in the same IPC 4 digit group. Essentially my measure here assumes that those measures are more substitutable than complementary.

Another patent measure that captures the technological content of the invention is the Trajtenberg et al. (1997) originality and generality measure. The generality measure is however built with forward citations which are subject to serious issues of truncation (see Hall et al. (2001) among others that document this.). Therefore I choose to look only at the originality measure which is built using backward citations. The originality measure is built like a Herfindahl index on the technology codes in a patent's citations. This measure is higher when the set of technology codes in the cited patents are more diverse. The assumption in this originality measure is that a patent is more original when it covers a wider set of technology codes, when it has a larger breadth. This might not be an exact match with the average person's impression of what constitutes originality however there is some evidence that an invention is more original when it covers a more diverse set of technological fields (see Angrist et al. (2020) and Beckman (2005)). Furthermore originality is an abstract concept that will at best be captured by a proxy and this measure is widely accepted in the literature.

The originality measure construction is not as computationally intensive as the proximity measure therefore I can use the full technology codes to build an alternative measure. The originality measure is a measure of originality for each patent. Since I am interested in the firm's decisions, I want to aggregate this to the firm level. I do this in two ways - by taking the mean and the max. The mean is the intuitive choice since it is the average originality within the firm. However in the case of technological content, using the maximum can also make sense as it can be argued that the technological borders of a firm are defined by the most original inventions and not the average invention (see Henkel and Rønde (2018)). The Appendix has more details on the construction of these measures as well as more details on the data cleaning and construction process.

2.3.2 Summary Statistics

Table 1 summarizes the main variables and provides some descriptive statistics. It shows that the average originality is higher for measures built with the full technology code as opposed to the 4 digit code. This is logical since originality is higher when the set of technology codes is higher. This measure, like the Jaffe proximity measure, does not take into account proximity between technology codes. So two technology codes like "G02B 1/02" (optical elements made of crystals) and "G02B 1/06" (optical elements made of fluids in transparent cells) are considered completely different despite both being optical elements. As such, the average firm originality built from full technology codes are often on average higher than the maximum firm originality built from 4 digit technology codes. This displays a disadvantage of using the originality measure - the nominal levels of originality cannot be easily compared to other originality measures. Instead, it is mainly useful to compare the same originality measure with different subsets of the sample or over time. The Pearson correlation between the average 4 digit IPC originality measure and the average full digit IPC originality measure is 0.6669. In comparison the correlation between the average 4 digit IPC originality measure and the firm maximum 4 digit IPC originality measure is

0.8772. The correlation between the average originality built with 4 digit IPC technology codes and the average originality built with the 4 digit CPC technology codes is 0.8279.

Variable Name	Count	Mean	Std	Min	Q25	Q50	Q75	Max
Mean Originality - 4 digit IPC	504266	0.6249	0.2155	0	0.5075	0.6724	0.7873	0.9996
Mean Originality - full IPC	504266	0.8604	0.1358	0	0.8283	0.9012	0.9439	0.9998
Max Originality - 4 digit IPC	504266	0.6799	0.2214	0	0.5787	0.7449	0.8437	0.9998
Mean Originality - 4 digit CPC	588300	0.6333	0.2098	0	0.5242	0.6789	0.7894	0.9997
Jaffe Proximity	378236	0.5286	0.4012	0	0	0.5774	1	1
Adjusted Proximity	378236	0.6074	0.4467	0	0.0517	0.7056	1	2.052
Complementary Proximity	378211	0.0513	0.0967	0	1.716e-3	1.526e-2	5.191e-2	0.7148
Knowledge Stock	403033	29.91	276.7	1	1.276	3.550	10.02	30669

Table 2.1: Basic summary statistics

Table 1 also summarizes the different proximity measures. We see that the Jaffe proximity has many zeros and ones. This is to be expected since it does not take into account the different spillovers between technology codes. The spillover adjusted proximity measure is always equal to or larger than the Jaffe proximity because it essentially keeps the Jaffe measures - which would be the ones along the diagonal of the weighting matrix - and adds the off-diagonal spillovers. This also means that the adjusted measure is no longer bounded between 0 and 1. Finally the complementary proximity measure is much smaller in magnitude than the other proximity measures and that is to be expected because it keeps only the off-diagonal elements in the weighting matrix. Since the vast majority of patents are more likely to be filed with full technology codes under the same 4 digit code than under different 4 digit codes, the weights along the diagonal are much heavier than off the diagonal. Since I remove the diagonal elements to avoid confounding with substitution effects, I am left with much smaller weights. I avoid normalizing the weighting matrix to give me a proximity between 0 and 1 because in this way, I can compare between the different proximity measures. The difference between the Jaffe proximity and the adjusted spillovers proximity captures essentially only the spillovers. This measure is not quite the same as the complementary proximity because I build the weighting matrix for complementarity from the patent level which results in smaller weights in the off diagonal matrix when compared to the firm level spillovers weights. The correlation between the Jaffe proximity measure and the adjusted proximity measure is 0.9540 while the correlation between the Jaffe proximity measure and the complementary proximity measure is only 0.17436. As expected, the correlation between the adjusted proximity and the complementary proximity is in between those two measures at 0.4584.

Moreover, the proximity measures calculate the correlation of a firm's first year technological position with the technology codes of the firm's *new* patent filings over time. Namely, the new patent filings make up the change in the firm's position. If I were to calculate the firm's *full* position, I would add the count of technology codes in previous patent filings. However this would clearly give a much higher proximity since the patents filed in the first year would still be counted in the full position.

Finally, Table 1 shows that the standard deviation of the proximity measures is quite high relative to its mean. This might imply that proximity is quite volatile. However the measures in this table are calculated over all the firm-year observations. We will see in the results that they actually follow quite predictable patterns. I also summarize the firm size proxy knowledge stock in Table 1. This gives us a rough idea of the distribution of firm sizes in my sample. While the mean knowledge stock is 29.91, the median is only 3.55 and the maximum is 30669 (IBM holds the title of maximum knowledge stock in my sample). This implies that the distribution is highly skewed. As such I define size quantiles to categorize the firms instead of using nominal values. This avoids having outliers influence the results.

Table 2 compares the size distribution of firms by their primary IPC 1 code. We see the large degree of heterogeneity between industries and again the skewness of the size distribution. At the 95th quantile, it would appear that the C class has the largest firms and that class G is one of the classes with smaller size firms. However, when we look at the largest firms by primary IPC 1 digit codes, we see that G actually has some of the largest firms (including IBM and Microsoft) and that the C class has medium sized firms, becoming sixth ranked of the 8 different 1 digit classes. Furthermore if we look at the originality and proximity measure averages by 1 digit IPC codes, we see that the C class has the highest average originality. This corresponds to a high complementary proximity however it is the lowest in the conventional Jaffe proximity measure. This makes sense since intuitively, originality should be the inverse of proximity. Note however that this relationship is more subtle because proximity is in relation to a firm's first year patenting choices and not to the theoretical technological frontier.

1 digit IPC: Description		Q25	Q50	Q95	Q99.9	Originality	Proximity	Adjusted Proximity	Complementary Proximity
A	Human Necessities	1.197	3.445	53.02	5792	0.604	0.6056	0.7419	0.0953
B	Performing Operations; Transporting	1.444	3.6	53.27	9270	0.5909	0.4853	0.5134	0.0181
C	Chemistry; Metallurgy	1.966	5.152	226.31	4358	0.6743	0.4669	0.6152	0.1016
D	Textiles; Paper	1.197	3.496	79.63	659.2	0.5831	0.5213	0.5523	0.0219
E	Fixed Constructions	1	2.85	40.23	3911	0.5451	0.5718	0.5958	0.0155
F	Mechanical Engineering; Lighting, etc	1.522	3.795	64.96	13483	0.6004	0.4699	0.508	0.0249
G	Physics	1	3	55.43	30658	0.5969	0.5837	0.6377	0.0288
H	Electricity	1.723	4.464	129.78	11767	0.6018	0.5232	0.5847	0.0357

Table 2.2: Summary statistics by 1 digit IPC technology codes.

The quantiles are defined using the discounted knowledge stock as a size proxy. The originality measure is built using 4 digit IPC codes, the proximity measure is the Jaffe (1987) proximity measure, the adjusted proximity measure is the Bloom et al. (2013) measure and the complementary measure is built with the complementarity weighting matrix as described in Section 2.3.

2.4 Empirical Strategy

As discussed in Section 2.1, there are many reasons for a firm to exhibit some degree of inertia in its innovation decisions. It is interesting to quantify inertia and examine its driving factors in new firm entrants to better understand their innovation incentives and how they can affect the sector in later years.

To study these patterns and quantify the degree of persistence in initial conditions, my general approach is to estimate a function of the form:

$$P_{i,t} = f(\tau, X_i; \beta) + \gamma_t + \epsilon_{i,t} \tag{2.1}$$

where $P_{i,t}$ represents the proximity measure or the originality measure described in Section 2.3 for firm i in year t. τ is the index for firm age defined as $\tau = t - t_i^0$ where t_i^0 is the firm's entry year. And X_i represents the firm's initial conditions which includes the firm's primary technology sector, D_i^s - I assume that firms first choose their technological sector before beginning their

R&D and entering the market. β is a vector of parameters and γ_t is a set of year fixed effects. The year controls are added to capture any overall time trends.

My primary objective is to estimate $f(\tau, X_i; \beta)$. This function describes the average proximity or originality of a firm who entered with initial conditions X_i at age τ. I will look at the effect of different initial conditions based on different hypothesis later.

For a baseline, I consider the case of the pure age and technology sector effect and move the rest of the initial conditions variables to the controls. To allow for maximum flexibility for the effect of age on my dependent variable, I separate the age variable into dummy variables and define $f(\tau, X_i; \beta)$ as $f(\tau, D_i^s; \beta) = (\beta_0 + \beta_s D_i^s) D_i^\tau$. Note that both β_0 and β_s are parameter vectors on firm age, which will be from 0 to 20 in my analysis here. I add the technology sector dummies to control for sector heterogeneity however I do not want these terms to affect my vector of average age effects, β_0. Therefore I follow Guerts and Biesebroeck (2016) and impose a restriction on the β_s parameters. Namely I add a constraint where the summation of the β_s parameters must add up to zero. $\sum_\tau \sum_{s \in \mathcal{G}} \beta_{s,\tau} = 0$. Where $\mathcal{G}$ is the set of technology sectors as defined by 1 digit IPC codes. I also add in another set of sector dummies without the age interaction to control for the pure technological sector effects. These decisions make my specific baseline regression model:

$$P_{i,t} = \sum_\tau (\beta_0 + \sum_{s \in \mathcal{G}} \beta_s D_i^s) D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{2.2}$$

Age and year are clearly exogenous variables so I do not have any endogeneity issues. The technology sector and other firm characteristics are fixed variables here so I also do not have any endogeneity issues. The sole concern may be measurement error in the variables. If there is an imperfect match between the firm and the patents I might be missing some patents that the firm has filed or I could have wrongly assigned some patents to a firm. Since my observations are defined by the algorithm-cleaned applicant filing name[5], it is quite likely that there are a few errors. If my firm name cleaning was not stringent enough, I might have grouped firms that have a similar name but are not in fact the same, together. On the other hand, if the algorithm was too stringent, I will have missed some applicants that should actually have been grouped together. I have done numerous checks in developing the name cleaning algorithm to minimize

[5]See the appendix for more on this.

these errors however they may still exist.

Assuming the firms are correctly assigned, it is still possible for some innovation measures to experience measurement error. One of the reasons for introducing the weighting matrix in the construction of the proximity measure is to decrease this issue. The conventional Jaffe proximity measure is subject to too many values on the boundaries of zero and one and this effect is exacerbated when a patent has few technology codes; see Section 2.3 for more discussion on this.

The originality measure is also subject to measurement error as was already discussed in section 2.3 where we compared the values from the 4 digit originality measure with the originality measure constructed from full technology codes. In addition, Hall in Trajtenberg et al. (1997) suggests that originality is naturally biased. She suggests that since originality is based on backward citations and that the set of patents that are available to be cited is increasing over time, originality will increase with time mechanically - since more technology codes that are cited will mean a higher originality and having a larger set of potential patents to cite also increases the likelihood of citing more different technology codes. At the time her article was written, we did see an increasing trend in originality that suggested this was the case, however, with the 2017 Patstat vintage we see that since 2008, average originality has in fact been decreasing.

I believe Hall's argument is based on the assumption that patent citations are chosen to list the knowledge and technology in the citation that was used in developing the invention that is to be patented - as we do in scientific articles. However citations serve a slightly different purpose in patents. First although the applicant can choose some citations, the final say in what citations are listed is made by the patent examiner. This already implies that patent citations added by the patent examiner were not known or deemed useful in the development of this invention by the applicants or inventors of the patent. Instead, the citations made by a patent are used to delimit the boundaries of the technological content of the patent. In theory the citations are meant to capture the existing knowledge and inventions that are closest to the new patent application. It is not evident that these boundaries change in any systematic way hence I suggest that this process is not subject to the mechanical bias Hall was suggesting. It might be subject to changes in patenting policy or practices however. For instance, it has been observed that the EPO and the USPTO follow different practices in assigning citations. Here I focus on US firms so the patents filed outside of the US will consist of a small proportion of my dataset which I assume will not influence my results. The year dummies included in the model will capture any changes that occur in the patent citations practice over time.

It is not evident how measurement error on a firm's entry year, which I use to build the firm's age variable, may affect my model. Although a firm may have been founded before the first year they start patenting, this discrepancy does not necessarily affect the future way the firm develops its technological position. One possibility may be that the firm has an advance on the future R&D projects it does in terms of years measured in my data. This might show up in my data as firms that patent more initially. In terms of the firm life cycle, it might lead to a faster fall in proximity as the life cycle might show up more compressed/shortened. Thus I would expect that if this is an issue, it would bias the coefficients downwards.

Finally the technological sector definition is also subject to measurement error. Rather it is an imperfect measure of what I want to capture. In constructing a primary technological sector I have to choose one sector. In Section 2.3 I already detailed how I dropped the firm observations with uncertain primary technology codes. However, other than a data measurement issue, this definition is also subject to a logical issue since a firm, particularly larger firms, are composed of multiple product lines. In some cases their products and corresponding technologies can be very different (for example in firm conglomerates). This is an issue I mentioned when describing the construction of the weighting matrix at the firm level following Bloom et al. (2013). However it also becomes a problem here in defining the primary technological sector a firm is in. It is not obvious how a firm should be assigned a technological class if they are involved in the R&D of very different technologies. For instance, General Electric in my dataset, is classified under the 1 digit IPC code F which is the Mechanical Engineering sector. However at the more granular aggregation of 3 digit IPC codes, General Electric classifies as "C08" (Organic Macromolecular compounds; their preparation or chemical working-up; compositions based thereon) and then returns to the "F" class with "F01D" (Non-positive-displacement machines or engines) at the 4 digit IPC code level. Similarly Intel is classified as "H" (Electricity) at the 1 digit level however it classifies as "G06" (Computing; calculating or counting) and "G06F" (Electric digital data processing) at the more disaggregate 3 digit and 4 digit levels. This implies that General Electric has a very specialized division on non-positive-displacement machines or engines where they are perhaps one of the leaders and pushing the frontier, however they also have a division that works on organic macromolecular compounds which patents a lot and more broadly than the non-positive-displacement machines or engines group since the primary code 4 digit code does not go under the “C08” section.

How does this affect our estimates? In theory if an firm is classified in the wrong category and it is at the extreme end of the distribution of one of the variables, this could bias our estimates. For example if the dependent variable were firm size, then General Electric and Intel would clearly affect the estimates as they would have a differential effect depending on whether they are classified in one sector or another. A large firm that gets classified in one sector will increase the average of the whole sector to offset this, the coefficients on the other smaller firms in the sector will decrease. However my dependent variable is not size, it is originality and proximity. Neither measure is likely to have many outliers and further more, it is not obvious that any one particular kind of firm is more likely to be one of the outliers if they exist. For instance, although General Electric is one of the five largest firms in terms of knowledge stock in my sample, it is not necessarily an aberrant data point in the distribution of proximity or originality. Essentially the size of the firm does not have any weight here, so my model is not sensitive to a few firms that are difficult to classify. Furthermore, none of my explanatory variables are in nominal levels so they are not sensitive to outliers either.

Finally, I also include some variables to control for firm characteristics. These are essentially the initial conditions and choices that the firm makes before the start of the observations for the dependent variable. I assume a firm follows the following timing: A firm/applicant begins with a choice of technological field. It then builds a team of people (the inventors listed on the patent) to work on the research. These people come into the firm with their own backgrounds and some may have had experience in entrepreneurship or experience in R&D and patenting. At this time the firm also looks for partners to join in the R&D process as well as spending resources to invest in physical capital such as machines and equipment. The outcome of this process is summarized in a patent application filed at the patent office. It is only from then on that I begin to have observations.

When proximity is the dependent variable, the values start in the year after, firm age 1, since the values at age 0 are irrelevant (it would be measuring proximity of the technological position to itself). With originality, the dataset starts at age 0 (the first year the firm enters). Since the proximity measures start at age 1, I include the originality of the firm's first year as a firm control. To give maximum flexibility to the model I categorize the originality into three groups of low, medium and high where a firm is categorized as a low originality entrant if it's originality is below the 50th quantile; it is labeled as a medium originality entrant if it is between the 50th and 75th quantile, and it is labeled a high originality entrant if its originality is above the 75th quantile. The quantiles are defined by year and therefore the quantile thresholds are changing depending on the firm's entry year.

In addition, I can glean some information from the patent data to capture some of the information on the people connected with the firm prior to the patent application. Namely, since Patstat is nearly the entire patent population, I can see whether the inventors of the patent have been involved in a patent previously. As discussed in the appendix, the applicant and inventor table in the database is subject to typos, therefore this tracking of the inventors is imperfect, however I would suggest that the majority of the inventors are properly tracked as they are less exposed to errors from name changes or in identifying subsidiaries then the firm applicants are. By tracking the inventors, I can infer who has had prior experience patenting and with this I can create an indicator variable for whether a firm has at least one person with experience patenting before. The prior experience patenting that an inventor has might be a signal that the inventor is more skilled at innovating and therefore might develop more original ideas and inventions. On the other hand, an inventor with experience patenting will have a build up of knowledge stock on the previous work he/she has done. This might influence him/her to patent in areas closer to that knowledge stock which might limit the originality of the research. I will explore the impact of experience explicitly in a section later.

Finally, with the patent application data I can see whether a firm patents its first patent with multiple applicants. Having multiple applicants on an application can mean different things. This could be a measure of the external relationships the firm has and can potentially be a signal of the resources the firm has access to. It may also simply be that the other applicant(s) are the other people involved in the R&D. In the Patstat dataset the people involved in the R&D are listed as inventors while the firm who hires the inventors is the applicant. However some employment contracts may include an allowance for the inventors to share in the intellectual property rights and they would therefore be listed as applicants (or assignee's which is the term the USPTO uses). Furthermore, this measure may also be confounded with the error introduced by firm subsidiaries.

In theory, I want my firm level observation to be the entity that is making the R&D project decisions. For large firms with different subsidiaries, this could mean different things for different firms. Which entity to list as the R&D decision maker will depend on the firm structure. Some firms operate with a very centralized structure while others take a much more decentralized approach. Specifically subsidiaries are still at a level of independence higher than a firm branch and it is reasonable to expect that it is making many of its own decisions. However in very centralized structures, this is less the case, since officially, it is the owners of the firm's/subsidiary's equity who have the most decision making power. For my purposes of identifying entrants, I would ideally group the subsidiaries with their ultimate parent firms to avoid having faux entrants into the dataset. I already do this to the extent that is possible with only names, however some subsidiaries might be missed. When a subsidiary files a patent, it is likely to include its parent firm as a co-applicant. Therefore by including a dummy variable for whether the firm's first patent included multiple applicants will control for some of these effects. Although I cannot distinguish them separately, I suggest that it is sufficient for the purposes of a control variable.

While the existence of inertia in a firm can largely be established with Equation 3.2, I am also interested in how the degree of inertia differs depending on starting conditions. To investigate this I will look at how the initial originality of the firm affects its future behavior and I will look at how previous experience within the founding team affects the development of the firm. In these cases the regression model is:

$$P_{i,t} = X_i(\beta_0 + \beta_s D_i^s)D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{2.3}$$

This model includes the starting condition of interest as X_i and it is interacted with the age dummies as well as the sector terms. My estimate of interest will be the β_0 coefficients which describe how the firm life cycle dynamics are different depending on the initial originality of the firm or the prior experience of the firm.

Then, in the next section, I address the long standing debate in the firm innovation literature on whether small firms or large firms are more innovative. To do this, I add firm size into the regression. This will enter in the interaction term with age to disentangle the age and size effects that are often confounded in the literature. Since firm size is highly skewed, I transform the measure into four dummy variables based on the firm's ranking in the size distribution by technology sector. The groups are delimited by yearly quantile thresholds of 25, 50, 90, and 99. To be exact, this means that I calculate the 25th, 50th, 90th and 99th quantile of the firm size distribution by 4 digit IPC technology classes each year. I then assign firms to a group each year; therefore a firm's group can be reassigned over time. This measure is no longer a pre-sample variable as I expect the main variation in size to occur when the firms are older.[6] Therefore when I look at the variation in firm life cycles by firm size, it is no longer the average of the same set of firms. Firms can switch between size categories as they grow over their life cycle. The regression with firm size can be explicitly written out as:

$$P_{i,t} = D_{i,t}^{size}(\beta_0 + \beta_s D_i^s) D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{2.4}$$

Where $D_{i,t}^{size}$ is as described above, a set of dummy variables for firm size groups that can change over time. Notably, the firm size is categorized based on firm patenting. Thus this model captures a slightly different measure to firm size since it uses a patents as a proxy.[7]

The econometric consideration in this regression is the implication of using a dynamic size variable as opposed to a fixed pre-sample variable. To avoid any confounding effects of timing when aggregating by year, I use the knowledge stock proxy, categorized into four groups, lagged by one year for the $D_{i,t}^{size}$ measure. This avoids any issue of a firm's proximity/technological choices interacting with the firms knowledge stock over the period of the year. If, however, proximity influences the knowledge stock of the firm in the next period there could be an issue of serial correlation. Intuitively, the proximity of a firm's technological position is a measure agnostic to how large it is, however since the two variables are constructed from the same dataset, there is a small possibility that a connection exists that will introduce serial correlation.

