Firm R&D Inertia

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Abstract

Firm R&D decisions are likely to have lasting consequences. Here I will document patterns of firm technological position over its 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 be different depending on the firm size and degree of concentration in the sector.

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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 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 expertises 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 this association.

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. In microeconomics, studies do not usually look past one period in time. In macroeconomics, studies often abstract from the different product lines by aggregating them into firm level sales or growth or they model product lines that are independent of one another (see Klette and Kortum (2004), Akcigit and Kerr (2018), etc.). These common approaches fail to account for firm inertia in technological space.

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 build 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 are 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. Lee (2020) 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.

Shifting away from the focus on initial conditions, I also address whether firm size has an effect on inertia. 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 the mechanism he called 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 growth 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 contribute to the economy differently through their technological positioning. In particular, understanding how new firms develop will help us understand the competitive dynamics of an industry. 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 to not patent their inventions and keep them as trade secrets. The data shows that technological sectors follow a similar life cycle as industries with a U shaped dynamic of concentration over time.

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 position. Looking at innovation in terms of technological content allows us to disentangle these two types of innovation strategy.

Overall, the existence of firm inertia means each decision in product research and development 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 provides a literature review on the studies concerned with firm path dependency as well as a discussion of the literature on competition dynamics. Section 3 describes the dataset and sample construction choices. Section 4 discusses my econometric approach while Section 5 presents the main results. Section 6 concludes.

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. However, 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. They propose that manager incentives are a cause of inertia. With a theoretical model, Casamatta and Guembel show that when managers are concerned about their legacy, they can entrench a firm on one path and generate inertia. Another study that addresses firm inertia is Ruckes and Ronde (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 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

[1] Absorptive capacity is a term coined by Cohen and Levinthal (1990) which refers to the ability of a firm

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 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. 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 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.

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.

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), a paper also often cited in the exploration and exploitation literature, 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 the technological life cycle 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 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.

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 that are 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 digitalized.[3]

[2] See Acemoglu (2002) among others

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

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.

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. 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, it is not standard to use yet, and it may be subject to a break from the changes in technology class definitions. Therefore I focus my analysis on the patents that have IPC codes. 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.

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 introduce a weighting matrix between the technology codes that captures spillovers between technology codes. They build the weighting matrix by calculating the correlation between patent classes that are filed together within a firm.

I modify this measure in a way that I suggests 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. It could be argued that different products within a firm are likely to be complementary products and therefore technology codes between the two are possibly 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 the measure I build starts at the patent level where I use the set of technology codes within a patent. In addition, to ensure that I am only measuring complementarity and no 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 chose to only look 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 patent level measure. 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 Roende (2018)).

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. This leads to an average firm originality built from the full technology code to be 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 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 the complementarity construction from the patent level. This 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.

Also to note, 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: 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 3.

Finally to summarize on 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. Figure 1 plots the average originality for new firms and for twenty year old firms. This shows that traditionally, new firms were more original on average however they have recently been overtaken by older firms and both groups are now showing a fall in originality from their highs in the mid 2000s.

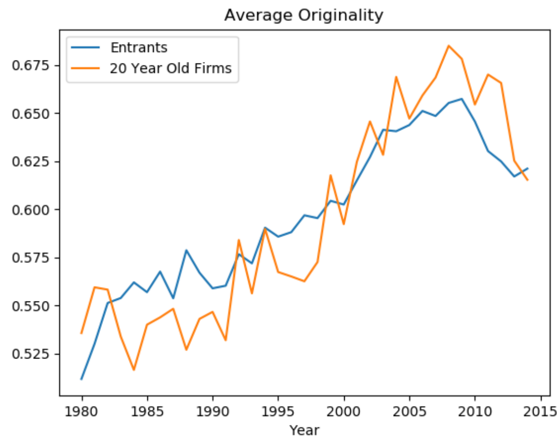

Figure 1: Average 4 digit IPC code originality over time.

4 Empirical Strategy

As discussed in Section 1, there are many reasons for a firm to exhibit some degree of inertia in its innovation decisions. It is interesting to study how inertia occurs in new firm entrants to better understand their innovation incentives and how they can affect the sector in later years. In particular, I am interested in how initial choices and conditions affect a firm's technological position.

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

$$P_{i,t} = f(\tau, X_i; \beta) + \gamma_t + \epsilon_{i,t} \tag{1}$$

where $P_{i,t}$ represents the proximity measure or the originality measure described in Section 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 τ. I will look at the effect of different initial conditions based on different hypothesis.

For a baseline, I look at 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 $f(\tau, D_i^s; \beta) = (\beta_0 + \beta_s D_i^s) D_i^\tau$. I add the technology sector dummies to control for sector heterogeneity however I do not want these terms to affect my average age effect, 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. $\sum_{s \in \mathcal{G}} \beta_s = 0$. 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:

$$P_{i,t} = \sum_{\tau} (\beta_0 + \sum_{s \in \mathcal{G}} \beta_s D_i^s) D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{2}$$

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[4], 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 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 proxim-

[4] See the appendix for more on this.

ity 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 3 for more discussion on this.