[6] I will also include some results based on static initial firm size groups as well.

[7] See the appendix for a discussion and interpretation of this measure.

To address this, I follow Guerts and Biesebroeck (2016) who suggest a couple different methods. In particular, I apply their method of using the firm's beginning of period and end of period size classifications and split the firm into two weighted by one half each.[8] This allows me to use fixed size measures instead of the dynamic ones which reduces any potential issues of serial correlation. Including a set of observations that use the end of period size categories is also useful for capturing more of the variation in size when firms are older, as opposed to using only the initial size of the firm when it enters since I expect that size variation to be quite small at entry. Nonetheless, I keep this method mainly as a robustness check as I do not expect the serial correlation to be substantial and it is preferable to use the time-varying lagged size variables.

Together with firm size, I also explore the effects of concentration on firm's innovation strategies. Here I pose the question of whether entrants have a different role in overall sector dynamics depending on the competitive situation of the sector. There is a growing literature on how entrants affect other firms in the industry and their role in the economy as a whole. Here I will construct both a static and dynamic grouping of firms by the concentration of their technology sectors. I will then document some trends that shed light on how different degrees of competition affect entrants innovation strategies as well as how entrants can impact future competition.

The general consensus in the firm dynamics literature is that new entrants are a potential threat to incumbents and this potential future threat is one of the incentives for existing firms to continue innovating. So my question is, what affects the potency of this entrant threat? It is unlikely that the level of an entry threat is unchanged for all time and all environments. This is a motivation for this study overall. It is useful to better understand how firm's develop over their life cycle in terms of their technological position in order to start measuring this degree of "threat" for implications on dynamic competition. In particular, I suggest firms that grow quickly and enter the top quantile of their technological sector are the firms who pose the highest threat to incumbents. As such, I will look at how the largest firms are positioned with respect to their initial position.

I also explore how the concentration of a firm's technological sector affects the firms degree of inertia and originality. This is done by first building a measure of concentration for the 4-digit

[8] This method dates back to Prais (1958)

IPC technological sectors by year.[9] Then I choose to categorize firms into groups by the concentration of their primary 4-digit IPC sector to keep the regression tractable. I assign one group for firms under the 25th concentration quantile, one group for firms between the 25th and 50th quantile, another between the 50th and 75th quantile, another between the 75th and 90th quantile, and lastly a group of entrants who enter in the most concentrated sectors - the 90th to 100th quantile. To build these estimates, I stick with the model described in equation 2.3 and use this grouping by concentration as the $X_{i,t}$ measures.

By grouping firms by the concentration of their technological sector, we can investigate how the degree of competition affects firm innovation strategies. In particular by looking at innovation choices with respect to the technological positioning we can identify whether differentiation is a strategic reaction to concentration.

2.5 Results

I first provide different measures to summarize the average age effect. Then section 2.5.2 estimates the effect of the entrant's initial originality and section 2.5.3 explores the impact of having prior experience. Then, I introduce size in section 2.5.4 and examine whether the degree of inertia is different depending on the size of the firm's knowledge stock. Finally, I discuss the implications on the overall technological sector in section 2.5.5 and in particular I examine whether the concentration of the sector affects behavior in young firms.

2.5.1 Basic Results

Figure 2.1 displays the basic results of firm inertia. It plots the β_0 coefficients on the age dummy variables from the model described in equation 2 using the Jaffe proximity measure. This captures the average effect of firm age on proximity to its first year technological position, controlling for the technological sector variation, the firm fixed characteristics and the year effects. We see clearly that the proximity is higher at the beginning of the firm life cycle and declines quite steadily. My focus on the entry year simplifies my estimate to measuring only the persistence of the initial technological position. The first age vector was dropped to avoid collinearity therefore

[9] See the appendix for more details on how this was constructed.

the plot starts from age 2. This also means that we have to interpret the coefficients as relative to the first year average.

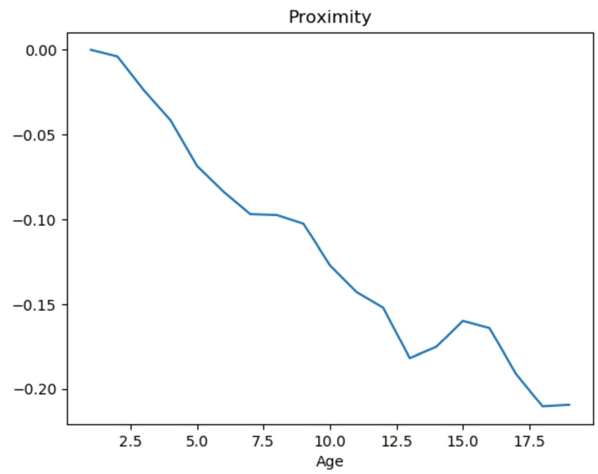


Figure 2.1: Average age effect on Jaffe proximity to firm initial position
This figure plots the coefficients from the model described in equation 3.2. The line represents the average Jaffe proximity by firm age controlling for sector and year fixed effects and firm characteristics. The proximity measure compares the entrant's technological position to its first year technological position. For firm controls I include the firm's initial conditions, namely, its initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality group is.

We can compare figure 2.1 to 2.2a which uses the adjusted proximity measure proposed by Bloom, Schankerman and Van Reenen.[10] The two have very similar trends. However if we focus only on the proximity in complementary fields, the decline is much less clear. Figure 2.2b plots the complementary proximity measure described in Section 2.3. This measure removed all direct overlap between technology fields so we expect the magnitude to be much lower. The pattern is quite noisy and looks largely flat for the period I am studying. It seems to fall later in the life cycle, however it is not a clear trend.

[10]For the purpose of conciseness, figure 2.2a and all remaining figures will be in the appendix.

While these regressions have confirmed that firms do exhibit inertia, it is not clear how the entrants' proximity evolves relative to other firms. In particular, I am interested in evaluating how long it takes for a given firm to arrive at a technological position that is equally distanced to its initial position as the incumbent firms in the sector. To do so, I construct another set of proximity measures that compare the position of the incumbent firms to the initial technological position of each entrant in the same sector over time.[11] This measure of incumbent proximity is essentially a baseline of the technological evolution in the sector. Note that it is not quite a measure of the technological evolution that would occur without entrants as the threat of entrants can be a competitive motivation for incumbents to innovate which could lead to endogenous effects.

To measure when entrants reach a technological position that is similarly distanced to its initial position as the incumbents in the sector, I calculate the difference between the entrants age-varying proximity and the incumbents proximity. This is used as a new dependent variable in the model described in equation 2. Figure 2.3a plots the result of this regression using the Jaffe proximity measure. As expected, the average difference in proximity between the entrants and the incumbents is higher in the early years of the firm and declining over time. And the trend is very similar when taking the difference using the spillovers adjustment to calculate the proximity measures.

We can also look solely at the incumbent's proximity to new entrants in their sector. Although we have already established in figure 2.3a that the entrants have a higher proximity to their initial inventions than incumbents, we surprisingly see in figure 2.4 that the trend is also decreasing for incumbent proximity over the entrants life cycle. This means that new entrants and incumbents are not completely independent, otherwise we would expect this figure to be flat. Instead, we see that incumbents also patent in closer proximity to the patents new entrants are filing and that this proximity declines over time. The fact that it is not flat implies that the technological sector follows an overall evolution and that new entrants also follow the trends. However I cannot distinguish whether this is coming from knowledge spillovers from the incumbent firms, knowledge spillovers from the entrant or due to a parallel exogenous process like changes in university curriculums or government research agendas or another effect. Section 2.5.3 will explore

[11] I define an incumbent as a firm that is at least twenty years old.

the impact of having prior experience patenting. This experience is likely to partially come from incumbent firms, therefore this indicator may be a way to test spillovers from incumbent firms to new entrants. I will return to this issue there.

Finally, I am interested in understanding the consequences of inertia. In particular, how does it correspond to the firm's overall originality. Figure 2.5a shows the pattern for average originality built from 4-digit IPC codes. The originality is at first decreasing and then starts to increase after around ten years. However the estimates are quite volatile. On the other hand, figure 2.5b shows that the average of the maximum firm originality is increasing over the firm life cycle and this trend is very robust. It is arguable whether the mean firm originality or the maximum firm originality is the best indicator of firm innovation. While the mean is the default in the innovation literature, it can be reasoned that the maximum originality is the better indicator since it is the invention pushing the innovation frontier. If we take the maximum firm originality to measure firm innovation, then figure 2.5b would suggest that older firms are the more innovative ones. However if we take the average firm originality as the measure, then the age effect is less clear.

2.5.2 Initial Originality

So far we have looked at firm proximity measured in relative terms to the initial position. We have also studied originality on its own. However we have not examined the two together, namely we have not looked at whether and how the originality of the firm affects its degree of inertia. In Lee (2020) we saw that startup patenting patterns have changed over time and in particular that their initial originality has been decreasing. Here I explore the ramifications of this overall fall in initial originality and document some facts about the dynamic consequences.

To investigate this, I group new entrants into low, medium, and high categories depending on their initial originality. The low originality entrants are defined as the entrants that fall into the bottom 50th quantile of the originality distribution in their entry year. The medium group consists of the firms between the bottom 50th and 75th quantile and the high originality group is defined as firms with initial originalities in the top 25th quantile. Figure 2.6a plots the estimates from equation 3 using initial firm originality categories in the interaction term. We see that the low originality entrants tend to continue innovating in close proximity to their initial position while the high originality entrants innovate the furthest from their initial position although the decline is the slowest.

However when we compare the firm's proximity with the incumbents in the sector (see figure 2.6b) we see that low initial originality entrants are the least inert in relative terms - the difference for them falls the fastest. This can be consistent with figure 2.6a when we consider the behavior of the other firms in the industry as well. As we saw in figure 2.4, there tends to be trends in the overall evolution in technological content with the average new entrant also following these trends. However the average low originality entrants are likely to be a laggard to these trends, therefore incumbent firms' are less sensitive to their entry and we expect the pattern for incumbent firms to be more flat. This would correspond to a faster fall in the proximity differences for low originality firms.

Figure 2.7 then shows the trends in the complementary proximity by initial originality groups over the firm life cycle. We see that the order when it comes to complementarity is inversed. The high initial originality entrants are patenting the most in complementary areas. This difference stays quite persistent and we see the gap between medium and high originality entrants increasing over time. A high originality entrant may be confident in its initial invention and therefore may be more comfortable with expanding into complementary fields. In contrast, a low originality entrant may recognize that their initial position is less original and therefore needs to put more effort into solidifying that initial position before exploring complementary areas. Indeed we see that the low originality entrants slowly increase their complementarity as they age however it remains much lower than the high originality entrants. We might also expect to see an increase for medium and high originality entrants, however figure 2.7 shows their average declining over the firm life cycle. Since these proximities are constructed in comparison to the first year's measure we only capture the proximity to the first year. As an entrant explores new areas it may find new inventions that lead it to continue exploring new areas which lead it farther from its initial position as it has spent less time enforcing its initial position. The fact that a new entrant enters with a high originality may also be a signal for its propensity to explore. The entrant may in general have less of an affinity to remain in the same technological areas. In contrast low originality entrants, who survive, appear to be more entrenched in their initial positions and therefore tailor their future R&D decisions to build off it. This indicates that some firms specialize more in exploration while others specialize more in exploitation.

Lastly, we can examine the average firm originality trends. Figures 2.8a and 2.8b confirms that high initial originality firms remain at a high level of originality for quite long. This is true for both their average originality and their maximum originality. We see however that the medium and low initial originality firms increase their originality over time and by the time they are 20 years old, their originality levels have largely converged. Note that originality is a measure with an upper bound, therefore the high originality firms are unlikely to increase their originality indefinitely.

2.5.3 Initial Experience

This section will explore the impact of having prior experience patenting. Experience has been recognized by many papers as a driving factor in firm success (see Gompers et al. (2010), Chatterji (2009b), Chatterji (2009a), etc.). Experience can be viewed as a signal for skill, perhaps a higher absorptive capacity and it is intrinsically a proxy for knowledge stock. Here I explore its impact on firm inertial tendencies.

I find in figure 2.9a that a new entrant who has at least one person on the team with previous experience patenting is likely to continue patenting in closer proximity to its initial position over time than firms with no experience. This implies that experienced entrants associate a value with strengthening their initial position.

As mentioned in section 2.5.3, experience is likely to come from incumbent firms. Thus this indicator may be a way to measure spillovers effects from incumbent firms to new entrants. On the other hand, an inventor who works in an existing firm could simply continue inventing in that firm if it were relevant to the firm. Instead, the action of leaving the firm and starting a new firm implies that the innovation is more radical and arguably of less value to the incumbent firm.[12]

This is in fact what we see. Figure 2.9b compares the differences in proximity between the entrants and the incumbents by experience history. We see clearly that the behavior is very

[12] The average entry originality from an experienced entrant is 0.6212 while the average entry originality for an entrant with no experienced members is 0.5769. This indicates that experienced entrants do tend to enter with a higher originality.

different between the two and that they diverge in time. Experienced entrants do not decrease their proximity much relative to the incumbents. Since we have seen that the proximity is falling within the experienced entrant, this means that the proximity of incumbents is falling even faster. On the other hand, the entrants with no experience are more quick to move away from their initial positions.

In terms of complementarity, we again see a large gap between the experienced and inexperienced entrants (figures 2.10a and 2.10b). Although the gap is large, the trend is quite similar, complementary proximity to the first year is increasing at first then declining. When removing the proximity of the incumbent firms however, we see that the complementarity is increasing quite steadily although it is slower for entrants with no experience particularly in the five to fifteen firm age group.

Figures 2.11a and 2.11b show the trends for originality. The maximum originality is increasing for experienced entrants and remains fairly flat for entrants with no experience. However the trends are inconclusive for average originality; there is a lot of noise and little difference between the experienced and inexperienced entrants. This implies that the average invention developed by the experienced entrants is not highly original. As we saw in figure 2.9a, experienced entrants associate a value with more proximity. This implies that they are developing follow on innovations that are not necessarily very original, which would bring the average originality of the firm down. However we see that the maximum originality of the experienced entrants is increasing, implying that while a large portion of their research is in incremental innovations on their initial invention, they also make an effort to develop original innovations.

2.5.4 Size and Age Interactions

As referenced earlier, there is an ongoing debate about the differential role of firm size on innovation. This is further confused with the effects of firm age. This section attempts to address this issue and disentangle the age and size effects. As described in section 2.3, I define the size of the firm by its discounted count of patents and then group them into quantiles by their ranking in the size distribution of their primary sector each year. As has been vastly documented in the literature, the firm size distribution is highly skewed, therefore I delimit the groups by the 25th, 50th, 90th and 99th quantiles. I will look at both a dynamic firm size grouping and a static grouping based on the initial firm size. The dynamic measure is a time varying classification of firm size which means that the ranking of the firms is changing and they may be moving between quantile groups over their life cycle.

Figure 2.12a displays the estimates on proximity by age and dynamic size quantiles. We see that the largest firms are the most inert. The largest firms are the earliest to flatten their slope which becomes relatively flat through ages five to twenty. Around ages ten to fifteen, we see the firms in the second largest firm size category also becoming more inert. Although the firm size category may change for the firms over their life time, the proximity measure is always with respect to the firm's initial position. This implies that there is a certain degree of entrenchment for firm's to reach the large sizes. The largest firms have the highest proximity averages, meaning that their patents are very concentrated around their initial position. This is even more clear since firm size is calculated based on number of patents and in general a higher count of patents increases the likelihood of patenting in more technological classes which would correspond to a lower proximity.

Looking at firm size can help us understand the dynamics of competition. In particular, we can infer from this figure which new entrants become future competitors. When an incumbent is considering its incentives to innovate, it will evaluate the threats new entrants pose. I suggest that the entrants who pose the largest threat are the ones that are the largest when they get older. This would be the firms in the top 99th quantile in the later years in my figure. Perhaps surprisingly, these firms are not the ones doing a high amount of exploratory research, instead figure 2.12a shows that these firms are the most inert. They have really strengthened their initial position. I then check the average initial originality of these groups by the size category they are in when they are 20 years old. I find that the smallest firms had an average originality of 0.56, the second group had an average originality of 0.55, the third had an average of 0.57, the fourth had an average of 0.58 and the largest firms had an average initial originality of 0.60. This suggests that although the largest firms have a high degree of inertia, they are inert around an initial position that is highly original.

The complementary proximity figure (figure 2.12b) shows a noisy relationship with size and complementarity. The general trend for all size groups is decreasing. Although for the smallest firms it appears to increase for the first 10 years. Yet when we look at the complementarity proximity with the incumbent proximities subtracted, the smallest firms are one of the slowest to increase their complementarity. This suggests that they enter into sectors that already have clear incumbent leaders - even though the small firms in these sectors work to expand in complementary areas, the incumbent firms are more effective. Figure 2.13b shows that this gap doesn't last however which suggests that there is a selection effect, and the small firms that remain are ones that have expanded into complementary areas.

We might expect that the firms who remain small when they are over 15 years old are firms that specialize in one area. However these results suggest the opposite. The firms that remain small are innovating more in complementary areas.[13] This suggests that small firms can compete with large incumbents in two ways. One way is to dig into their initial positions and grow by building around it, another way is to stay small and innovate in other technological positions. The next section will look at concentration and strategic reactions in more detail.

The largest firms do not have a clear pattern in terms of complementarity growth. Since they are categorized in the top 1 percentile, the number of firms in the group is much smaller and therefore more sensitive to individual firm variation. Furthermore, recall that the firm size categories are changing over time, this means that a firm categorized in the 90th to 99th quantile when 10 years old may have moved to the 99+ quantile by the time it is 15 years old or vice versa. This resorting between groups over time will add even more noise.

In comparison, the originality results in Figure 2.14b suggest that the largest firms are the least original in terms of maximum originality while the small firms are the most original for the first ten years. However Figure 2.14a suggests that the smallest and largest firms both have the highest average originality for at least the first 10 years. This is consistent with the patterns that we saw with respect to proximity.[14] The largest firms had a high initial originality and were the most inert. Having a high degree of inertia suggests that they did not push the boundaries on maximum originality, however they also had a higher starting originality - staying inert around

[13] Of course, recall that my definition of firm size is constructed from the number of patent filings which is only a measure of the firm's R&D size. A small number of patents may reflect a small firm or it could suggest that the firm has turned its efforts to producing and commercializing its inventions.

[14] After 12 years the large firms jump to a very high originality. This could be due to firms changing their firm size group. Plus, there are very few firms in the largest category so it is quite sensitive to any changes.

a generally high initial originality meant that their mean originality remained quite high.

In contrast the second largest set of firms, the firms in the 90th to 99th quantile, are the least original. Figure 2.12a shows that these large firms have a high degree of inertia and Figures 2.14b and 2.14a show that they have a relatively low originality. Since the size classes are lagged in the model, this suggests that the large firms are less original due to their size. Large firms do not experience competitive pressures that push them to innovate in new areas. The average originality trend for the other size groups seems to be flat for about ten to fifteen years before slightly increasing.

The picture is a bit different when we categorize the firms by a static initial firm size. With a fixed size class, there is no resorting between quantiles over time. Figure 2.15a shows that when we look only at the firm's initial size, it is the small and medium firms who are more inert while the large firms start with a higher proximity but are quicker to move away from their initial positions. Starting in a large firm size category may mean different things. It may be that the firm is in a too narrowly defined technology sector. Although in building my dataset, I require that all sectors have at least five firms it is possible that this is not strict enough. Being in the large firm size quantile of the technological sector from the start could also mean that this sector is very young and there are not many firms yet. Starting in a young sector may be an indicator of the firm's propensity to be original. If the sector is young, there would be little expertise to build off of and the new firms must have been doing rather radical innovation. Plus, if the sector is young, the technology may not be validated nor recognized yet. So the firms with a high propensity for originality may prefer to continue R&D on other innovative projects instead of staying around their initial position. This could be why I see the steep decline in proximity for initially large firms although I cannot confidently identify the sector age so I cannot say for sure.

In terms of complementary proximity, it is again the large firms who have the lowest degree of complementary proximity although their trends are quite noisy (see Figures 2.15b and 2.16b). With respect to originality, we see that the smallest firms have the highest average for maximum originality while the largest firms have the lowest. The small firms that enter in a sector with already many large firms will have to differentiate themselves by being more original, therefore we see that the max originality is higher for them. In Figure **??**, the small firms also have a relatively high mean originality however it is overtaken by firms that start in the 90th to 99th quantile who have a much higher and increasing mean originality. This reflects the low degree of inertia that these large firms show however it is a bit surprising that it does not correspond to a higher maximum originality.

2.5.5 Sector Concentration

The section above on firm size has already discussed some possible effects of competition on firm inertia. Here I will accompany those results with some more figures that include the degree of concentration explicitly calculated as a Herfindahl index on firm's patent portfolios.

From Aghion et al. (2005) we expect that competition and innovation will have an inverted-U relationship. In their study, they find that competition will drive neck-and-neck firms to innovate more however it discourages laggard firms from innovating.[15] They also construct a measure of technological distance based on total factor productivity and show that it increases with competition. Here, I utilize the patent technology codes to build a more precise measure of technological distance and I focus on new entrants who I assume enter as laggards into a technology sector.

Figure 2.17a shows that firms in more concentrated technology sectors will move away more from their initial technological position to relieve some competitive pressure from incumbents. This extends the finding in Aghion et al. (2005) that technological distance increases in more highly concentrated industries to hold concentration in technological sectors as well. On the other hand figure 2.17b displays the correlation between complementary proximity and concentration. Here we see that proximity falls for an increase in concentration from the least concentrated sectors, however it then rises again as concentration increases albeit not to equal levels as the least concentrated sectors. These are cross sectional exploratory figures. Below are the more rigorous results controlling for different year and sector fixed effects.

Figure 2.18a shows the estimates for average proximity for firms grouped by the concentration level of their primary technology sectors. Here the concentration categories are dynamic and

[15] Hashmi (2013) looks at the UK market and finds that the relationship between competition and innovation in the product market is mildly negative. Hashmi does not find the inverted-U but suggests that this is because industries in the UK are more neck-and-neck than those in the US.

thus sectors and corresponding firms may be changing groups over time. We see that the young firms in the highest concentrated sectors are the least inert. These may be firms in the early stages of the technological sector life cycle. Figure 2.25 shows the average Herfindahl index for the sectors over their life cycle.[16] Each sector starts with few firms at the beginning then see their Herfindahl index fall as entry increases into the sector. Eventually there are some dominant firms who beat the competition that leads to exit and more concentration in the sector.

The young firms in concentrated sectors have the lowest proximity to their initial position. With the incumbent trends removed, Figure 2.19a, the firms in highly concentrated sectors start with a slightly higher proximity although this falls quickly below the levels of the others. This suggests that a young firm that enters in a competitive sector reacts to the competition by differentiating itself from existing technologies. On the other hand, the firms in the medium concentration sectors appear to be the most inert. These sectors can be considered neck-and-neck sectors where innovation maybe a way to escape the competition. Here we see that instead of a low degree of inertia where firms are carving out new technological spaces, as we see for new firms in highly concentrated sectors, the firms in these medium concentration sectors are relatively inert in terms of their technological position. They put more effort into strengthening their initial position. This suggests an inverted-U shape for firm R&D inertia by the concentration of the technological sector the firm is in.

If we examine concentration on the complementary proximity measure (see figure 2.18b, we see that the firms in the medium concentration sectors have the highest degree of complementary inertia while the firms in the low and high concentration sectors have the lowest degree of complementary proximity. This again suggests an inverted U relationship where it is the firms in the medium concentration sectors that are competing the most. By expanding into complementary fields, they are escaping the direct competition although they also have a high degree of inertia which suggests they are also building around their initial positions. With the incumbent trends removed, the medium concentration firms are surpassed by the highly concentrated firms. This suggests that the young firms in the highly concentrated sectors are innovating in complementary areas much more to differentiated themselves.

[16]See the Appendix for a discussion on the potential measurement concerns for the technological life sector.

In relation to the firms' originality (Figures 2.20b and 2.20a), we see that within the young firms it is the firms in the medium concentrated sectors who have the highest level of originality both in terms of average originality as well as maximum originality. Young firms in a neck-and-neck sector have the most incentive to conduct original innovation as they arguably have the best balance of market contestability and market appropriability.[17] In comparison, a firm in a low concentration sector has a high degree of market contestability but little appropriabiilty and a highly concentrated market has a high degree of appropriability yet little contestability. This is reflected in the patterns we have seen. Firms in the highest concentration sectors are the least inert as they have the most to gain if they can gain market share. The new firms who enter in concentrated markets are lagging the large leading firms so moving away from the position of the large firms is a way to decrease the competitive pressure. Whether they are moving into complementary areas or something else is not clear. In Figure 2.18b it looks like they also move away from complementary areas however in Figure 2.19b, they seem to be increasing for the first ten years.

2.6 Conclusion

In this paper, I provide evidence on the existence of firm inertia in technological space. I then investigate the factors that affect the degree of firm inertia and what this means for overall firm originality. I suggest that a better understanding of these dynamics will help us understand the dynamics of competition.

I focus on young firms in general, with most of my study on firms from 0 to 20 years old. In particular, this allows me to define some fixed firm characteristics from the initial conditions and analyze their effects. I find that firms with a high initial originality are the least inert while low originality firms are the most inert. This ordering is inversed when we look at complementary proximity suggesting that the high initial originality firms are expanding into complementary fields. This translates into firm originality over time where we see that the initial high originality firms remain at a high level of originality in terms of both the maximum and the average although the gap decreases over time.

[17] See Shapiro (2012) and Arrow (1962)

I then estimated the importance of prior experience for new entrants. The experienced entrants were more inert in both the traditional sense of proximity as well as the complementary measure. This has an ambiguous effect on firm average originality however we clearly see that the maximum firm originality is increasing for experienced entrants.

Next I evaluated size effects which show that larger firms are the most inert. I suggested that these firms are the most likely entry 'threats' to incumbent firms in terms of dynamic competition. Looking at the initial originality of the firms by their 20 year old firm size groupings, I find that the largest firms had on average the highest initial originality suggesting that they began with an original invention and then built up their position around it. This corresponds to a lower maximum originality but a higher average originality over its life cycle.

I then explored the effects of competition on innovation strategies by explicitly calculating the Herfindahl index for 4-digit IPC technology sectors. The patterns imply different strategies in reaction to different levels of competition. For young firms in highly concentrated sectors, we see that they have a low degree of R&D inertia. This means that their method of escaping the competition is to differentiate themselves from the leader firms in their sectors. On the other hand, young firms in neck-and-neck sectors have a relatively high degree of inertia as well as high originality. This suggests that these firms compete by building up their initial positions.

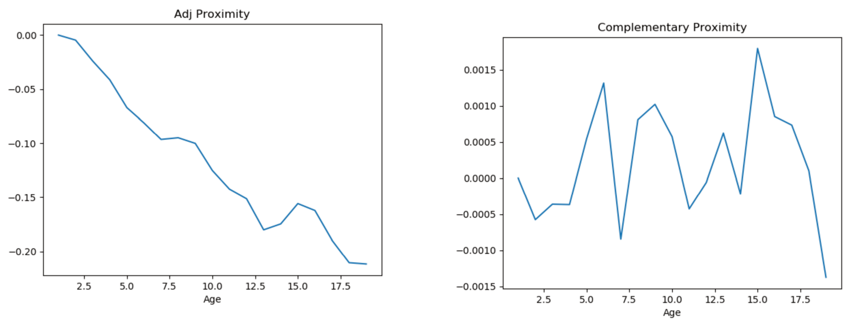
Finally I compare all my results on firm proximity with firm originality to explore the effects of firm proximity on its patenting originality. While the results on mean firm originality are often inconclusive, the results on maximum firm originality have some clear outcomes. Overall, maximum firm originality is increasing as the firm ages. However large entrants have a low maximum originality, experienced entrants have a high maximum originality, high initial originality entrants remain at a high degree of originality and it is in the firms in the neck-and-neck sectors who have the highest originality among young firms.

Notably, I do not prescribe a policy for what is the right degree of inertia in a firm. The section on prior experiences shows that experienced entrants have a higher average level of inertia. The fact that this is the case suggests there are benefits to inertia. In looking at firms by their dynamic firm size grouping, it is also the firms who are more inert in the larger firm size groups. Going back to Hansen and Freeman's observation about firm selection processes. It is possible that some degree of inertia is good for the firm. The norm in the literature on innovation economics is to encourage more innovation and more original innovation. This might not necessarily be the best for the firm, however the effect on overall welfare in the economy is a bigger question.

Although I would like to analyze how firm inertia affects competition dynamics in the sector, this analysis stops short of that. However I document that experienced entrants and entrants with an initial high originality appear to be contributing the most in terms of innovation. When exploring the sector concentration effects, it appears to be the firms in the medium concentrated sectors that are the most inert. They also have a high measure of originality and therefore this suggests that they compete by building up their initial original positions. The firms in the highly concentrated sectors have the lowest degree of inertia which suggests a different type of innovative reaction to competition. When evaluating the threat from new entrants that incumbents face, it appears that it is the new entrants who are initially more original and who have a high degree of inertia that are the most viable threats to incumbents.

A Results and Figures

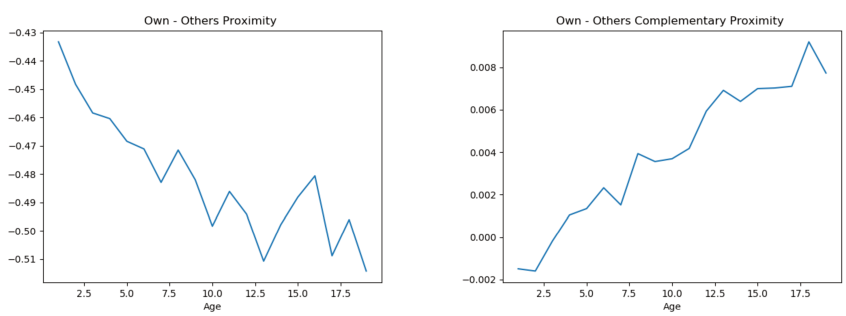
This section gathers the results that are referenced in the main text. The corresponding full regression results will be made available in an online appendix.



(a) By adjusted proximity as defined in Bloom, Schankerman, and Van Reenen (2013)

(b) By complementary proximity

Figure 2.2: Average age effect on alternative measures of proximity to initial position
These figures plot the coefficients from the proximity regressions. This represents the average proximity by firm age controlling for industry, year and firm fixed characteristics. The included controls are the firm's initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality groups is.



(a) Jaffe Proximity Difference

(b) Complementary Proximity Difference

Figure 2.3: Average age effect on the difference between the firm's proximity to its initial position and the proximity of the incumbent firms
These figures plot the coefficients from the regression with the proximity difference between the entrant and the incumbent as the dependent variable. The additional variables are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality groups is.

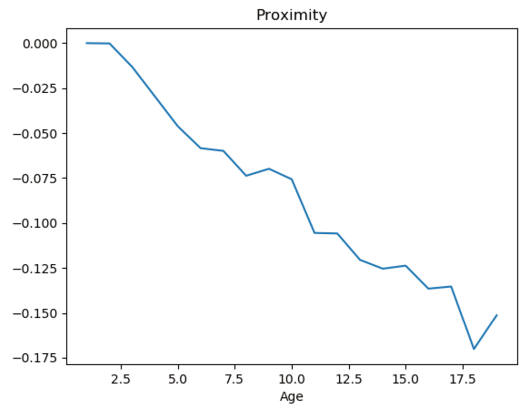
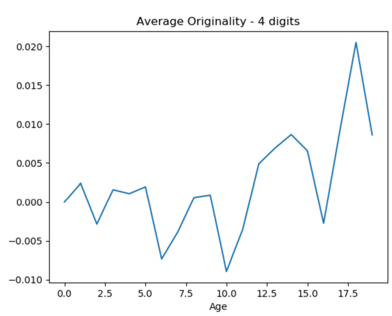
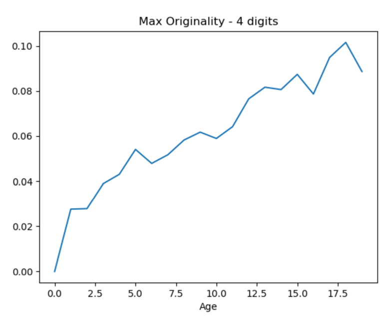


Figure 2.4: Average age effect of incumbent firm's proximity to a given firm's initial position
These figures plot the average proximity of the incumbent firms to the entrants initial position by firm age. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality groups is.

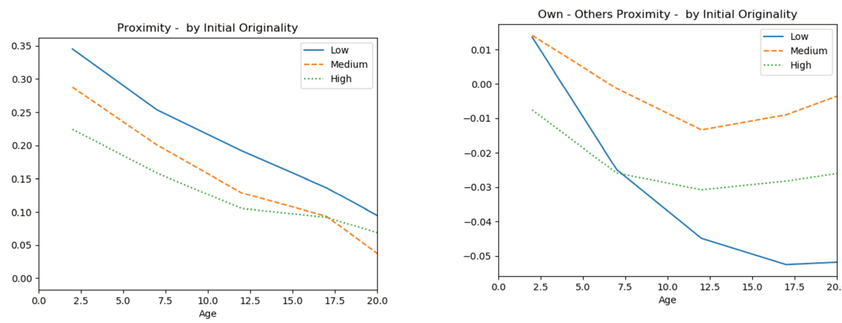


(a) Average Originality



(b) Max Originality

Figure 2.5: Average age effect on firm originality
These figures plot the firm originality. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality groups is.



(a) Entrants' Jaffe Proximity

(b) Difference in Proximity between Entrants and Incumbents

Figure 2.6: Average age effects by initial originality on proximity measures
These figures show measures built from the average Jaffe proximity for firms grouped by initial originality category. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.

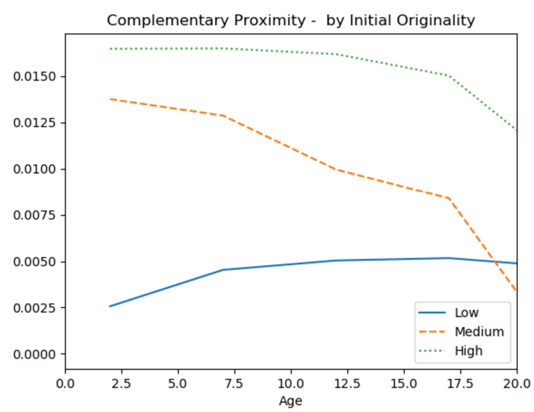
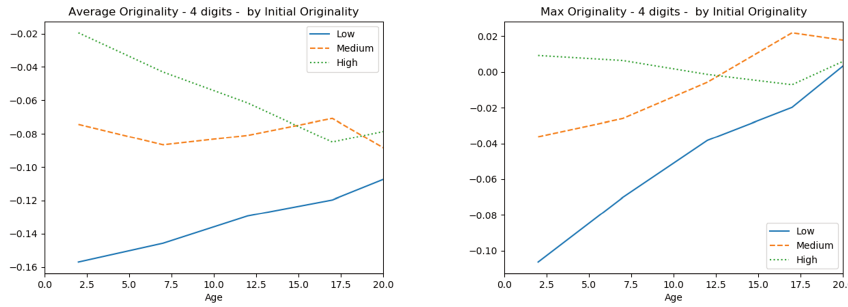


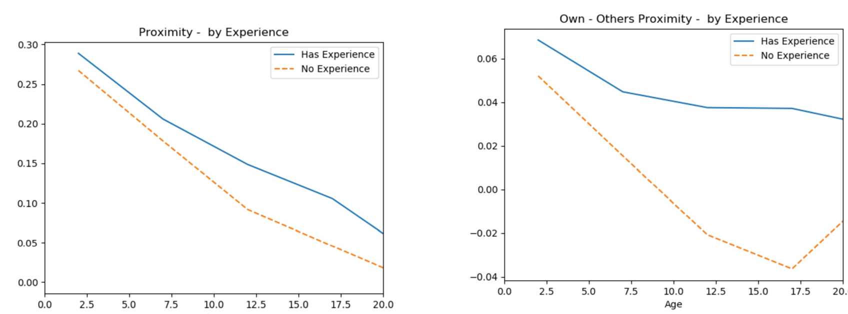
Figure 2.7: Average age effect by initial originality on complementary proximity
This figure plots the average entrant complementary proximity by initial originality category. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.



(a) Average Originality

(b) Max Originality

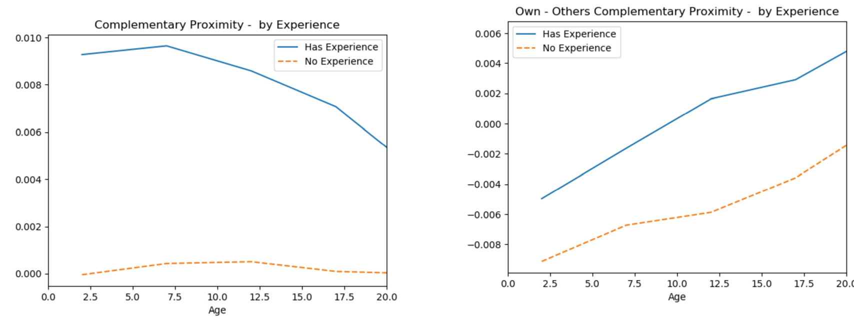
Figure 2.8: Average age effect by initial originality on firm originality
These figures plot the entrant's originality built from 4-digit IPC codes grouped by firms' initial originality. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.



(a) Entrants' Jaffe Proximity

(b) Difference in Proximity between Entrants and Incumbents

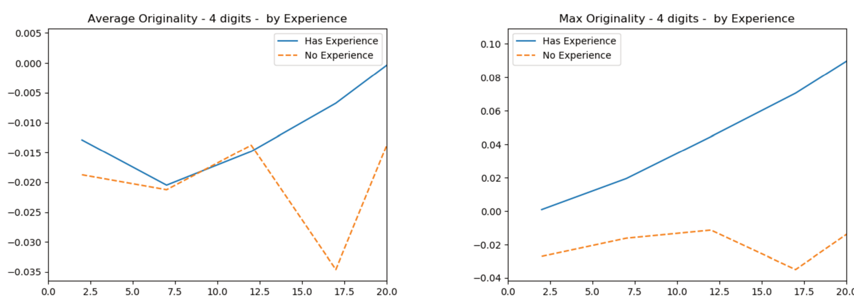
Figure 2.9: Average age effect by previous experience on proximity measures
These figures show measures built from the average Jaffe proximity for firms grouped by previous patenting experience. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.



(a) Entrants' Complementary Proximity

(b) Difference in Proximity between Entrants and Incumbents

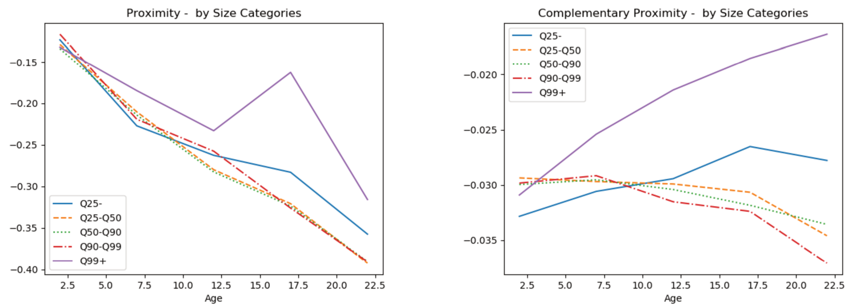
Figure 2.10: Average age effect by previous experience on complementary proximity measures
These figures show measures built from the average complementary proximity for firms grouped by previous patenting experience. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.



(a) Average Originality

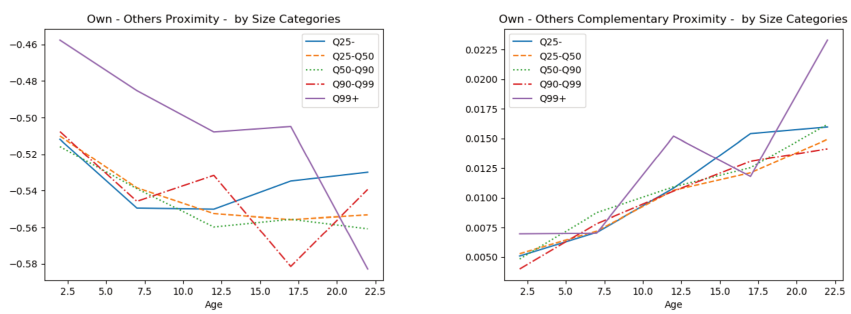
(b) Max Originality

Figure 2.11: Average age effect by previous experience on firm originality
These figures plot the entrant's originality built from 4-digit IPC codes grouped by firm's previous experience. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it first patented with other applicants, and its initial originality category.



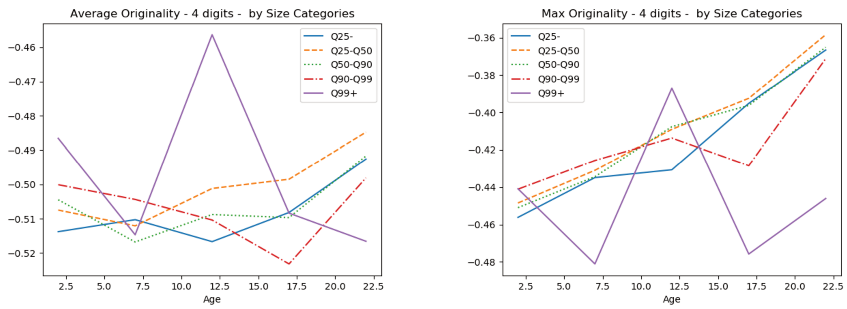
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.12: Average age effect by dynamic firm size on proximity measures
These figures plots the entrants' proximity by dynamic size categories. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



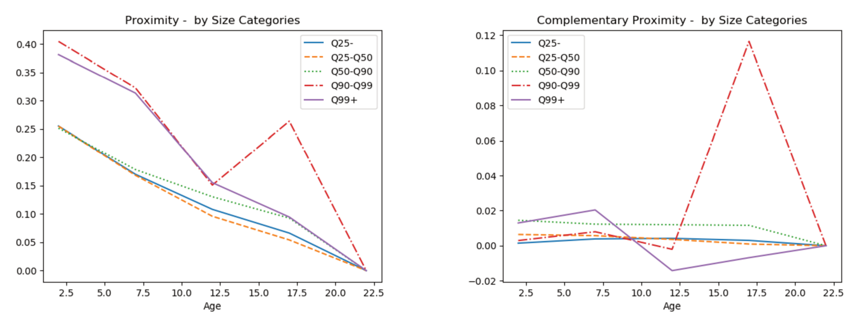
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.13: Average age effect by dynamic firm size on proximity differences between the entrant and the incumbents
These figures plots the entrants' proximity with incumbent trends removed by dynamic size categories. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



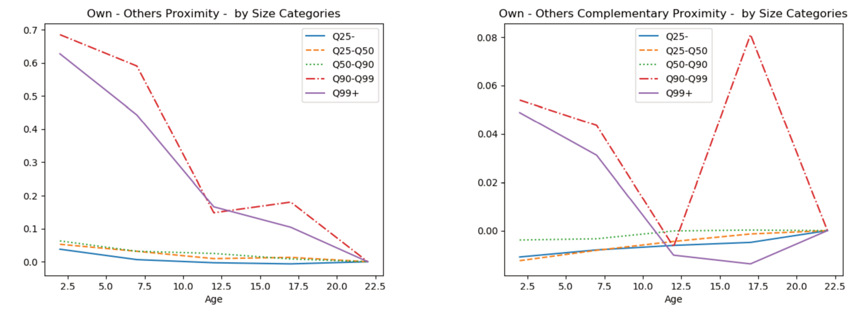
(a) Average Originality (b) Max Originality

Figure 2.14: Average age effect by dynamic firm size on firm originality
These figures plot the entrant's originality built from 4-digit IPC codes grouped by firm's dynamic size categories. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it first patented with other applicants, and its initial originality category.



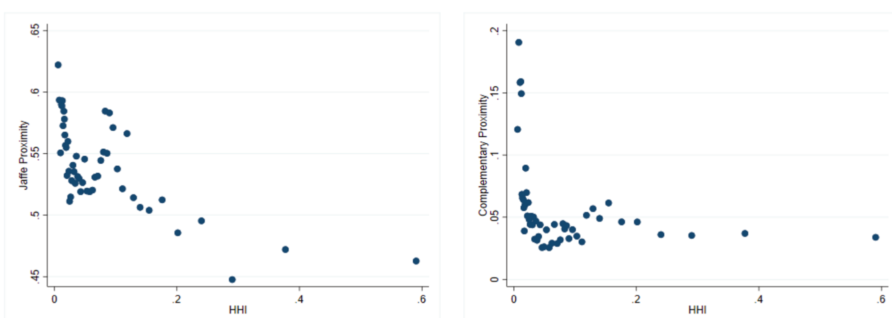
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.15: Average age effect by initial firm size on proximity measures
These figures plots the entrants' proximity by initial size groups. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



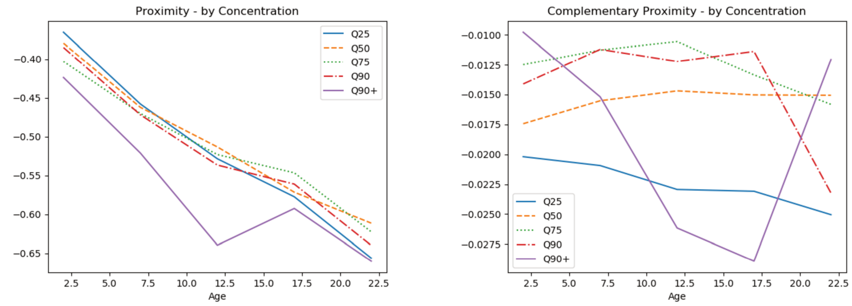
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.16: Average age effect by initial firm size on proximity difference between the entrant and the incumbents
These figures plot the entrants' proximity with the incumbent trends removed by initial size groups. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



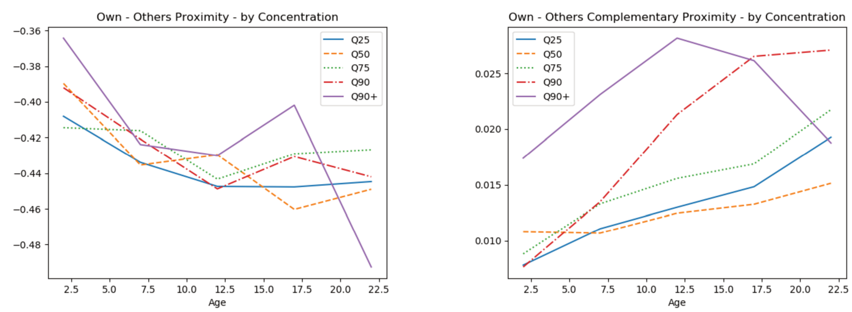
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.17: Binned scatter plot of proximity by concentration
These figures show binned scatter plots of the firm proximity measure to the concentration of the technological sector it enters in. This is a cross section of firms aged 10-20 and the x axis uses the degree of concentration the firms primary sector was in when it first entered.



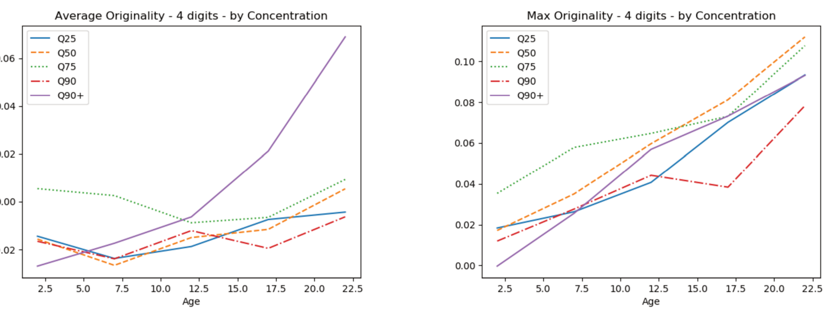
(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.18: Average age effect by sector concentration on proximity measures
These figures plot the entrants' proximity by dynamic sector concentration quantiles. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



(a) Jaffe Proximity (b) Complementary Proximity

Figure 2.19: Average age effect by concentration on proximity difference between the entrant and the incumbents
These figures plot the entrants' proximity with the incumbent trends removed by dynamic sector concentration quantiles. The additional controls are year, the firm's primary 4 digit IPC code, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



(a) Average Originality

(b) Max Originality

Figure 2.20: Average age effect by concentration on firm originality

These figures plot the entrant's originality built from 4-digit IPC codes grouped by firm's dynamic sector concentration quantiles. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it first patented with other applicants, and its initial originality category.

B Details on Data

In 1999 the United States legislation passed an act that changed how patent information was diffused. Prior to the American Invents Act (AIA) only patents that were granted would be published to the public. The AIA changed this to make all patent applications public regardless of grant status. Although the act was passed in 1999, the changes do not become apparent in the dataset until 2001. This means the dataset changes from covering only granted patents to covering all patent applications. To avoid this discrepancy I use only granted patents.

Patstat covers patent filing from the 18th century until today. It has organized the information in patent filing into many datasets. The database is organized into different tables for patent applications as well as patent publications, technology classification codes, applicants and inventors, citation between patents etc. Furthermore there is a grouping done by the patent office to identify patent families (see Martinez et al.). Patent families are a better grouping of the patent filings because one invention can be filed multiple times under different filing numbers with the content slightly changed. Patent families also group patents that are filed in multiple patent offices meaning in different countries. I use the earliest filing year in the patent family as my year of patent filing even though it may be a later application that ultimately gets granted. I choose the earlier date because by that date the firm has already essentially completed an invention.

The information on applicants and inventors in patent data is notoriously messy. There are often typos of the applicant names and addresses. However, in addition to the typos, the more serious problem is that one applicant may file a patent under one name then file another patent under another name. This can happen when a firm changes it's name; it can also happen when a firm's subsidiary files under a different name. Another issue with the applicant data in patents is that it does not identify whether the applicant is a person or a firm or a university etc. The EPO does a cleaning on this data in an attempt to consolidate applicant names and identify whether the applicant is a firm, individual or other entity. I use the EPO's applicant type identification to also identify the firm applicants. However I do a further cleaning on the names which has already been detailed in chapter 1. Therefore, a firm is a patent applicant identified as a company by the EPO and grouped by similar names. Limiting the dataset to only US firms gives me 240750 firms. This corresponds to 3170674 patent families.

Along a similar reasoning I may be able to infer the age a firm exits as the year it last patents. This assumption is however much stronger than the one for entry. Firm exit is hard to identify in my dataset since firms do not necessarily patent each year. I need to assume that firms exit when they no longer patent. In reality we do not know if the firm has really shut down or is simply redirecting efforts away from R&D to commercializing the product.[18] Although I cannot say with certainty that a firm exits after it stops patenting, I CAN say with certainty that a firm survives as long as it continues patenting. In general this measure is some more information I can glean from the patent data however it is really noisy and I only use it in robustness checks.

The other measures I build are knowledge stock and patent citations. I use knowledge stock primarily as a proxy for firm size. It is created by taking a discounted sum of the number of patents a firm has filed which is conventional in the literature. This is may be a crude measure of firm size in terms of sales or employees however I suggest it is a better measure of a firm's R&D team size and human capital. With respect to how size can affect a firm's technological development, it is arguably more likely that the size of the R&D team is the more important. A larger R&D team (aka. more input resources into the research process) is likely to result in more patenting output. Nonetheless this measure of knowledge has also been used in the literature as a proxy for overall firm size (see Aghion et al. (2016)). The argument is that patents are filed in order to protect an invention for commercial reasons. Therefore firms have an incentive to file more patents when they can benefit from a larger market. And a larger market corresponds to a larger firm size. Taking the knowledge stock as simply a size of a firm's patent portfolio will allow us to measure the effect of technological push on innovation. In Chapter 1, we discussed the different ways push and pull factors affect innovation. A build up of knowledge stock in a particular technological position is going to be a factor that pushes for more innovation in similar technological fields.

The common innovation patent measures in the literature are simply a count of patents or a citations adjusted count of patents. Here I also build the same measures for comparison. In particular, with patent citations, I can also identify the technological codes of the citing patents. As such, I can look at the citing patents and determine whether they are in the same primary

[18] I do have some information on patent renewal fees however it is not complete and many firms exit before the patent expires. If the patent is renewed, I can at least assume that the firm has survived until that year. The duration of monopoly rights a patent grants has changed a few times in the US. The standard today is 20 years

technological sector as the cited patent's owner. This is like a simplified version of the generality measure suggested by Trajtenberg, Jaffe and Henderson (1997) where I simply count the number of citations that come from the same technological sector versus the ones that come from different technological sectors to investigate who the firm is influencing. Since forward citations suffer from a truncation problem, I choose to avoid the problem by taking a larger buffer and ending my dataset in 2005. Since I am using the 2017 vintage, I expect the truncation issue is much minimized.

Extracting Firm Characteristics

The debate over whether young or old firms are more innovative was first expounded on by Joseph Schumpeter who himself seems to have changed his mind suggesting first that young firms are the driving force then arguing later in his life that large firms are the primary source of innovation. Since Schumpeter there have been many studies tackling this question without reaching a consensus. Part of the reason this might be so confusing is that the firm age and size terms are often used interchangeably and the empirical tests have usually used the small-large distinction. While it is often true that young firms are small and old firms are large, it is not always the case.

In order to define the firm life cycle I need to be able to determine firm age. This information is not explicitly available in Patstat. Instead I apply the assumption that firms that have patented sometime in their life are going to be patenting from the start. This means that I assume no firm enters without patenting out of the firms that do patent. In reality there could be a some firms that exist for a few years without patenting that later choose to patent. With this assumption I can infer the entry year of a firm from the first year it begins patenting. I verify this choice by comparing the founding dates of public firms from the Jay Ritter dataset with the first year a firm begins patenting in my dataset.[19] The match is usually quite good, with the most common discrepancy being only one year. I check a random selection of some of the larger gaps by manually finding the firm's founders and comparing it with the inventors on the patent. They are often a match. This implies that the R&D for these firms does start from the year in my dataset however the firm incorporation sometimes occurs many years after.

[19] See https://site.warrington.ufl.edu/ritter/files/2019/05/FoundingDates.pdf

A rough timeline of a new entrant's progression could look something like this: in the starting stages, they may begin with a person or group of people with an idea that is set in a particular technological sector. Then they gather more resources such as engineers and physical supplies to conduct the R&D and build the idea into a product. This R&D process establishes a technological position for the firm. With frictions and sunk costs associated with this initial position, firms inherently develop a comparative advantage in that position and therefore have incentives to continue building off it.

It is also useful to determine a firm's primary technological sector and explore the sector dynamics. Like industries in product space, technological sectors are also likely to be heterogeneous and have a life cycle pattern. I assume the main heterogeneity of sectors is their concentration. If a sector is highly concentrated, it is likely to be dominated by a few firms. When the few firms are large, they might disincentivize innovation in the sector because a new firm might expect it to be hard to compete. On the other hand more innovation in the sector, regardless of whether they are concentrated in few firms or not imply knowledge spillovers that will encourage more innovation in the area.

I define a firm's primary technology sector by calculating the number of patents filed in each IPC 4 digit code over the firm's lifetime. Then I designate the IPC code with the most number of patents as the firm's primary sector. There are some cases where two 4 digit IPC codes have the same count of patents, I choose to drop these cases to avoid excess noise in the data. If I were to wrongly classify firms into sectors, they are likely to behave differently than the real firms in that sector and they will simply introduce more noise. Another option is to use 3 digit or 1 digit IPC codes to allow for a broader definition of a technological sector. This decreases the cases where the primary sector is uncertain; however it also means a more aggregated sector definition that might include sub sectors that have very different trends. For example the "A61K" 4 digit IPC code is very different to the "A01B" IPC code. However they would both be grouped into the same sector if I use 1 digit IPC codes. Nevertheless, for tractability in the analysis I will sometimes use 1 digit IPC codes.

Finally I also group firms into categories by firm size and the concentration of their primary technological sector which is measured by the Herfindahl index. This makes the analysis more tractable and allows me to interact the firm age effects with these measures. For concentration, I group firms by the 25th, 50th, 75th, and 90th quantile that their primary technological sector is in each year. For size categories I define them by groups delimited by the 25th, 50th, and 90th quantiles each year.

C Additional Descriptive Statistics

Below I detail some additional descriptive statistics. Figure 2.21 shows the number of observations that I have by firm age and Figure 2.23 shows this by different firm groupings. I also display the average number of years (a.k.a. gap years) between patent application filings by firm age and different firm groupings (see Figures 2.22 and 2.24). This gap years measure provides a summary of patenting frequency.

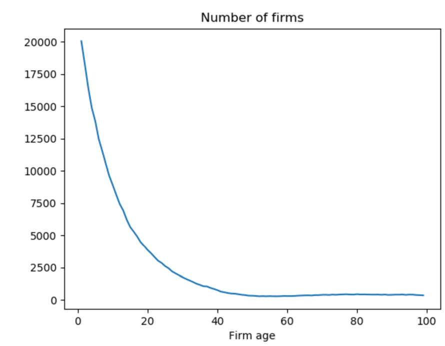


Figure 2.21: Number of observations by firm age
This figure shows the number of firm observations I have per firm age. The observations are based on patent application filings, not a stock of patents, therefore the lines are not necessarily decreasing.

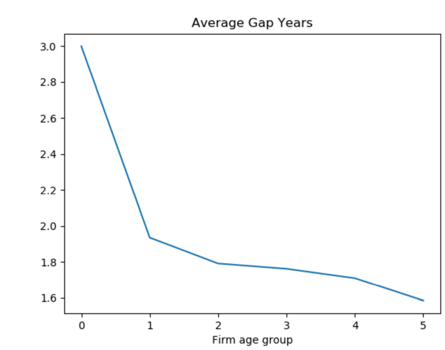
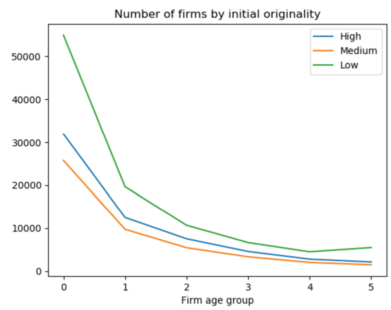
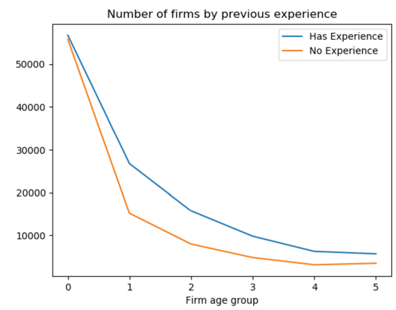


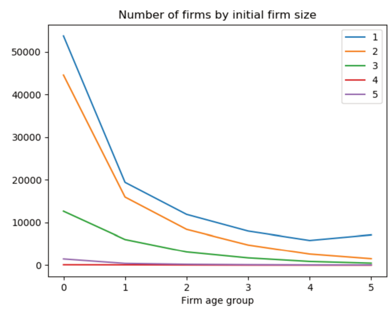
Figure 2.22: Average number of years between patent filings by firm age
This figure plots the average number of years before the next patent filing.



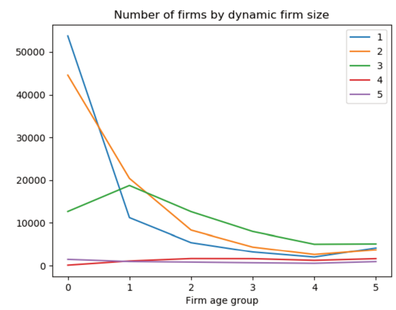
(a) By initial originality group



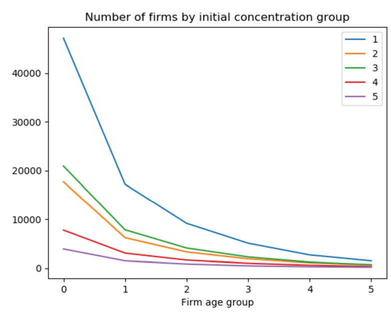
(b) By previous experience



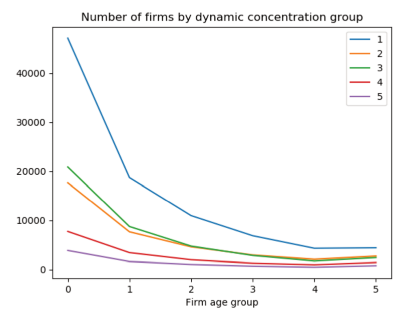
(c) By initial firm size group



(d) By dynamic firm size group

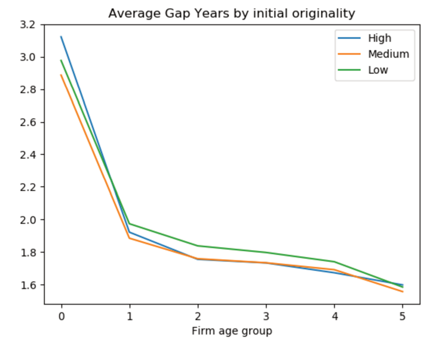


(e) By initial concentration group

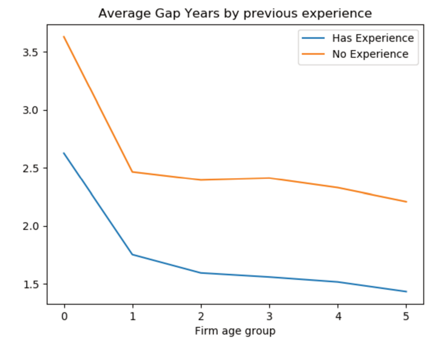


(f) By dynamic concentration group

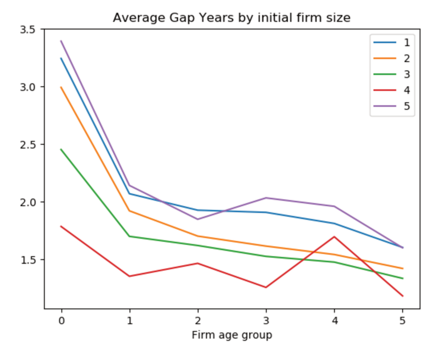
Figure 2.23: Number of observations breakdown



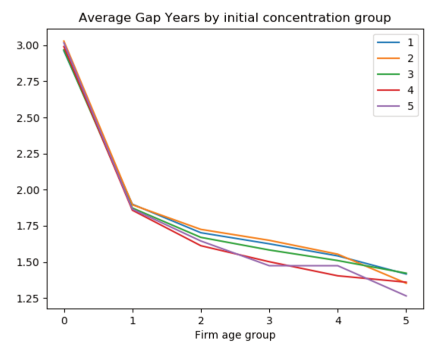
(a) By initial originality group



(b) By previous experience



(c) By initial firm size group



(d) By initial concentration

Figure 2.24: Average number of years between patent applications - breakdown

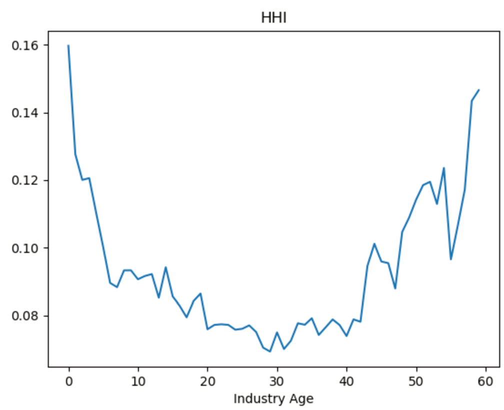


Figure 2.25: Median HHI of 4-digit IPC technology sectors
This figure shows the median 4 digit technology sector Herfindahl index where the Herfindahl index is calculated based on firm discounted knowledge stock measures on patent counts. Only industries under 60 years old are shown as the data is less complete in earlier years

Chapter 3

Regulation Timing on Green Innovation: The Case of Vehicle Emissions

Does regulatory leadership lead to more innovation? Here we study this question through the case of vehicle emission regulations. There have been multiple rounds of increasingly stringent vehicle emission regulations that require firms to innovate in order to continue selling in those markets. Through the use of patent data, we identify the related technologies and firms. We then use the staggered implementation of different levels of regulation to determine leader and follower countries. The findings show that there are innovation benefits to being a regulatory leader. Additionally, we provide evidence that firms with home countries that are regulatory leaders increase their innovation globally however this is only true for end-of-pipe technologies and for a broader early mover leader definition. On the other hand, the evidence is not conclusive for the stricter first mover leader definition.

Le leadership réglementaire conduit-il à plus d'innovation ? Nous étudions cette question en considérant le cas de la réglementation des émissions polluantes des véhicules. Plusieurs séries de réglementations sur les émissions des véhicules, de plus en plus strictes, ont oblige les entreprises du secteur automobile à innover. Grâce à l'utilisation de données de brevets, nous identifions les

technologies et les entreprises qui les développent et mesurons la qualité de l'innovation. Nous utilisons ensuite la mise en œuvre échelonnée des différents niveaux de réglementation pour déterminer les pays leaders et retardataires. Les résultats montrent que la mise en œuvre tardive de la réglementation est moins rentable. De plus, nous prouvons que les entreprises dont les pays d'origine sont des leaders en matière de réglementation augmentent considérablement leur innovation à l'échelle mondiale.

3.1 Overview

Can environmental policy be a driver of firm innovation? In what form (direction, scale, etc.) and under what conditions (timing, policy structure, firm size, etc.) can this happen? We attempt to answer these questions through the lens of vehicle emissions regulations. Historically, the introduction of environmental regulations were viewed negatively by firms as they believed it would increase costs and cause a general trade off in global competitiveness. A literature in the early 90s, beginning with Michael Porter argued that well designed regulations can in fact increase firm competitiveness by catalyzing innovation to the extent that it can offset the costs of regulation (see Porter and Van Der Linde (1995)). This argument has been adopted in the United States and other countries to push through tougher regulations.

Here we study the case of vehicle emissions regulations and provide evidence that policy makers can positively affect the innovation output within its borders as well as outside its borders through its domestic firms. Vehicle emission regulations are adopted in a large set of countries, they undergo multiple levels of stringency and are relatively comparable between countries - as such, they provide a good setting for studying this topic. A data collection effort was made to gather information on historical vehicle emission regulations. We build innovation indicators with the use of patent data which are used to investigate the push and pull dynamics of innovation creation. Additionally, different emissions control technologies are examined individually and their different properties are discussed.

Vehicle emission regulations impose an upper limit on the amount of pollutants that can be emitted from a car in every day use. These are enforced with driving tests that simulate everyday driving conditions that must be conducted before a new car model enters the market. These regulations are colloquially called standards although they are typically imposed by air quality agencies, federal transportation agencies or in the case of the EU, through EU directives and regulations.

In terms of environmental regulations, the transportation sector is usually treated separately from the rest of industry because the final amount of emissions results from consumer use. As opposed to the rest of industry for which CO_2 emissions are emitted during the production process, regulations in the transportation sector have to be imposed on the product itself. In the sense of Romer (1990) this implies a new product variety. Also, as previous vehicles and technologies become obsolete we encounter a situation of essentially mandated creative destruction as in Schumpeter and as modelled in Aghion and Howitt (1992).

A country may want to develop the relevant technologies earlier and therefore implement environmental regulations early as it expects it's domestic multinational firms will benefit for a longer time as other countries adopt later. We refer to this as the temporal dimension to regulations. Foreign firms with production in this country then have to decide whether they want to take on the costs and maintain a position in this country's market. As such, adopting a new regulation imposes a kind of trade barrier. In particular, there is evidence from the political economy literature that large domestic firms communicate with their country's government on a timing and scope that benefits them.[1] When there is a dialogue between domestic firms and government, we expect large domestic firms may have an impact on the regulation implementation timing while small domestic firms and foreign firms are forced to adapt. We cannot identify this influence explicitly however we do see indications that it occurs.

On the other hand, there may be high costs associated with the development of the new technologies. These costs generally decrease as a knowledge stock forms for the technology. Thus from this perspective, countries also have an incentive to free ride and adopt the regulation later.

3.1.1 Literature Review

The Porter hypothesis has been studied with respect to a variety of regulations and under a variety of conditions. For instance Xepapadeas and de Zeeuw (1998) develop an early theoretical model for Porter's hypothesis. Greaker (2003) also builds a model that shows if emissions are an inferior or normal good input then strong environmental policies can lead to an increase in firm competitiveness. See Ambec et al. (2011) for a survey. Empirically, Qiu et al. (2017) show that regulation can spur firm entry. Jaffe and Palmer (1997) find that lagged environmental compliance costs have a positive effect on R&D investments. Dechezleprêtre and Glachant (2014) study the different effects of domestic versus foreign policies on innovation in the wind industry. Sen (2015) shows that environmental policies have a negative effect on innovation however the effect

[1] see Zingales (2017) and Saikawa (2013)

is diminished by agency effects. Johnstone et al. (2010) find that more targeted regulations and subsidies are required to induce innovation on more costly technologies.

More specific to vehicle regulations, Crabb and Johnson (2010) find that CAFE regulations have no effect on car innovations however oil prices do affect innovation. Dou and Linn (2020) find that passenger vehicle fuel economy regulations have led to a general shift in demand away from new vehicles. D'Haultfoeuille et al. (2016) investigate how CO2 vehicle emissions were affected by an energy label requirement and a feebate on CO2 emissions. Allcott and Knittel (2019) examine the question of whether consumers are poorly informed about fuel economy through two experiments. Gerard and Lave (2005) provide an anecdotal overview of technological developments in the early rounds of vehicle emission regulations. In particular they expound on the role of catalytic converters in 1975 and the three-way catalyst in 1981. Levinson (2019) provides evidence for a more asymmetric effect on househfolds of energy efficiency standards as opposed to fuel taxes.

Popp (2002) estimates the effect of energy prices on energy efficient innovations. Isaksen (2020) discusses the empirical issues of self selection, anticipation, aggregation etc. on the effects of international pollution protocols and still finds that they have led to emissions reductions. Popp et al. (2010) provide a survey about how incentives to develop new environmentally friendly technologies became a policy focus. aus dem Moore et al. (2019) study how the EU ETS affects firm holding of fixed assets. While Levinson (1996) investigates how the stringency of state environmental regulations can affect establishment location choices. Brunnermeier and Cohen (2003) show that changes in pollution abatement expenditures affect patent output. They also test whether enforcement had an effect on innovation incentives and find no evidence.

Other studies that focus on demand pull effects on innovation include Peters et al. (2012) who discuss how demand pull policies can create significant innovation spillovers which would discourage domestic policy makers from implementing regulation. They find no evidence that domestic technology push policies foster innovative output outside of national borders. Verdolini and Galeotti (2011) discuss the push and pull effects of innovation in an international setting and show that a higher technological and geographic distance leads to less knowledge spillovers. Finally, Wang et al. (2019) investigate the pull effect from a different source: the stock market. Essentially, they question whether stock market valuations of environmentally friendly information lead to an actual environmentally friendly outcome.

The remaining of the chapter proceeds as follows: Section 3.2 below gives an overview of the regulatory and patent datasets, section 3.3 describes the empirical model, section 3.4 presents our main results, robustness checks, a technology breakdown and section 3.5 concludes.

3.2 Data Description

Here we describe the various considerations concerning the collection of the vehicle emissions regulations as well as the choices made when building our innovation measures.

3.2.1 Regulation Data

A combination of air pollution concerns led to the Air Pollution Control Act of 1955 in the United States which was signed into law by Eisenhower on July 14, 1955. At this time, the scope was simply to "provide research and technical assistance relating to air pollution control" and the act mostly called on states to take charge and prevent air pollution at the source. It wasn't until 1963 that the first version of a federal legislation: the Clean Air Act (CAA) was instated and only in 1968 did the CAA amendments include a provision on vehicle emission limits. The first substantially stringent limits were passed in 1970 and required emission reductions of 90% from the levels at the time. Implementation had been scheduled to take effect in 1975 but were delayed due to technology limitations and were instead implemented progressively with full scale being reached in 1979.

In parallel, vehicle emissions legislation was beginning in other countries as well. Notably Japan first introduced carbon monoxide (CO) emissions in 1966. They then announced limits on CO, hydrocarbons (HC) and nitrous oxides (NOx) in 1970 with an implementation date of 1973. However with the Muskie proposals and the announcement of substantially more stringent regulations in the US, the Japan Central Council for Environmental Pollution Control responded with a proposal for more stringent exhaust emission standards in 1971. These limits were set in 1975 and remained for sixteen years although revisions to test procedures effectively made them more severe.

Emissions standards in Europe were first formulated by the United Nations Economic Commission for Europe (UN-ECE). However the UN-ECE has no enforcement power and therefore relies on the individual member countries to adopt and enforce the regulations. The first framework for vehicle regulations was set in 1970 with the 70/220/EEC Directive. This was the first to outline a test procedure and made reference to an end-of-pipe air filter technology for the exhaust system although the purpose of this directive targeted vehicle sound pollution. Limits on pollutant emissions were officially introduced on June 26, 1991 with Council Directive 91/441/EEC - globally known as Euro 1 - amending Directive 70/220/EEC. This defines the scope of our regulatory variable:

"This Directive applies to the tailpipe emissions, evaporative emissions, emissions of crankcase gases and the durability of anti-pollution devices for all motor vehicles equipped with positive ignition engines and to the tailpipe emissions and durability of anti-pollution devices from vehicles of categories M1 and N1 (1), equipped with compression-ignition engines covered by Article 1 of Directive 70/220/EEC in the version of Directive 83/351/EEC (2), with the exception of those vehicles of category N1 for which type-approval has been granted pursuant to Directive 88/77/EEC"

The baseline EU regulations set limits for different pollutants measured in g/km, as shown in Table 3.1. Our final regulatory dataset was selected to cover 95% of global vehicle and vehicle parts imports.[2]

Starting from the regulatory dataset used in Perkins and Neumayer (2010), we updated and expanded the information to cover more countries and more years. Some sites and organizations tracking this information are: Concawe, Transport policy, MECA, CAI for Asia, UNEP, etc.. However the information is often incomplete and sometimes inconsistent between sources so we often dive deeper into the respective problem countries and look for original regulatory documents.[3]. This, of course, is a constant work in progress as we do not claim to have found the entire population of regulatory documents.

[2]Measured from CEPII's Baci trade dataset at the HS6 level. This captures 75 countries.

[3]See Appendix D for the various sources. The set of documents collected will be eventually available online

Tier	Date	CO	THC	NMHC	NOx	HC+NOx	PM	PN [#/km]
Euro 1	07/1992	2.72	-	-	-	0.97	-	-
Euro 2	01/1996	2.2	-	-	-	0.5	-	-
Euro 3	01/2000	2.3	0.2	-	0.15	-	-	-
Euro 4	01/2005	1	0.1	-	0.08	-	-	-
Euro 5	09/2009*	1	0.1	0.068	0.06	-	0.005**	-
Euro 6	09/2014	1	0.1	0.068	0.06	-	0.005**	6×10^{11}

Table 3.1: Summary of Euro regulations

EU emissions standards for passenger cars (M1):
Table from: https://www.dieselnet.com/standards/eu/ld.php
Note that prior to Euro 5, passenger vehicles above 2500 kg were type approved as category N1 vehicles. Measurement units for CO, THC, NMHC, NOx, and PM are in g/km.
* 01/2011 for all models
** Applies only to vehicles with direct injection engines

The problem with not having a full population of documents is that we cannot guarantee the dates that we have noted. Our regulatory dataset is constructed from implementation dates however sometimes we only have the announcement document that specifies an implementation date. In reality that implementation date may have changed and is in fact rather frequently delayed for various reasons. If we do not find the document for the date change/delay, then we do not have the correct implementation date in our dataset. At the same time, one can argue that the announced implementation date is the most important date as it is the date firms expect apriori and is arguably the schedule they innovate according to. Nonetheless government policy generally accommodates national interests so when the regulation is too stringent for the technology at the expected implementation date, it may get delayed to allow for technology to reach that level. This occurred in the US during their initial introduction of emissions regulations. The announced implementation date of 1975 was delayed and instead introduced progressively since the technology was not available at the time. Similarly, European Council Directives specifically mention that they have taken into account available technologies:

"Whereas the work undertaken by the Commission in that sphere has shown that the Community has available, or is currently perfecting, technologies which allow a drastic reduction of the limit values in question for all engine sizes" - Directive 91/441/EEC, amending 70/220/EEC

Another reason for regulation delay is delay of available resources, namely fuel availability. Brazil for instance, had to delay their passenger car diesel regulations in 2009 due to lack of available 50ppm fuel. We do not track fuel regulations as, to the best of our knowledge, their main impact is on the final implementation date of vehicle emissions regulations. The relevant technologies for fuels have little overlap with the technologies in emissions control. Of consequence however, may be regulations on fuel economy (CO_2 levels). The US began its Corporate Average Fuel Economy (CAFE) standards in 1975 requiring car manufacturers to reach 27.5 miles per gallon (average mpg) for passenger cars (PCs) by 1985. They were then tightened to 35.5 mpg in 2007 to be achieved in 2016 and in 2011 the new target was set to 54.5 mpg for implementation in 2025. In the EU, fuel economy standards began later but once introduced were more stringent than the US standards at the time. It was announced in 1998 that CO_2 emissions were to be reduced by 25% by 2008. Fuel economy standards target the general functioning of the vehicle and therefore may overlap with technologies we identify for emissions of other greenhouse gases. As discussed later in our analysis, we include some robustness checks on specific technologies, namely end-of-pipe technologies such as catalytic converters, that are theoretically unaffected by fuel economy regulations.

Figure 3.1 below illustrates the regulation specific (estimated) market size changes over time.[4] We clearly see two cycles in the lifetime of each regulation. The early regulatory movers make up the first cycle during which the market size increases globally until some countries in that set move on to a higher regulatory level. This causes a large drop in market size for the previous regulation and a comparable increase in the new regulation. Overtime however, laggard countries will continue to adopt the older regulation and this causes another cycle for this regulation.

Appendix C provides more details of this data collection process including Figure 3.2 which displays the implementation years of each country by regulatory level in my final dataset.

3.2.2 Patent Data

Our measures of innovation are built from PATSTAT (spring 2017 version), a database on patent documents maintained by the European Patent Office (EPO). There are over 100 countries and regions covered in the database with an application filing year going as far back as the mid 1800s. This database covers essentially the population of European patents and contains very comprehensive coverage of many other countries.

[4] The market size is calculated using imputed sales which are described further in section 3.2 and the appendix.

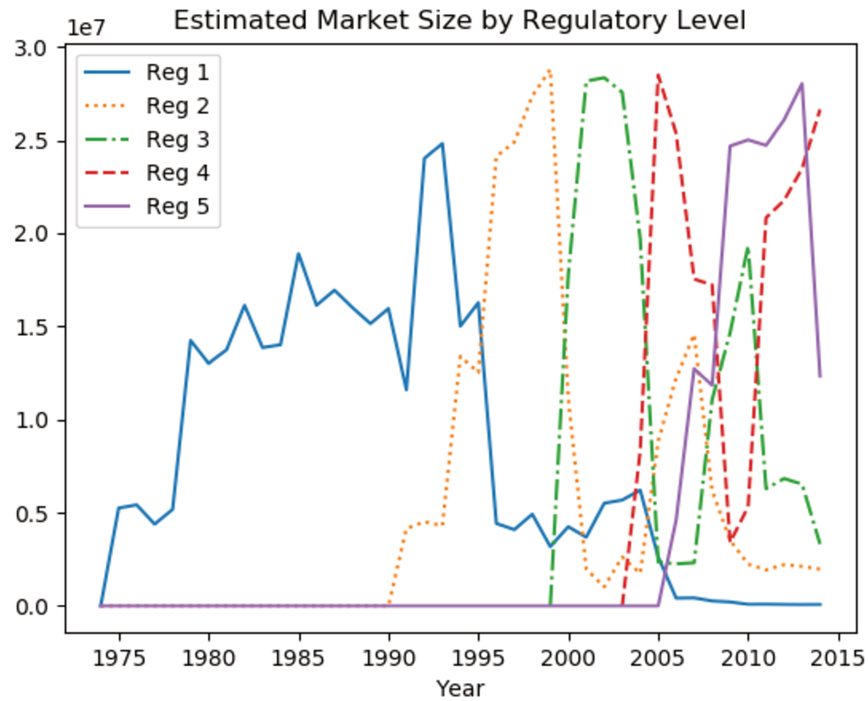


Figure 3.1: Estimated market size by regulation level
The estimated market size of each regulatory level over time. The market size is estimated based on passenger car sales in each country. See Appendix C for more details.

Proper use of the database requires in depth knowledge of each country's policies and idiosyncrasies as well as their changes over time.[5] The database consists of one table on patent application filings containing information on filing dates, authenticator office, number of applicants, number of inventors, patent family size, priority patent identifier, application type, corresponding publication id, granted status, etc.. There is similarly a table on patent publications including information on the patent authenticator, the publication kind, the publication date, whether the publication was granted, the publication claims, and more. In addition, there is a table on people, either applicants or inventors, and their name, address details and estimated sectors.

[5]For example, the Japan Patent Office imposes an additional fee on each claim after the first. Therefore on average, Japanese patents have a lower number of claims. Number of claims have been suggested as a patent quality indicator as they define the boundaries of the technology covered in the patent. However due to issues such as country specific rules, we will not use it as an indicator.

Finally, there are the tables that connect the applications and publications to people, the publications with other publications and application filings by citation, and the application filings to their priority filing. There are also smaller tables that add very specific information such as the text of abstracts, patent family citations, legal events, technology codes (IPC, CPC), product codes (NACE2), and some information on the non-patent literature collected through citations information.

We restrict our dataset to $1970-2013$ because 1970 is the year we first observe regulatory discussions while 2013 is chosen to avoid issues with substantial lags in data collection from different patent offices. All of the final countries in our regulatory dataset have some patent data up until 2015 however data completeness is not guaranteed and thus we use 2013 to leave a buffer. The buffer is also important in our quality measure built from citations as they are subject to truncation. Studies have shown that most of a patent's citations are made in the first five to seven years after publication however some continue to accumulate citations afterwards.

In order to evaluate the effect of emissions regulations on innovation, we need to identify the relevant technologies. Using the table on International Patent Classification (IPC) technology codes we identify the relevant emissions control technologies and aggregate them into the categories: integrated technologies, end-of-pipe technologies, general emissions control technologies, and zero-emission vehicles technologies (see Hascic et al. (2008), Volleberg (2010), and Aghion et al. (2016) for more details). Our baseline measure will be the general emissions control technologies which consist of end-of-pipe and integrated technologies. In theory, this is the set of technologies directly impacted by regulatory change. We do not include zero emission technologies as we expect them to react differently. Our assumption of standard specific technologies is perhaps most relevant for end-of-pipe technologies as these are add-on components that directly target pollutants. Integrated technologies include fuel injection technologies, airfuel ratio sensors, crankcase technologies, exhaust gas re-circulation technologies, and ignition timing technologies. The specific IPC codes are listed in Appendix A. We identify vehicle patents by the technology field number 32 provided in Patstat.

In our final dataset we restrict to firms that have patented at least five times in each country over our time period. This gives us a total of 592 firms with headquarters in 48 countries.

3.3 Empirical Model

In order to test our hypothesis that regulatory leadership leads to innovation leadership, we develop a specification to test whether being an early mover country leads to more innovation in firms.

Our baseline specification is a poisson fixed effects panel regression developed at the firm-country level for firm i in country c at year t:

$$P_{ict} = \alpha_1 Leader_{ct} + \alpha_2 Follower_{ct} + \alpha_3 X_{ict} + \sum_{r=1}^{5} \gamma_r \mathbb{1}[Reg_{ct} = r] + \gamma_{ic} + \gamma_t + \epsilon_{ict} \tag{3.1}$$

Where P_{ict} is our innovation measure that captures the amount of patent applications made by firm i in vehicle emissions control. $Leader_{ct}$ is an indicator variable for whether the country c was a regulatory leader in year t. We will provide some different measures of regulatory leadership however the baseline measure is defined as a country that is that has implemented the maximum stringency regulation and that the country applied the regulation within the first two years it was adopted globally. If there were no countries that implemented the regulation in the second year, we take the 'second' year as the next year a country implemented the regulation. We will provide robustness checks where $Leader_{ct}$ is only defined as the country or countries who were the first to implement the regulation as well as when the $Leader_{ct}$ measure covers the first three years of regulation implementation globally. The $Follower_{ct}$ measure is an indicator variable that captures the countries who implement the most stringent regulation after the leaders. Therefore the definition of this measure varies in relation to the definition of the $Leader_{ct}$ measure. Notably, this measure is still a measure of when the country adopts the most stringent regulation globally. The null case is when the country is at a weaker regulatory level.

We include dummy variables, Reg_{ct} , for all five regulatory levels separately because each regulatory level has its own idiosyncrasies. They do not necessarily increase technology requirements at the same pace nor by equal degrees of stringency. The γ_{ic} are firm-country fixed effects and γ_t are year fixed effects. The year effects will control for global trends in patenting including international changes to intellectual property rights. Finally, the X_{ict} are firm country controls which consist of an emissions control technology knowledge stock measure.[6]

Our main coefficients of interest are α_1 and α_2 which capture the effect of being a leader or follower on firm innovation. Following our hypothesis, we expect that α_1 will have the largest magnitude and be the most significant in terms of effect on patenting output of emissions control technologies. We are also interested in the difference between α_1 and α_2 to test whether there is a significant difference between being a leader and a follower. α_1 and α_2 will capture the regulatory demand pull effect on firm innovation. I can also investigate the technology push effect through the knowledge stock measure which will be captured through α_3. The X_{ict} is a logged measure so α_3 will measure the change in innovation output from a percentage change in the firm's knowledge stock and if the technology push effect exists, we expect this coefficient to be positive.

Our baseline specification captures both the push and pull effects of innovation creation typically described in the literature. A regulation imposed change in market definition makes up the demand pull effect while previous build up of knowledge and patent stock facilitates new inventions and therefore 'pushes' innovation forward. In addition, our specification removes concerns about market size changes by building the model at the firm-country level instead of firm-level. With firm-country fixed effects, we capture the variation in country demand and control for the firm's specific market share in each country. Regulation timing adds a temporal dimension to studies of environmental regulation on firms and firm innovation that have not been extensively studied to the best of our knowledge.

In terms of endogeneity concerns, all our regulatory measures are exogenous assuming that individual firms cannot influence their respective countries regulatory decisions.[7] The only variable that may be subject to endogeneity is the knowledge stock variable which is built from patent counts. We address this by lagging the knowledge stock variable as is common in the literature.

[6] We proxy for X_{ict}^{EC} with patent stock calculated from the traditional inventory method with a 15% discount rate ($\rho = 0.15$). To be precise:

$$x_{ict}^{EC} = P_{ict}^{EC} + (1-\rho) * x_{ict-1}^{EC}$$

The final X_{ict} measure is the log of x_{ict} lagged by one year.

[7] This assumption may questioned in reality as there have been studies in political economy about how firms try to influence policy making through their lobbying efforts.

The other concern is a timing around the time of patent filing. By the time a patent is filed, there has already been a substantial amount of time and effort put into developing the technology which may have started quite a bit earlier. Although we would ideally like to have this date of when the R&D began, this data is not available publicly. The only innovation measure we have are patents which are a measure of innovation output. This is the reason we mentioned in Section 3.2 for why we use the regulation implementation date instead of the announcement date. Firms have an incentive to patent their inventions as late as possible to minimize the risk of other firms imitating their technology or free-riding on their R&D efforts. This is why we suggest that the implementation date is the date they will file patents for technology that are relevant to that regulatory stringency. A regulation is in practice announced much earlier and may be inducing firm innovation from that point on, however we suggest that this induced innovation does not appear publicly as patents until the implementation date.

Next we revisit our main question and ask how does a firm's home country regulations affect its innovation elsewhere. To do so, we include home leader and follower variables into the specification as such:

$$\begin{aligned} P_{ict} = {} & \alpha_1 Leader_{ct} + \alpha_2 Follower_{ct} + \beta_1 HomeLeader_{it} + \beta_2 HomeFollower_{it} \\ & + \alpha_3 X_{ict} + \sum_{r=1}^{5} \gamma_r \mathbb{1}[Reg_{ct} = r] + \gamma_{ic} + \gamma_t + \epsilon_{ict} \end{aligned} \tag{3.2}$$

The $HomeLeader_{it}$ and $HomeFollower_{it}$ measures are variables that indicate whether the firm's home country is a regulatory leader or follower.[8] The definitions of leader and follower are the same as the ones described above. Here these home regulatory measures become firm-year specific measures as we assume the firm's home country does not change.

Although there are benefits to increased innovation overall in its country, a policy maker is arguably more concerned with the competitive advantage of its domestic firms.[9] To investigate how a policy maker's regulatory timing affects its domestic firms, we examine β_1 and β_2 from (3.2). If the policy maker has an effect on firm innovation outside of just its domestic borders,

[8] We identify a firm's home country based on the first two characters of the firm's BvDid from Orbis.

[9] There are many studies that find innovation advantages from geographic proximity due to local spillovers.

we expect to see a significant coefficient on $HomeLeader_{it}$ and $HomeFollower_{it}$. If being an early mover policy maker has an effect on domestic firm innovation, we expect to see a positive coefficient on $HomeLeader_{it}$ and we expect it to be significantly different from $HomeFollower_{it}$.

Finally, we are also concerned with the duration of the effect of the policy maker on its domestic firms. To examine this duration, we then run the above regression (3.2) on different lags for the home regulatory variables. Lasting effects should be captured in the coefficients on the different $HomeLeader_{it}$ and $HomeFollower_{it}$ lags.

3.4 Results

Table 3.2 presents our core results. All columns control for firm-country fixed effects and include a full set of year dummies. The dependent variable is a count of emissions control patent applications filed by a given firm in a given country in a given year and the definition of the leader variable is based on the first 2 years of regulation implementation. Column (1) displays the result from equation 3.1. It shows that being a regulatory leader leads to a significant and positive effect on patenting in emissions control technologies. In fact the coefficient on Leader suggests that there is a 19.7% increase on patent applications due to being a regulatory leader. However being a regulatory follower has no effect on innovation in emissions control technologies; the coefficient on Follower is insignificant. Furthermore the chi square statistic confirms that the leader and follower coefficients are significantly different at the 1% level.

Column (1) also shows that having a higher knowledge stock leads to more innovation which we expect to have from the technology push effect. The coefficients on the regulation dummy variables are also displayed to show the variation in regulatory level on patenting. It appears that the second regulatory level had the strongest effect on innovation. The first level is also quite high, then the effect on innovation diminishes. Regulation 5 in particular has an insignificant coefficient. This may be due to the fact that our dataset stops early on in the cycle of the fifth regulatory level. The identification of the relevant technologies for regulation five may also be subject to measurement error as those technologies may be quite new and different to the techologies in the other regulations. In particular, our identification of emissions technologies was based on Hascic et al. (2008) which was published in 2008. At this time, Euro 4 had just passed

	(1)	(2)	(3)	(4)	(5)
Leader	0.1970***		0.1565***	0.1895***	0.1770***
	(0.0385)		(0.0375)	(0.0380)	(0.0394)
Follower	-0.0083		0.0114	-0.0060	-0.0028
	(0.0382)		(0.0349)	(0.0368)	(0.0366)
Home Leader		0.0873***	0.0733***	0.0520**	0.0482**
		(0.0230)	(0.0248)	(0.0236)	(0.0236)
Home Follower		-0.0161	0.0171	-0.0063	-0.0097
		(0.0270)	(0.0265)	(0.0244)	(0.0247)
Knowledge Stock	0.3812***	0.3814***	0.3912***	0.3825***	0.3818***
	(0.0092)	(0.0092)	(0.0095)	(0.0092)	(0.0092)
Regulation 1	0.4047***	0.4287***		0.4107***	0.4006***
	(0.0668)	(0.0687)		(0.0653)	(0.0666)
Regulation 2	0.6645***	0.6920***		0.6648***	0.6567***
	(0.0903)	(0.0946)		(0.0886)	(0.0901)
Regulation 3	0.2810***	0.3343***		0.2996***	0.2748***
	(0.0707)	(0.0772)		(0.0693)	(0.0710)
Regulation 4	0.2315***	0.3001***		0.2596***	0.2286***
	(0.0774)	(0.0845)		(0.0743)	(0.0778)
Regulation 5	0.0256	0.1473*		0.0048	0.0146
	(0.0852)	(0.0860)		(0.0852)	(0.0844)
Year FE	y	y	y	y	y
Firm-Country FE	y	y	y	y	y
Sales control	y	y			y
Number of Observations	207262	204747	204772	204772	204747
Number of groups	13227	13089	13089	13089	13089
Number of firms		529	529	529	529
chi2 leader - follower	30.34		13.71	24	22.1
chi2 home leader - home follower		21.07	6.31	7.18	7.26

Table 3.2: Baseline regressions

are the baseline poisson regressions with the count of emissions control patents as the dependent variable. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in some of the regressions to control for changes in a country's demand over time. See the appendix for more information on the construction of the sales measure.

the peak of its first cycle and Euro 5 had just started. As it has been suggested that emissions control technology is standard specific, there may simply not be enough data to evaluate and identify the dominant technologies for Euro 4 and Euro 5.[10]

[10]See Lee and Berente (2013) on dominant technologies

Another possibility is the impact of what we now know as cheating scandals among some large car manufacturers in the more recent years. Although these scandals have been largely focused on diesel engines, and we use petrol regulations, there are potential technology spillovers since we are not able to perfectly separate the two in our dependent variable. However we expect that this effect should be small since it only covers a handful of firms while we have hundreds of firms in our dataset, however there could also have been cascading effects if assembly firms decreased their demand for these technologies from smaller more specialized firms. Furthermore, since a substantial part of research and development on reducing vehicle emissions has become more software related in recent years, patent data may be deteriorating as an innovation measure as software code is more likely to be kept secret and intellectual property rights are not well established for software code yet.

In Columm (2) we provide a baseline for the effect of home-country regulation timing on innovation output in other countries. The coefficient on Home Leader shows that being a regulatory leader leads to positive and significant effects on innovation for your domestic firms. The magnitude of this effect, 8.7%, is however smaller than the effect in Column (1) which is to be expected. Home-country regulatory leadership is a more indirect measure of regulatory leadership than the Leader measure in Column (1). On the other hand, the insignificant coefficient on home follower implies that implementing a regulation late leads to no impact on your domestic firm's vehicle emissions control innovation output. This is the same case as in the direct country regulatory follower measure.

Notably, in this study, we do not explicitly investigate the reasons for this difference in innovation output. It could be that once the technology is developed it is available in some capacity for the firms in late-mover countries to use. There could be a free rider effect in the late mover countries. This implies that the firms in the late-mover countries do not have to invest in high R&D costs to develop the technology and can simply use the technology once it is developed. However the fact that there are intellectual property rights means they cannot access the technology for free. If being a late mover meant having access to a larger knowledge pool of relevant technologies that would then facilitate follow on inventions, we would expect the number of patent applications to increase for late movers. Here, since the measure is insignificant and in fact slightly negative, implies that the firms in follower countries have decreased their innovation in emissions control technologies. They have perhaps shifted their R&D focus to other innovations so they simply do not focus on R&D. They instead may choose to license the technology or buy the vehicle component to assemble if it is a component that can be added-on as in end-of-pipe technologies which I will visit later.

Columns (3), (4), and (5) present the results from equation 3.2 where we include the direct country leader and follower measures with the indirect home-country leader and follower measures. The different columns include different control variables. Namely in column (3) we do not use regulation dummies, column (4) includes the regulation dummies and column (5) includes and regulation dummies as well as a country level sales control variable. The sales control variable represents the sales of passenger cars in the country over time. This variable is included to capture variation in the country's market over time - as the level of the sales by country should be captured in the firm-country fixed effects. This variation may be important in developing countries that have seen a large increase in usage of passenger cars like China and India. However the data on passenger car sales is not available for all countries over the entire time period, therefore I use an imputation method to fill in the missing values. This methodology is described in Appendix C. Nevertheless, any imputation will introduce more volatility into the measures and requires strong assumption as the data points are not randomly missing. Therefore we often present the results without the sales control for a robustness check.

As seen in columns (4) and (5), the estimates are very robust to the inclusion of the sales variable. In general, when the direct country regulatory timing measures and indirect home-country regulatory timing measures are included together, the magnitudes of the two effects diminishes slightly. However both the Leader and Home Leader coefficient estimates remain positive and significant. Including the sales control in column (5) decreases the magnitude of the regulatory leadership effect for both the direct country and home country. While comparing columns (3) and (4) suggests that when the regulatory levels are not controlled for, the home-country leader effect is over estimated while the direct country leader effect is under estimated.

Table 3.3 displays the results when we use the stricter definition of leadership where a regulatory leader is the first to implement the maximum regulatory level - it is a first mover. This means we define leader as the countries that implement the regulation in the first year it appears globally.

	(1)	(2)	(3)	(4)	(5)
Leader	0.2055***		0.2302***	0.2491***	0.2392***
	(0.0469)		(0.0509)	(0.0474)	(0.0481)
Follower	0.0448		0.0399	0.0371	0.0353
	(0.0354)		(0.0309)	(0.0337)	(0.0347)
Home Leader		0.0064	-0.0130	-0.0556*	-0.0620**
		(0.0298)	(0.0324)	(0.0299)	(0.0298)
Home Follower		0.0301	0.0513**	0.0279	0.0241
		(0.0238)	(0.0233)	(0.0217)	(0.0221)
Knowledge Stock	0.3812***	0.3810***	0.3906***	0.3824***	0.3816***
	(0.0091)	(0.0091)	(0.0094)	(0.0092)	(0.0091)
Regulation 1	0.4210***	0.4422***		0.4362***	0.42120***
	(0.0667)	(0.0686)		(0.0646)	(0.0664)
Regulation 2	0.6737***	0.7129***		0.6896***	0.6785***
	(0.0904)	(0.0950)		(0.0884)	(0.0906)
Regulation 3	0.2792***	0.3549***		0.3143***	0.2829***
	(0.0717)	(0.0771)		(0.0705)	(0.0718)
Regulation 4	0.2389***	0.3220***		0.2796***	0.2386***
	(0.0784)	(0.0843)		(0.0752)	(0.0786)
Regulation 5	0.0875	0.2014**		0.0856	0.0900
	(0.0939)	(0.0906)		(0.0958)	(0.0933)
Year FE	y	y	y	y	y
Firm-Country FE	y	y	y	y	y
Sales control	y	y			y
Number of Observations	207262	204747	204772	204772	204747
Number of groups	13227	13089	13089	13089	13089
chi2 leader - follower			17.29	27.12	27.2
chi2 home leader - home follower		0.74	5.75	10.82	11.75

Table 3.3: Regressions with leader defined as first-mover

These are the poisson regressions with the count of emissions control patents as the dependent variable and the leader variable defined as countries who implement the most stringent regulatory level in the first year it appears globally; this is the strictest measure of leader. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in some of the regressions to control for changes in a country's demand over time.

In column (1) we again see that being a leader has a direct positive and significant effect on firm innovation output of about 20%. Now the estimate on Follower is more positive albeit still insignificant. The estimates on technology push and controls for each regulatory level remain very similar to Table 1. However in column (2), the home-country leader measure is no longer significant. This suggests that the home-country effect mainly comes from countries that are second to implement the regulation. Being a regulatory first mover imposes many more restrictions on your domestic firms and this seems to imply that your domestic firms become less focused on its foreign markets.

The fact that the home-country regulatory measures are not significant imply that either the regulation is too strict and the innovation at the time is not ready to be patented or the regulation was subject to lobbying from its domestic firms which would confuse the effect of timing on innovation. See Grey (2018) for a discussion on how corporate lobbying plays a role in environmental regulations or Zingales (2017) for a more general discussion of corporate lobbying.

These political economy implications were mentioned earlier. Countries that are first movers are likely to be influenced by lobbying from their large domestic firms on the timing of the implementation. If the domestic firms are able to influence the implementation timing, they may have filed the relevant patents before the implementation date as the grant process takes some time. Although it varies by country, patent applications usually get published after a delay so the domestic firms may optimally file their patents earlier. Foreign firms however may be more hesitant to file early in another country even if there is a delay as they likely cannot influence the regulation implementation date. An analysis to do in future work would be two stratify the sample by firm size as we would expect it is the large firms who have the power to influence policy makers.

Columns (3), (4), and (5) in Table 3.3 show the estimates when both the direct country and indirect home-country regulation leadership measures are included. These columns show that a home-country first mover in fact has a negative effect on innovation output in other countries. This effect is weakly significant and consists of a 5 to 6 % negative effect. This could be consistent with a shift to earlier patenting due to influence on the regulatory process. If the firm's home-country was a regulatory first mover, and the firm filed the relevant technologies for this regulatory level before the first date of implementation, then the firm will also file this technology in other countries earlier too because international intellectual property rules state a maximum delay between filings of the same invention in different countries.

On the other hand, we have already seen in Table 3.2 that home countries that are early movers have a positive and significant effect on firm innovation output in other countries - where early mover was defined as the first two years instead of only the first year.[11] Therefore, although the political lobbying process is likely to be a part of the reason, clearly another part of the explanation is due to the regulation being too stringent. As our regression is run on firm-country fixed effects, they variation between firms is controlled for. Therefore, small firms, who may not be able to influence domestic regulation implementation are treated equally to large firms. For the small firms, we see that they lose out in a first-mover country as the regulation is likely too stringent for them in the first year of implementation and it is only in the later two or three years that they catch up with the innovation filings, which explains the positive effect we see on Home Leader in Table 3.2.

Similarly Table 3.11 in the appendix shows the estimation results when the leader measure is defined by the first three years of global regulation implementation. The coefficients are broadly the same as in Table 3.2 except the estimate on Follower is now significantly negative. This means that the positive innovation effects come mainly from the second and third regulatory movers; afterwards a country that changes to the maximum regulatory level experiences a significant negative effect on patent filings.

So far we have established that there is an early mover advantage to regulation implementation for domestic firm innovation. We are now interested in the persistence of this effect. To study this, we introduce the home-country leader and home-country follower measures with different lags. Table 3.4 displays the results for these regressions. The regulatory leadership measures here are based on the first two years of regulation implementation. Similar to the results in table 3.2, the estimates on Leader and Home Leader are both positive and significant with the direct Leader effect having a magnitude of three times larger than the home-country leader effect. Furthermore the home-country leader effect is only significant at the 5% level. The effect stays quite persistent as the lags increase on the home country regulatory measures. In fact, the estimates increase until the third lag before decreasing. This implies that being a regulatory early mover as a policy maker will lead your domestic firms to increase their innovation output in other countries for multiple years.

[11] Note that the first 'two years' is not literally the first two years but the first two years that have seen an increase in regulation implementation.

	(1)	(2)	(3)	(4)	(5)
Leader	0.1745***	0.1740***	0.1687***	0.1689***	0.1722***
	(0.0396)	(0.0391)	(0.0390)	(0.0392)	(0.0395)
Follower	-0.0052	-0.0076	-0.0054	-0.0060	-0.0068
	(0.0364)	(0.0367)	(0.0366)	(0.0363)	(0.0360)
Home Leader (t-1)	0.0535**				
	(0.0227)				
Home Follower (t-1)	-0.0060				
	(0.0250)				
Home Leader (t-2)		0.0556**			
		(0.0228)			
Home Follower (t-2)		-0.0018			
		(0.0240)			
Home Leader (t-3)			0.0597***		
			(0.0225)		
Home Follower (t-3)			-0.0086		
			(0.0239)		
Home Leader (t-4)				0.0518**	
				(0.0219)	
Home Follower (t-4)				-0.0088	
				(0.0236)	
Home Leader (t-5)					0.0446**
					(0.0215)
Home Follower (t-5)					-0.0112
					(0.0237)
Number of observations	204066	203417	202702	202038	201330
Number of groups	13081	13073	13063	13054	13040
chi2 leader - follower	22.18	22.73	21.8	23.15	24.66
chi2 home leader - home follower	7.78	8.2	11.34	9.28	7.73

Table 3.4: Regression with home regulatory variables lagged

These are the poisson regressions with the home regulatory measures lagged and the leader variable defined as countries who implement the most stringent regulatory level in the first two years it appears globally. The dependent variable is the count of emissions control patents. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

The evidence that the innovation increases for multiple years may imply different stages of innovation. When the regulation is first implemented, the innovation that is mandated is a product innovation. It is a regulation that imposes a limit on vehicles emissions which therefore affect the 'product' characteristic of emissions intensity. In theory the regulation essentially nullifies all previous vehicles produced and creates a competition for the market among the vehicle manufacturers. The first firm to develop the technology will get the entire market at least for the time until the next firm develops a technology that can meet the regulation requirements.

However emissions reducing technology have a very high cost. Since the firm knows that other firms will develop the needed technology as well, this encourages the firm to continue innovating to lower the marginal costs on the invention even after it has developed the technology relevant to the regulation. These follow-on innovations may be more incremental but still very important to the firm's competitiveness. As such, regulatory leadership has an effect over multiple years. In addition, more early innovations will increase the firm's knowledge stock in those areas which will further increase the innovation output through the technology push effect in future years.

Following the political economy argument, we would expect the dominant technologies to be implemented earlier than the home country regulation implementation date while we expect the follow-on incremental innovations to expand after the implementation date. As such, we measure the importance of the innovation output through a count of patents weighted by the number of citations received. Table 3.12 displays the results when we use this citation weighted measure as the dependent variable. The estimates on both leader and follower are negative now. Recall that these coefficients are measured with respect to the third case which consists of when the country is at a regulatory level below the maximum. To have negative coefficients on both the leader and follower measures implies that the most important innovations occur during the time a country is below the maximum regulatory level. This may be during an anticipation period when firms know a country will soon increase its regulation stringency or it may simply be an effect of being a very late mover. We cannot disentangle these effects however we suggest that the anticipation effect is much more likely.

Table 3.12 taken together with table 3.2, suggests that the more cited inventions are developed before the implementation date of the regulation and that the incremental innovations which induce fewer citations are made after the implementation date. This may also be due to clusters of patenting of emissions control technology corresponding to the changes in regulation stringency. It has been suggested that the different levels of emissions limits correspond to different technologies. As such, if there is a finite number of patents filed related to this relevant technology, and they are more likely to cite each other than other technologies, then it can result mechanically that the earlier patents have more citations than the later patents.

Tables 3.13 and 3.14 in the appendix display the results with different home country regulation lags for the first-mover leader definition and first-three-year-mover leader definition. Table 3.13 shows that the estimates with the first-mover home country measure remain insignificant with the different lags as was discussed in table 3.3. Table 3.14 presents the estimates with the leader defined with the three year ordering. The coefficients on the direct leader and indirect home leader variables are positive and significant and with magnitudes similar to those in Table 3.2. The coefficients on the follower measures here however are negative. For the direct follower measure the effect is negative and significant at the 5% level while the indirect home-country follower measure begins negative but insignificant and becomes more negative and more significant as the lags increase. We do expect the estimates on the home regulatory variables to decrease as the lags increase though it is interesting that this effect mainly appears in the follower measure.

So far the count data model we have used are poisson regressions with fixed effects. These are the most commonly used in the literature and the most robust of the count data models however they are also subject to certain constraints. The other count data models do not have true fixed effects. Their indicator variable will rather capture a dispersion measure instead. Nonetheless, table 3.15 in the appendix includes a robustness check with a zero-inflated poisson regression on the different definitions of leader. Notably, the direct leader coefficient has the largest positive and significant effect. The effect is also positive and significant for the direct follower effect. However the home leader and home follower variables are insignificant except for the third version where leader is defined as a country that changed to the maximum regulation in one of the first three years.

3.4.1 Technology Breakdown

We have so far treated the broad category of emissions control technologies but we can also disaggregate them to better identify relevant technologies. Emissions control innovations are largely made up of integrated technologies and end of pipe technologies.[12] A separate but related technology are the zero-emmission vehicle technologies which we will brieflt visit as well. Integrated technologies are part of the general functioning of the car. They include fuel injection

[12]See Appendix A for the detailed identification of each type of emissions control technology.

inventions, exhaust gas recirculation, crankcase emissions control, airfuel ratio, sensors, and on board diagnostics. These are technologies that will also help the general fuel economy of the car which is, although an environmental issue, also a property demanded by consumers as it translates into less money spent on fuel. As such, integrated technologies are not only affected by vehicle emissions regulations and we would expect them to be less responsive to changes in emission regulations. End of pipe technologies mostly consist of catalytic converters. Exhaust gas re-circulation technologies can arguably be included but here we follow Hascic et al (2008) and consider them part of the integrated technologies group. End-of-pipe technologies are modular components added to the end of pipe, to treat the emissions output from the combustion process. They can be more precise in targeting a specific pollutant. Intuition suggests that these technologies should be more responsive to regulation changes. Furthermore, since catalytic converters are an add-on component, they do not necessarily have to be developed by traditional car manufacturers and therefore may entail a different set of firms.

Table 3.5 summarizes the results when only end-of-pipe patents are counted in the dependent variable. We see that the results are largely the same as the results in table 3.2. The magnitudes of the positive coefficient on Leader and Home Leader is even larger for end-of-pipe technologies than for overall emissions control technologies. Since catalytic converters can target a specific pollutant, they may be more relevant for certain regulations. We investigate this in the estimates on the regulation levels however the results do not suggest any major differences to those in table 3.2. Table 3.16 displays the results using end-of-pipe technologies as the dependent variable and regressing on different home leader and home follower lags. The results are largely similar to the overall emissions control technology results. We see that the leader and home leader measures are both significant and positive and that the home leader coefficient decreases as the lags increase.

We look at integrated technologies next. In table 3.6 we see that being a home leader has a positive and significant effect when measured alone, however when it the direct leader and follower measures are included, the home regulatory measures lose their significance. The magnitude of the direct leader effect is smaller than for end-of-pipe technologies which is consistent with out expectation that integrated technologies would be less responsive to emissions regulations. The fact that the home regulatory measures are insignificant are also consistent with this expectation. Table 3.17 also confirms that the home regulatory measures remain insignificant at different lags

	(1)	(2)	(3)	(4)	(5)
Leader	0.2495***		0.1822***	0.2231***	0.2173***
	(0.0546)		(0.0452)	(0.0511)	(0.0539)
Follower	-0.0912		-0.0320	-0.0803	-0.0790
	(0.0672)		(0.0489)	(0.0628)	(0.0627)
Home Leader		0.1157***	0.0775***	0.0728***	0.0717**
		(0.0295)	(0.0299)	(0.0278)	(0.0279)
Home Follower		-0.0499	-0.0155	-0.0223	-0.0235
		(0.0411)	(0.0343)	(0.0316)	(0.0319)
Regulation 1	0.3211***	0.3487***		0.3193***	0.3151***
	(0.0737)	(0.0776)		(0.0725)	(0.0734)
Regulation 2	0.5314***	0.5610***		0.5223***	0.5193***
	(0.0999)	(0.1066)		(0.0988)	(0.0995)
Regulation 3	0.2921***	0.3197***		0.2921***	0.2820***
	(0.0767)	(0.0806)		(0.0762)	(0.0765)
Regulation 4	0.2210***	0.2830***		0.2268***	0.2148***
	(0.0818)	(0.0915)		(0.0802)	(0.0825)
Regulation 5	-0.0425	0.1042		-0.0609	-0.0582
	(0.0855)	(0.0875)		(0.0846)	(0.0844)
Year FE	y	y	y	y	y
Firm-Country FE	y	y	y	y	y
Sales control	y	y			y
Number of Observations	134580	133664	133705	133705	133664
Number of groups	7943	7875	7876	7876	7875
chi2 leader - follower	65.54		32.99	51.07	51.32
chi2 home leader - home follower		32.64	13.38	14.1	14.17

Table 3.5: Regressions with the End-of-Pipe patent count as the dependent variable. These are the poisson regressions with the dependent variable as the count of end-of-pipe patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first two years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

as well. This suggests that the home-country effects in the overall emissions control technology measure are primarily driven by end-of-pipe technologies.

Finally, zero-emission vehicle (ZEV) technologies are another type of innovation that would address the issue of vehicle emissions. The main categories of ZEV technologies are electric vehicles, hybrid vehicles and hydrogen cell technologies. The goal of this category of technologies is, as the name suggests, to emit zero pollutants. As such, this would be a big leap from the incremental improvements on vehicle emissions addressed by the end of pipe and integrated technology

	(1)	(2)	(3)	(4)	(5)
Leader	0.1821***		0.1576***	0.1898***	0.1763***
	(0.0402)		(0.0422)	(0.0411)	(0.0419)
Follower	-0.0018		0.0181	0.0031	0.0064
	(0.0383)		(0.0371)	(0.0375)	(0.0373)
Home Leader		0.0541**	0.0435	0.0199	0.0153
		(0.0248)	(0.0272)	(0.0258)	(0.0257)
Home Follower		-0.0219	0.0110	-0.0146	-0.0184
		(0.0278)	(0.0283)	(0.0261)	(0.0264)
Regulation 1	0.4263***	0.4526***		0.4358***	0.4248***
	(0.0732)	(0.0750)		(0.0716)	(0.0731)
Regulation 2	0.7028***	0.7318***		0.7072***	0.6985***
	(0.0992)	(0.1038)		(0.0974)	(0.0993)
Regulation 3	0.2945***	0.3500***		0.3144***	0.2874***
	(0.0781)	(0.0848)		(0.0766)	(0.0787)
Regulation 4	0.2417***	0.3103***		0.2718***	0.2374***
	(0.0857)	(0.0925)		(0.0822)	(0.0862)
Regulation 5	0.0496	0.1731*		0.0284	0.0408
	(0.0943)	(0.0963)		(0.0944)	(0.0935)
Year FE	y	y	y	y	y
Firm-Country FE	y	y	y	y	y
Sales control	y	y			y
Number of Observations	189652	187600	187625	187625	187600
Number of groups	11932	11826	11826	11826	11826
chi2 leader - follower	19.62		9.41	17.23	15.68
chi2 home leader - home follower		9.25	1.65	1.98	1.94

Table 3.6: Regression with the Integrated Technology patent count as the dependent variable
These are the poisson regressions with the dependent variable as the count of integrated technology patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first two years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

innovations. Since this technology, when available, will have zero emissions, it will meet all levels of regulatory limits. Thus we would expect that regulation timing issues do not have a direct impact on the innovation output of these technologies. However these technologies may be subject to spillovers from other emissions control technologies and therefore may also follow the trends of emission control technologies.

Table 3.7 displays the results with the dependent variable as a count of ZEV patents. We

	(1)	(2)	(3)	(4)	(5)
Leader	0.1170		0.1849*	0.1368	0.1550
	(0.1155)		(0.0989)	(0.1080)	(0.1093)
Follower	-0.2002**		-0.1481*	-0.2447***	-0.2467***
	(0.0951)		(0.0818)	(0.0919)	(0.0909)
Home Leader		-0.0567	-0.0792*	-0.0797*	-0.0765*
		(0.0588)	(0.0471)	(0.0443)	(0.0446)
Home Follower		0.0482	0.1012*	0.1166**	0.1200**
		(0.0654)	(0.0538)	(0.0510)	(0.0513)
Regulation 1	0.3817**	0.3912**		0.3872**	0.3870**
	(0.1895)	(0.1951)		(0.1880)	(0.1891)
Regulation 2	0.7734***	0.7330***		0.7924***	0.7914***
	(0.2468)	(0.2651)		(0.2485)	(0.2484)
Regulation 3	0.5793***	0.5255***		0.5902***	0.6104***
	(0.1779)	(0.1855)		(0.1735)	(0.1809)
Regulation 4	0.5093***	0.5248***		0.5040***	0.5290***
	(0.1869)	(0.2011)		(0.1813)	(0.1897)
Regulation 5	0.4668***	0.6461***		0.5073***	0.5023***
	(0.1648)	(0.1952)		(0.1653)	(0.1663)
Sales control	y				y
Number of Observations	101421	100449	100449	100449	100430

Table 3.7: Regressions with the count of zero emission vehicle patents as the dependent variable These are the poisson regressions with the dependent variable as the count of Zero Emission Vehicle patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first two years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

see that the direct regulatory leader effect is insignificant and the follower effect is negatively significant. For the home regulation measures, the estimate on home leader is negative and weakly significant while the home follower coefficient is weakly positively significant. This could be interpreted as a firm being more focused on the regulation specific technologies when its home country is a leader in that regulation, this would take away resources from R&D in ZEV technologies. However spillovers from the emissions control technologies developed during the early years of a new regulation implementation would spillover into innovation efforts in ZEV technologies. Therefore there may be a resource substitution effect as well as a spillover effect. The direct measure of leader and follower has a stronger resource substitution effect and may be why the follower coefficient is negative and significant.

3.5 Conclusion

To put this in perspective, our study of vehicle emissions regulations strategy is also part of a wider literature on global policy strategies between countries. Here we help elucidate certain characteristics that affect global strategy games with respect to green innovation. A particularity about environmental regulations is that the direction (more stringent limits in this case) is clear at least in the short term. As there is a certain, almost unanimous, urgency worldwide to mitigate climate change. This assurance essentially removes a factor of uncertainty in firm and governmental expectations. They can expect that regulation will move in one direction and they can choose whether to be leaders or followers in this action. Being a first mover has the risk of higher short term costs as well as the potential for developing a framework too idiosyncratic for further adoption. Certain technology developments will be applicable and relevant regardless however there may be a cost to switching regulatory frameworks later on.

Our results provide evidence that there are higher innovation benefits to being a regulatory early mover. Furthermore we find that there is a sustained positive effect on firm innovation from being an early mover. However the effects on domestic firms from being a **first** mover are different. This may be due to political economy issues which may introduce endogeneity into our specification, or this may be simply due to the large technological gap associated with being an early mover. Our breakdown of the emissions control technologies by end-of-pipe and integrated technologies show both types of technologies react to a direct country leader measure however the home country effect is only positive and significant on end-of-pipe technologies. For policy makers, this suggests that being an early mover positively benefits their domestic firms through their innovation output in end-of-pipe technologies but it does not have much of an effect on the integrated technologies.

Our analysis leads to some interesting questions for further research. For instance, how do other kinds of innovation react to changes in these regulations? Are these regulations cannibalizing the R&D investment that would have been put into other areas or does it increase total R&D output? Also, how has the timing of these regulations affected firm productivity? Competitiveness? Employment? Firm entry and exit dynamics? Has it created new opportunities for small and specialized firms? Catalytic converters, as add-on components, seem to be largely developed by a different set of firms. And how have changes in market structure been affected by pre-existing market positions? If a firm is a leader in emissions control technologies maybe they have less incentive to develop zero emissions vehicle technologies. As such, they maintain their high market share for the short term but when ZEV technologies reach maturity they are left catching up. This poses the question: have regulations been too focused on incremental change instead of radical innovation?

A IPC Codes

Table 3.8: Integrated Technology IPC codes and Description

Technology	IPC Codes	Description
Airfuel ratio	F02M 67	Apparatus in which fuel injection is effected by means of high pressure gas, the gas carrying the fuel into working cylinders of the engine (e.g. air injection type) - using compressed air for low pressure fuel injection apparatus
Airfuel ratio	F02M 23, 25	Apparatus for adding secondary air to fuel-air mixtures
Airfuel ratio	F02M 3	Idling devices for carburetors (with means for facilitating idling below operational temperatures
Sensors	F01N 11	Monitoring or diagnostic devices for exhaust gas treatment apparatus
Sensors	G01M 15/10	Testing of internal combustion engines by monitoring exhaust gases
Fuel injection	F02M 39 - 63, 69, 71	Fuel-injection apparatus /Arrangements of fuel injection apparatus with respect to engines/ Pump drives adapted to such arrangements, etc.
On Board Diagnostics	F02D 41 - 45	Electrical control of supply of combustible mixture or its constituents/ Conjoint electrical control of two or more functions e.g. ignition, fuel air mixture, recirculation, supercharging, exhaust gas treatment, etc.
On Board Diagnostics	F01N 9	Electrical control of exhaust gas treating apparatus
Exhaust gas recirculation	F01N 5	Exhaust or silencing apparatus combined or associated with devices profiting by exhaust energy
Exhaust gas recirculation	F02B 47/08, 10	Methods of operating engines involving adding non-fuel substances including exhaust gas to combustion air, fuel, or fuel-air mixtures of engines.
Exhaust gas recirculation	F02D 21/06 - 10	Controlling engines characterized by their being supplied with non-fuel gas added to combustion air, such as the exhaust gas of engine, or having secondary air added to fuel-air mixture
Crankcase emissions and control	F01M 13/02, 04	Crankcase ventilating or breathing
Ignition timing	F02P 5	Advancing or retarding electric ignition spark
Fuel efficiency	B62D 35, 37/02	Vehicle bodies characterised by streamlining/ stabilising vehicle bodies without controlling suspension arrangements
Fuel efficiency	B60C 23	Devices for measuring, signalling, controlling, or distributing tyre pressure or temperature, specially adapted for mounting on vehicles
Fuel efficiency	B60G 13/14	Resilient suspensions characterised by arrangement, location, or type of vibration-dampers having dampers accumulating utilisable energy
Fuel efficiency	B60K 31	Vehicle fittings, acting on a single sub-unit only, for automatically controlling vehicle speed, i.e. preventing speed from exceeding an arbitrarily established velocity or maintaining speed at a particular velocity
Fuel efficiency	B60T 1/10	Arrangements of braking elements by utilising wheel movement for accumulating energy

Table 3.9: End-of-Pipe Technology codes and Description

Category	Technology	IPC Codes	Description
End of Pipe	Exhaust Apparatus	F01N 3	Exhaust or silencing apparatus having means for purifying innocuous or otherwise treating exhaust by means of air
End of Pipe	Catalytic converters	B01D 53/92, 94, 96	Catalytic converters, lean NOx catalysts, NOx absorbers, regeneration (CAT), by catalytic processes/ regeneration, reactivation or recycling of reactants
End of Pipe	Catalytic converters	B01J 23/38 - 46	Catalysts comprising metals or metal oxides or hydroxides; of noble metals' of the platinum group metals.

Table 3.10: Zero Emissions Vehicle Technology codes and Description

Category	Technology	IPC Codes	Description
Zero emission vehicles	Electric vehicles	B60L 11	Electric propulsion with power supplied within the vehicle
Zero emission vehicles	Electric vehicles	B60L 3	Electric devices on electrically-propelled vehicles for safety purposes; Monitoring operating variables, e.g. speed, deceleration, power consumption
Zero emission vehicles	Electric vehicles	B60L 15	Methods, circuits, or devices for controlling the traction - motor speed of electrically propelled vehicles
Zero emission vehicles	Electric vehicles	B60K 1	Arrangement or mounting of electrical propulsion units
Zero emission vehicles	Electric vehicles	B60W 10/08,24,26	Conjoint control of vehicle sub-units of different type or different function/ including control of electric propulsion units, e.g. motors or generators / including control of energy storage means / for electrical energy, e.g. batteries or capacitors
Zero emission vehicles	Hybrid vehicles	B60K 6	Arrangement or mounting of plural diverse prime-movers for mutual or common propulsion, e.g. hybrid propulsion systems comprising electric motors and internal combustion engines
Zero emission vehicles	Hybrid vehicles	B60W 20	Control systems specially adapted for hybrid vehicles, i.e. vehicles having two or more prime movers of more than one type, e.g. electrical and internal combustion motors, all used for propulsion of the vehicle
Zero emission vehicles	Hybrid vehicles	B60L 7/1	Regenerative braking/ Dynamic electric regenerative braking
Zero emission vehicles	Hybrid vehicles	B60L 7/20	Braking by supplying regenerated power to the prime mover of vehicles comprising engine - driven generators
Zero emission vehicles	Hydrogen vehicles / fuel cells	B60W 10/28	Conjoint control of vehicle sub-units of different type or different function/ including control of fuel cells
Zero emission vehicles	Hydrogen vehicles / fuel cells	B60L 11/18	Electric propulsion with power supplied within the vehicle - using power supplied from primary cells, secondary cells, or fuel cells
Zero emission vehicles	Hydrogen vehicles / fuel cells	H01M 8	Manufacturing of fuel cells

B Additional Tables

Below are a series of tables referenced in Section 3.4.

Table 3.11 presents the results when the leader definition is based on the first three years a regulation is implemented.

Table 3.12 displays the results when we use the citations weighted count as the dependent variable.

Tables 3.13 and 3.14 show the home regulatory lag effects based on different definitions of the leader variable.

Table 3.15 does a robustness check on with the zero-inflated poisson regression model to account for the excess zeros. However, this model does not have true fixed effects.

Tables 3.16 and 3.17 show the persistent effects of home regulatory leadership when the dependent variable is end-of-pipe technologies and integrated technologies respectively.

	(1)	(2)	(3)	(4)	(5)
Leader	0.1637***		0.1602***	0.1552***	0.1495***
	(0.0388)		(0.0382)	(0.0373)	(0.0383)
Follower	-0.0886**		-0.0748**	-0.0759**	-0.0729**
	(0.0362)		(0.0343)	(0.0358)	(0.0357)
Home Leader		0.0720***	0.0659***	0.0422*	0.0389*
		(0.0237)	(0.0245)	(0.0228)	(0.0230)
Home Follower		-0.0593**	-0.0143	-0.0261	-0.0315
		(0.0285)	(0.0275)	(0.0259)	(0.0263)
Knowledge Stock	0.3803***	0.3807***	0.3903***	0.3813***	0.3806***
	(0.0090)	(0.0091)	(0.0093)	(0.0090)	(0.0090)
Regulation 1	0.3688***	0.4123***		0.3720***	0.3600***
	(0.0655)	(0.0685)		(0.0637)	(0.0651)
Regulation 2	0.6409***	0.6783***		0.6388***	0.6284***
	(0.0893)	(0.0941)		(0.0870)	(0.0888)
Regulation 3	0.2664***	0.3183***		0.2823***	0.2528***
	(0.0699)	(0.0767)		(0.0680)	(0.0700)
Regulation 4	0.20383***	0.2830***		0.2326***	0.1945**
	(0.0759)	(0.0841)		(0.0719)	(0.0760)
Regulation 5	0.0156	0.1357		-0.0047	-0.0007
	(0.0820)	(0.0840)		(0.0828)	(0.0807)
Year FE	y	y	y	y	y
Firm-Country FE	y	y	y	y	y
Sales control	y	y			y
Number of Observations	207262	204747	204772	204772	204747
Number of groups	13227	13089	13089	13089	13089
chi2 leader - follower	44.83		32.62	35.75	33.56
chi2 home leader - home follower		28.01	11.4	8.86	9.51

Table 3.11: Regressions with the leader defined as an early mover in the first three years of regulation implementation

These are the poisson regressions with the dependent variable as the count of emissions control patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first three years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1)	(2)	(3)	(4)
Leader	-0.1988**		-0.0975	-0.0999
	(0.0786)		(0.0645)	(0.0698)
Follower	-0.1524**		-0.0705	-0.1085*
	(0.0613)		(0.0535)	(0.0576)
Home Leader		-0.5093***	-0.5082***	-0.4972***
		(0.0578)	(0.0566)	(0.0548)
Home Follower		-0.2429***	-0.2378***	-0.2279***
		(0.0364)	(0.0355)	(0.0335)
Regulation dummies	y	y		y
Number of Observations	25639	25591	25591	25591
Number of Groups	4432	4414	4414	4414

Table 3.12: Regressions with the dependent variable weighted by number of citations

These are the poisson regressions with the dependent variable as the citation weighted count of emissions control patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first two years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1)	(2)	(3)	(4)	(5)
Leader	0.2214***	0.2135***	0.2006***	0.1891***	0.1919***
	(0.0480)	(0.0477)	(0.0485)	(0.0472)	(0.0471)
Follower	0.0346	0.0344	0.0358	0.0369	0.0374
	(0.0346)	(0.0346)	(0.0345)	(0.0346)	(0.0346)
Home Leader (t-1)	-0.0280				
	(0.0284)				
Home Follower (t-1)	0.0261				
	(0.0220)				
Home Leader (t-2)		-0.0062			
		(0.0282)			
Home Follower (t-2)		0.0267			
		(0.0217)			
Home Leader (t-3)			0.0037		
			(0.0276)		
Home Follower (t-3)			0.0225		
			(0.0215)		
Home Leader (t-4)				0.0032	
				(0.0270)	
Home Follower (t-4)				0.0192	
				(0.0209)	
Home Leader (t-5)					-0.0013
					(0.0267)
Home Follower (t-5)					0.0152
					(0.0207)
Number of observations	204066	203417	202702	202038	201330
Number of groups	13081	13073	13063	13054	13040
chi2 leader - follower	23.45	21.75	18.9	19.28	20.01
chi2 home leader - home follower	5.26	2.1	0.72	0.54	0.62

Table 3.13: Regression with leader defined as first mover and home regulatory measure lags

These are the poisson regressions with different lags on the home regulatory measures. The dependent variable is the count of emissions control patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first year it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1)	(2)	(3)	(4)	(5)
Leader	0.1471***	0.1433***	0.1423***	0.1421***	0.1437***
	(0.0383)	(0.0380)	(0.0377)	(0.0378)	(0.0380)
Follower	-0.0739**	-0.0739**	-0.0704**	-0.0703**	-0.0705**
	(0.0355)	(0.0354)	(0.0347)	(0.0345)	(0.0345)
Home Leader (t-1)	0.0450**				
	(0.0227)				
Home Follower (t-1)	-0.0305				
	(0.0260)				
Home Leader (t-2)		0.0518**			
		(0.0226)			
Home Follower (t-2)		-0.0345			
		(0.0254)			
Home Leader (t-3)			0.0544**		
			(0.0219)		
Home Follower (t-3)			-0.0437*		
			(0.0254)		
Home Leader (t-4)				0.0521**	
				(0.0216)	
Home Follower (t-4)				-0.0498**	
				(0.0247)	
Home Leader (t-5)					0.0473**
					(0.0212)
Home Follower (t-5)					-0.0526**
					(0.0243)
Number of observations	204066	203417	202702	202038	201330
Number of groups	13081	13073	13063	13054	13040
chi2 leader - follower	33.41	33.18	32.02	34.14	31.78
chi2 home leader - home follower	11.64	15.5	21.28	24.21	25.99

Table 3.14: Regression with leader defined by first-three-year mover and home regulatory measure lags

These are the poisson regressions with different lags on the home regulatory measures. The dependent variable is the count of emissions control patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first three years it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1) First year	(2) First two years	(3) First three years
Leader	0.3303***	0.2458***	0.2724***
	(0.0947)	(0.0666)	(0.0532)
Follower	0.1562***	0.1399***	0.0343
	(0.0462)	(0.0489)	(0.0576)
Home Leader	-0.0543	0.0474	0.0672*
	(0.0583)	(0.0383)	(0.0343)
Home Follower	0.0282	-0.0051	-0.0801**
	(0.0318)	(0.0346)	(0.0383)
Number of observations	219241	219241	219241

Table 3.15: Robustness check with zero-inflated poisson regressions

These are the zero-inflated poisson regressions. The dependent variable is the count of emissions control patents. The leader variable is defined differently in each column. Column (1) is the leader measure defined as countries who implement the most stringent regulatory level in the first year it appears globally, column (2) refers to the first two years and column (3) refers to the leader definition based on the first three years the regulation gets implemented. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1)	(2)	(3)	(4)	(5)
Leader	0.2162***	0.2163***	0.2095***	0.2051***	0.2052***
	(0.0539)	(0.0529)	(0.0539)	(0.0544)	(0.0545)
Follower	-0.0811	-0.0853	-0.0837	-0.0812	-0.0820
	(0.0627)	(0.0636)	(0.0630)	(0.0624)	(0.0621)
Home Leader (t-1)	0.0719***				
	(0.0273)				
Home Follower (t-1)	-0.0213				
	(0.0311)				
Home Leader (t-2)		0.0687**			
		(0.0281)			
Home Follower (t-2)		-0.0128			
		(0.0297)			
Home Leader (t-3)			0.0695**		
			(0.0278)		
Home Follower (t-3)			-0.0184		
			(0.0295)		
Home Leader (t-4)				0.0564**	
				(0.0273)	
Home Follower (t-4)				-0.0242	
				(0.0290)	
Home Leader (t-5)					0.0541**
					(0.0272)
Home Follower (t-5)					-0.0265
					(0.0287)
Number of observations	133060	132605	132196	131876	131523
Number of groups	7864	7859	7855	7854	7851
chi2 leader - follower	51.98	51.13	52.28	53.2	54.42
chi2 home leader - home follower	14.8	12.22	14.91	13.86	14.59

Table 3.16: Regression with dependent variable as end-of-pipe technologies and home regulatory measure lags

These are the poisson regressions with different lags on the home regulatory measures. The dependent variable is the count of end-of-pipe patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first year it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

	(1)	(2)	(3)	(4)	(5)
Leader	0.1728***	0.1713***	0.1654***	0.1660***	0.1692***
	(0.0419)	(0.0415)	(0.0412)	(0.0414)	(0.0416)
Follower	0.0042	0.0022	0.0046	0.0033	0.0023
	(0.0369)	(0.0372)	(0.0371)	(0.0369)	(0.0367)
Home Leader (t-1)	0.0231				
	(0.0248)				
Home Follower (t-1)	-0.0143				
	(0.0268)				
Home Leader (t-2)		0.0281			
		(0.0247)			
Home Follower (t-2)		-0.0110			
		(0.0258)			
Home Leader (t-3)			0.0346		
			(0.0244)		
Home Follower (t-3)			-0.0183		
			(0.0257)		
Home Leader (t-4)				0.0295	
				(0.0236)	
Home Follower (t-4)				-0.0176	
				(0.0253)	
Home Leader (t-5)					0.0232
					(0.0232)
Home Follower (t-5)					-0.0194
					(0.0254)
Number of observations	186906	186248	185586	184871	184167
Number of groups	11816	11806	11797	11786	11771
chi2 leader - follower	15.58	15.88	14.79	15.82	16.89
chi2 home leader - home follower	2.44	3.05	5.35	4.37	3.52

Table 3.17: Regression with dependent variable as integrated technologies and home regulatory measure lags

These are the poisson regressions with different lags on the home regulatory measures. The dependent variable is the count of integrated technology patents. The leader variable is defined as countries who implement the most stringent regulatory level in the first year it appears globally. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance with robust standard errors in parenthesis. Recall that the knowledge stock variable is lagged and logged with a 0.01 added beforehand to avoid losing all observations with any zeros. There are also firm-country fixed effects, year fixed effects and standard dummy variables for each regulation level. A constructed sales measure is also included in the regressions to control for changes in a country's demand over time.

C Additional Data Details

This section will provide addition details on the data choices made.

C.1 Regulatory Data Details

The statement on regulatory scope in the EU quoted in section 3.2 mentions different vehicle sizes. M1 refers to passenger vehicles with less than eight seats excluding the driver's seat. M2 and M3 generally cover buses, namely passenger vehicles with more than eight seats. N1 are vehicles used for the carriage of goods and having a maximum mass not exceeding 3.5 tonnes. Therefore, in general Euro 1 applies to light vehicles. There is similarly a Euro regulatory system that applies to heavy duty vehicles usually denoted by roman numerals but they were adopted a bit later and we will not cover them in our analysis.

Although these categories define our baseline regulation, different countries may have their own vehicle category definitions. In collecting regulatory data we may encounter countries that have different vehicle classification methods or in some cases simply no clearly defined vehicle categories. [13] The other vehicle categories that commonly appear are Light Duty Vehicle (LDV), Light Commercial Vehicle (LCV) and Passenger Car (PC), as well as medium and heavy duty vehicles (MDV and HDV respectively). If a country uses these classifications and the corresponding regulatory levels are different, we take the passenger car regulatory level for our dataset. Of note, these category definitions are often different between countries. Passenger cars are usually a separate category from light trucks which are usually under the LCV category, all of which are often under the LDV category. However this is not a given. Some countries, such as the United States, Argentina, Indonesia, etc. include light trucks (or at least a partial set of light trucks) in their passenger car definition. Similarly, some countries include SUVs in their PC definition (such as China) while others include it in LCV (such as Australia). Furthermore the definitions may change over time, for example, part of the Light Trucks category in the Netherlands was later categorized as vans. Even the technical specifications by category are different for PCs in different countries. The maximum number of seats for PCs in the United States is twelve while the maximum is ten in South Korea and nine in the EU and China. They also have different

[13] For example, the vehicle categories in Canada were not clearly defined for many years and some categories had the potential to overlap. "The Canadian National Collision Database (NCDB) system defines "passenger car" as a unique class, but also identifies two other categories involving passenger vehicles—the "passenger van" and "light utility vehicle"—and these categories are inconsistently handled across the country with the boundaries between the vehicles blurred"

Gross Vehicle Weight (GVW) maximums - the limit being 3856 kg in the United States and 3500 kg in the EU. These discrepancies may add noise to our estimate of market size by regulation however it is not clear that it introduces any bias.

Another source of noise in our regulatory dataset is the different driving cycles (a.k.a. procedure to measure and test emissions). This is different both between countries and over time and may affect the effective stringency of a regulation. Furthermore, driving cycles follow their own timeline, sometimes use different vehicle category definitions, and do not always match the announcement nor implementation dates of emission regulations. Japan is a particular case in that they use driving cycle changes to increase the stringency of their emissions control while keeping the nominal pollutant emissions levels fixed.

The test procedure in Europe (the New European Driving Cycle - NEDC) currently specifies the starting vehicle temperature, the terrain and environmental conditions (flat road without wind, or on a roller test bench indoors), a sequence of driving speeds, and what components can be removed or turned off (such as lights, air conditioning, etc.). Of note, the NEDC does not test uphill terrain and tests the vehicle at a maximum allowed acceleration time of 15 seconds from 0-50km/h whereas acceleration time in reality is generally around 5 to 10 seconds. This test procedure was designed to simulate typical driving conditions in a busy city and although it has been criticized for unrealistic measurements, we posit that it has still had consequential impact on emissions control technology research and development incentives in firms.

Although we attempt to determine equivalences between country regulation stringency, sometimes it is technically not possible to compare them as some countries may set limits based on g/kWh or %ppm or assign a fleet average, they may not specify vehicle types, engine or fuel types, test procedures, etc. In these cases, based on the information we have for each country, we follow the regulatory changes overtime and note an increase in their regulatory level when it changes substantially. This occurred a few times in data for countries in the middle east or Africa.

Another case encountered was that due to the emergence of three main types of regulation (EU, USA, Japan), some countries later defined their emissions limits on two or more of these types of regulation. Peru is an example that offers two options - the vehicle can meet either an EU limit or a US limit. Surprisingly, Peru's two options are not equivalent in terms of international comparisons. In 2003, their passenger vehicles (GVW $\leq$ 2.5 tonnes and number of seats $\leq$ 6) options are Euro 2 or US Tier 0. Then in 2007 the Euro limit became Euro 3 whereas the US option did not change. The generally agreed equivalence for US Tier 0 is Euro 1 and US Tier 1 is generally compared with Euro 2. In these cases, we note the less stringent requirement in our dataset. Countries might use these tactics as a kind of barrier to trade. Another reason could be the grey import market. Peru imports a number of used vehicles from countries that have moved on to more stringent regulatory levels.

Grey import vehicles are new or used vehicles that are legally imported by circumventing the official manufacturers' distribution channels. In general, the grey import market is an issue that we cannot capture in our data and therefore cannot control for. It has notably been observed for Japanese exports since regulations change frequently there. Other large flows are Singapore and Thailand for diesel 4x4 vehicles and Germany for used vehicles going to Eastern Europe or West Africa. In these cases, the relevant regulation to consider are the import rules. There is a large amount of variety between import regulations. Sometimes it is the same as the type approval regulation however sometimes it is more strict or more slack, the vehicle categories are sometimes different, sometimes the only limit is on vehicle age and sometimes the import requirement is a specific component rather than a regulatory level. For example, many South American countries such as Ecuador, El Salvador, French Guyana, etc., only, or in addition, require that imported vehicles have catalytic converters.

Since the beginning of Euro 1, there have been six stages of increasingly more stringent emission levels as summarized in Table 3.1 in Section 3.2 for petrol passenger cars. There are also regulations for Diesel cars that follow the Euro scheme. The pollutants targeted are the same as for petrol cars however diesel cars generally emit less CO and CO_2 but more NO_x and particulate matter. In light of the recent diesel emissions scandals we decide to focus on petrol emission regulations primarily.

Figure 3.2 below displays the implementation years of each country by regulatory level in my final dataset.

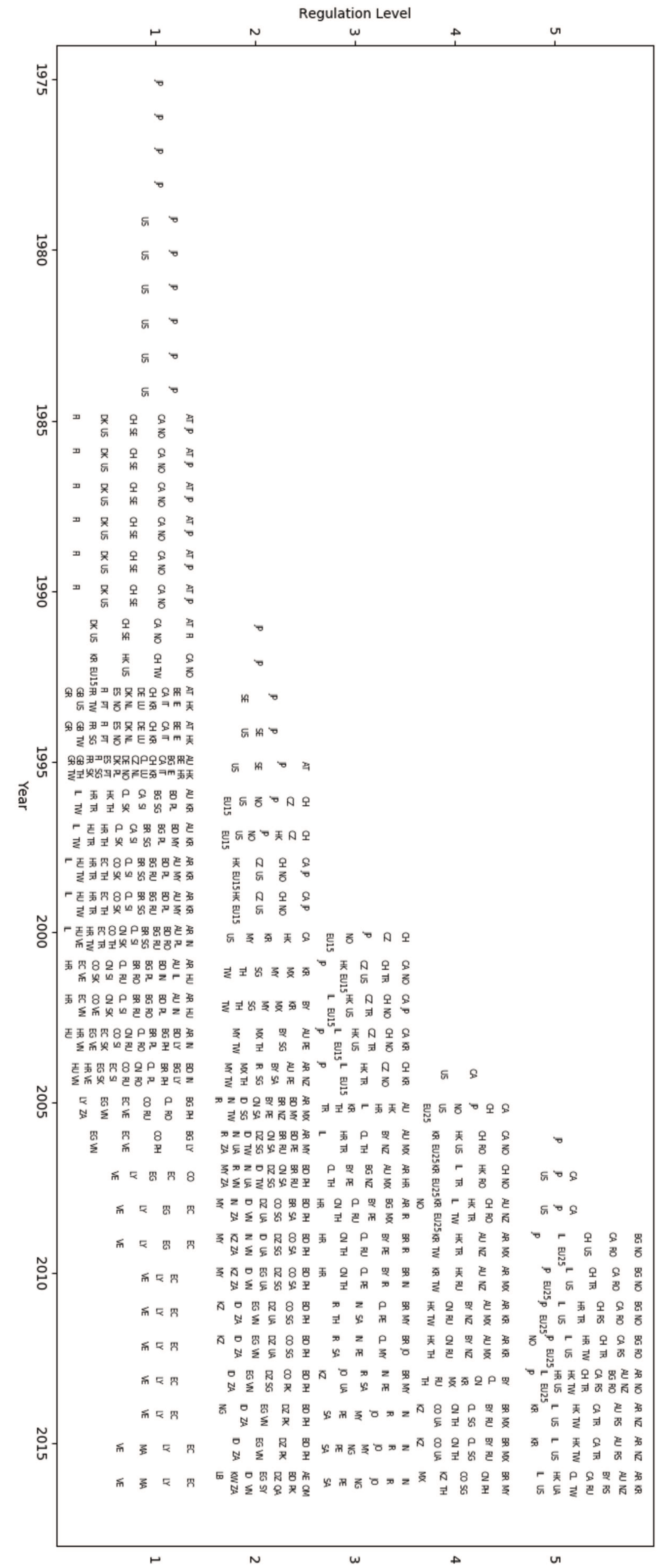


Figure 3.2: The implementation years of each regulatory level by country.

C.2 Patent Data Details

One of the principle issues for use of patents as an innovation indicator is the measurement of quality. A naive first measure would be the count of the number of patents. However patents can be very heterogeneous in terms of innovative content. Furthermore, there may be discrepancies between countries on requirements of novelty, etc. and this may also change over time. There have been many studies on patent quality but a consensus has not yet emerged. Traditionally, an indicator of quality were triadic patents (patents with applications in the United States, Europe and Japan), nowadays it is more common to include China and South Korea in this measure as well. However, either way, it is not the ideal measure for our purposes as it would over weigh our innovation measure towards those markets. Instead, a simple way to measure quality is to only count patents that have made applications in more than one country.

Since there can be substantial application, legal and possibly translation fees associated with each patent application, the decision to make a patent application must mean the expected payoff is higher than the costs.[14] Patents with applications in multiple countries are both an indicator of high quality as well as an indicator that the applicants are connected with multiple markets. It is obvious that applicants with activity in more than one market are the most likely to be affected by the relative timing of regulations. We therefore expect this high quality indicator to be more reactive than a simple count of all patents. Therefore, this is both an indicator of quality as well as a good selection of technologies that are most affected by the timing of regulation implementation.

Another common measure for patent quality is a value assigned based on forward citations. This implies that a patent cited ten times is worth more than a patent cited once. Jaffe and de Rassenfosse (2017) conduct a good survey of the current methods in this respect. One take-away is that the citing patents should themselves have a value and that it should be taken into account when valuing the cited patent. The ideal method would be to take into account the entire history of citations however this is not tractable given our resources and therefore we use a second order measure where we multiply the citing patents' value by a discount factor and add it to the nominal number of citations a patent has received. We still however have to interpret this

[14]Strategic use of patents, such as patent boxes and patent off-shoring for tax purposes, are becoming more and more common in recent years but arguably still a small part of the entire patent system. Here, we will assume only traditional use of patents.

measure with caution. Propensity to cite may have changed over time and different countries have different requirements for citations of prior art.

When calculating a value of firm innovation we can further improve upon this measure by dividing by the number of patent applicants. Commonly done in the literature, this is a better measure of the value of a patent to the firm as the applicants will split the benefits of the patent. To do this we simply divide by the number of applicants provided by PATSTAT.

For the next step of our analysis we merge patents to firms. Although PATSTAT provides a link between applicant and patent application, there is no structured procedure for noting applicant names. A single applicant may change the spelling of their name in different applications and in different patent offices. As such, simply using the PATSTAT applicant-patent application link table will result in much too many observations. There have been a number of attempts to harmonize the names in PATSTAT however they are subject to errors and although substantially cleaner, still encounter the same problem. To deal with this, we will use the firm-patent association dataset available in Orbis. Orbis is maintained by Burean Van Dijk and firms have a clear identifier with the associated patent application. Since Orbis includes firm financial measures, this will also allow us to merge with the financial information of the firm later on.

Patent applications can be filed in their respective national offices or in certain regional offices. The Patent Cooperation Treaty (PCT), signed in 1970, was designed to facilitate patent protection internationally. Similarly, Europe developed the European Patent Convention *"to strengthen co-operation between the States of Europe in respect of the protection of inventions"* in 1973. It established a system of law in Europe, for the 38 contracting states at the time, to allow a single procedure for the grant of patents that are ultimately subject to the same conditions as a national patent granted by that State.

In particular the EPO has an EP patent that can apply to all member states provided the applicant has paid the post grant fee in those states. As we are interested in the number of patents a firm holds at the country level, we infer the countries covered in an EP patent with the post grant fees. PATSTAT provides a legal event dataset that tracks changes made to a patent however this dataset is incomplete and, by construction, only covers the applications that have been granted. In order to assign a country to each EP patent application, we first use the legal event table to identify countries that received post grant fees. To be specific the legal event codes used were 'PGFP' (Post grant: annual fees paid to national office), 'AKX'(Payment of designated fees), 'AK' (Designated contracting states), and 'RBV' (Correction of designated states). If a patent application has an RBV correction, we use only those states. For the patent applications with no national information, we generate an estimate from the applicant history. To do so, we take the outer set of the countries listed in PGFP, AKX, and AK and we assign each country a fractional weight of $\{\text{number of patents per firm}\}^{-1}$ to get a firm distribution for each applicant. We then average these distributions over the set of applicants. If the EP patent does not have any applicant information, we assign estimated designated states and a corresponding probability from the year average.

Patstat contains data on different types of intellectual property. The EPO has categorized this into three categories: PI (patents for invention), UM (utility models), and DP (design patents). In our analysis we restrict to only the first category of patents. Utility models were designed to be a weaker form of intellectual property rights. The innovative requirement is less stringent and it is usually smaller firms that hold utility model patents. Since there are already issues with measuring patent quality, we decide to exclude these patents. Design patents are evidently less relevant for vehicle emission technologies and are excluded as well.

Since firm-country specific market size data is unavailable, we follow Aghion et al. (2016) to construct a proxy for market size from patent data. In particular we assume that the share of vehicle patents that a firm files in a country is proportional to the market share of that firm in that country. As such, we estimate the share of a firm's market in a given country from its patent applications then multiply by that country's total vehicle sales. We then aggregate over the countries in each regulatory level to get firm-regulation specific market size estimates which are used to plot the market sizes in figure 3.1.

C.3 Sales imputation

We imputed country passenger car sales for the construction of our market size variable. The initial data was gathered from OICA (Organisation Internationale des Constructeurs d'Automobiles) and certain country specific automobile associations that offered more extensive data, namely the American Automobile Manufacturers Association provided data as far back as 1970. OICA passenger car sales data began in 2005 and their passenger car registration data for European countries began in 1990. When sales data is unavailable, we proxy with registration data. When registration is also not available we impute the sales number from population data. The imputation is done separately for each country and their adjusted r squares are tracked. When we plot the residuals, they are fairly distributed. A couple countries, notably, China, has a lesser fit compared to the other countries. In comparison, when we regress on population, GDP, interest rate, and oil price, the explanatory variable of highest significance is GDP. The regression with both GDP and population generally provide higher r squares however the out of sample fitting sometimes give negative values. We therefore use a combination of population and GDP to impute country sales when the data is available and when the results are sensible. Otherwise we use only population data. The adjusted r squares are all above 0.80 and most are above 0.90.

Our reliable country sales data only goes back to 2005 (1990 for select countries) and sometimes even those data points are estimated. So we are arguably imposing a very strong assumption that the auto industry and consumer purchasing behavior remain the same over the years. In the robustness section we also included checks on the market size variable without multiplying by country sales and using population or GDP instead. Since our market share proxy is potentially very noisy, multiplying by imputed sales, another noisy variable, can be confounding.

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Conclusion

The primary objective of this thesis is to understand firm behavior and their interactions. To do so, the three chapters in this manuscript have explored the intersection of innovation, entrepreneurship and competition dynamics. Using patent data, I had very detailed information on firm technological content which allowed me to understand more intricacies in firm behavior. This is what I exploited to understand the decisions on types of R&D firms are making. In particular, this dissertation has focused on the type and originality of innovation and suggested that the implications are different than the common measures of innovation quantity or quality.

One area where the implications are different is in competition dynamics. The positioning of an innovation is associated with a degree of product differentiation. Models in industrial organization have shown that an increase in product differentiation is associated with a decrease in product market competition (as in the Hotelling model and ensuing literature). This is different to other models where innovation is included either through a decrease in marginal costs or an increase in product quality. Furthermore, studying the choices that young firms make begets the question of what the long term consequences of these patterns of product differentiation are. This issue joins with the Schumpeterian literature on growth through creative destruction and touches on antitrust considerations which are common threads throughout my research.

The factors that affect innovation can be broadly grouped into push and pull factors. This provides a natural structure to my research. In one chapter, I studied the innovation incentives exerted by the pull of potential acquirers on new start-up firms. In another work, I provide evidence of the direct push effect that occurs from having more expertise built up in one technological area than another. My third chapter that analyzed the pull effect imposed by policy changes on vehicle emission limits.

In my chapter titled "Buyouts and Start-up Innovation Incentives", I investigated how start-up innovation choices are affected by their exit options. There, I suggest that getting bought out has increasingly become a chief exit option for start-ups and that this has consequently affected their initial entry innovation strategy. Namely, if a start-up believes that getting bought out is their primary exit option, then they choose to further increase their likelihood of getting bought out by innovating closer to their potential acquirer, in a complementary sense. I show that this is indeed the case with data on firm patenting and their mergers and acquisitions history.

My second chapter, "Firm R&D Inertia", builds on my first chapter and examines the ramifications of a firm's initial innovation choices. I document empirical facts about the firm life cycle in terms of technological content and provide some stylized facts about the dynamics of technological sectors as well. This work emphasized the importance of initial starting points and confirmed the existence of inertia in firm R&D. It then provided evidence on how starting conditions such as initial firm originality and previous experience can affect the degree of firm inertia.

In "Regulation Timing on Green Innovation: The Case of Vehicle Emissions" (joint work with Antoine Dechezlepretre and Matthieu Glachant), I investigated the case where innovation is obligatory for firms in order to meet the stringent limits on vehicle emissions. As such, this is a regulation imposed demand pull factor on vehicle firms to innovate in emissions control technological areas. In this setting, we analyzed the question of whether policy makers have benefits to being early regulatory movers by testing whether their domestic firms benefit from the need to innovate early.

Together, these studies form a better understanding of firm innovation dynamics, interactions through competition and technological demand, and the characteristics of the industry life cycle.

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RÉSUMÉ

Cette thèse porte sur le comportement et les interactions des entreprises. Mes recherches examinent l'intersection de l'innovation, de l'entrepreneuriat et de la dynamique de la concurrence. En utilisant les données de brevets, j'ai des informations très détaillées sur le contenu technologique de l'entreprise, ce qui me permet de comprendre davantage les subtilités du comportement de l'entreprise, à savoir le type et l'originalité de l'innovation que l'entreprise fait. Mon premier chapitre analyse les incitations à l'innovation des start-ups exercées par les perspectives de rachat par les entreprises plus anciennes. Je teste l'hypothèse selon laquelle les start-up innovent dans des domaines plus complémentaires de leurs acquéreurs potentiels. Dans le chapitre deux, j'analyse l'impact à long terme des choix de positionnement technologique par les jeunes entreprises. Elle mesure l'inertie de ces positionnements. Elle présente également certains modèles visant à distinguer l'impact de la taille de l'entreprise et son âge sur son innovation. Enfin, le troisième chapitre analyse l'effet de changements de politiques publiques sur l'innovation, en prenant l'exemple de politiques limitant les émissions polluantes des véhicules. Je m'interroge notamment sur l'avantage comparatif qu'ont les pays à être les premiers à imposer de nouvelles normes sur les véhicules vendus sur leur territoire.

MOTS CLÉS

Innovation, entrepreneuriat, dynamique des entreprises

ABSTRACT

This thesis examines the intersection of innovation, entrepreneurship and competition dynamics. Using patent data, I have very detailed information on firm technological content which allows me to understand more intricacies in firm behavior, namely the type and originality of innovation the firm is doing. My first chapter analyzes the innovation incentives exerted by the pull of potential acquirers on new start-up firms. I test the hypothesis that start-ups innovate in closer complementary areas to their potential acquirers when they expect their primary exit strategy to be a buyout. In a complementary work, I document the long run impact of the initial positions new firms choose. This study provides a measure of the push effect from having expertise built up in a technological area. It also presents some patterns that disentangle firm size and firm age on innovation choices. Finally, my third chapter analyzes the pull effect on innovation imposed by policy changes on vehicle emission limits. This study addresses the question of whether there are early mover advantages for policy makers.

KEYWORDS

Innovation, entrepreneurship, firm dynamics