The originality measure is also subject to measurement error as was already discussed in section 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. The year dummies included in the model will capture that effect and 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 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 discussed in Section 3 when building the weighting matrix at the firm level following Bloom et al. (2013) for the proximity measure. 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 creating a start up 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 section 3 discussed, 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 will still 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. I cannot distinguish them separately, however for the purposes of a control variable I suggest that it is sufficient.

While the existence of inertia in a firm can largely be established with Equation 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:

$$P_{i,t} = X_i(\beta_0 + \beta_s D_i^s) D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{3}$$

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.

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 class 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.[5]

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:

$$P_{i,t} = D_{i,t}^{size}(\beta_0 + \beta_s D_i^s) D_i^\tau + \gamma_s + \gamma_t + \epsilon_{i,t} \tag{4}$$

Notably, the firm size variables are categorized based on firm patenting. Thus this model captures a slightly different measure to firm size since it uses a patents as a proxy.[6]

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.

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.[7] 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

[5]I will also include some results based on a static initial firm size as well.
[6]See the appendix for a discussion and interpretation of this measure.
[7]This method dates back to Prais (1958)

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 IPC technological sectors by year.[8] 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

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

100th quantile. To build these estimates, I stick with the model described in equation 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.

5 Results

I first provide different measures to summarize the average age effect. Then section 5.2 estimates the effect of the entrant's initial originality and section 5.3 explores the impact of having prior experience. Then, I introduce size in section 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 and in particular I test whether the concentration of the sector affects behavior in young firms.

5.1 Basic Results

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

We can compare figure 2 to 3a which uses the adjusted proximity measure proposed by Bloom, Schankerman and Van Reenen[9]. The two have very similar trends. However if we focus only on

[9] For the purposes of conciseness, figure 3a and all remaining figures will be in the appendix.

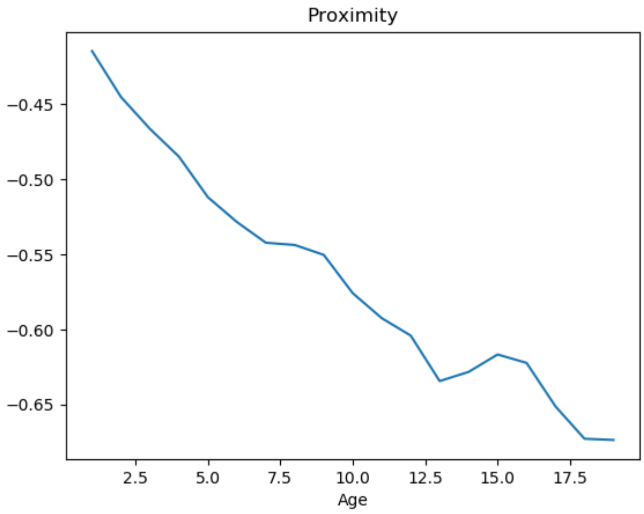

Figure 2: This figure plots the coefficients from the model described in equation 2. The line represents the average Jaffe proximity by firm age controlling for industry, year and firm fixed characteristics. The proximity measure compares the entrant's technological position to its first year technological 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.

the proximity in complementary fields, the decline is much less clear. Figure 3b plots the complementary proximity measure described in Section 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.

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.[10] This measure of incumbent proximity is essentially a baseline of the technological evolution in the sector. Note that it is not quite a mea-

[10] I define an incumbent as a firm that is over twenty years old.

sure 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 by equation 2. Figure **??** 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 **??** that the entrants have a higher proximity to their initial inventions than incumbents, we surprisingly see in figure 5 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 5.3 will explore 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 **??** 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

?? 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 **??** 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.

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 **??** 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.

However when we compare the firm's proximity with the incumbents in the sector (see figure **??**) 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 **??** when we consider the behavior of the other firms in the industry as well. As we saw in figure 5, 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 is 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 8 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 that 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 complementary 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 8 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 their propensity to explore. They 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 **??** and **??** 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.

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), **?**, 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 **??** 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 5.1, 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.[11]

This is in fact what we see. Figure **??** compares the differences in proximity between the entrants and the incumbents by experience history. We see clearly that the behavior is very 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 **??** and **??**). 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 al-

[11]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.

though it is slower for entrants with no experience particularly in the five to fifteen firm age group.

Figures **??** and **??** 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 **??**, 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.

5.4 Size and Age Interactions

As noted 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 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 **??** 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 increase in size as 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 **??** 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 averaged 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 **??**) 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 increase in complementary areas, the incumbent firms are more effective. Figure **??** shows that this gap doesn't last however. This 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.[12] 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 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 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.[13] 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 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 **??** shows that these large firms have a high degree of inertia and Figures 14b and 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 because of their size. They 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.

[12] 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.

[13] 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.

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 **??** 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 we see the steep decline in proximity for initially large firms although we cannot confidently identify the sector age so we 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 **??** and **??**). 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.

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.

Figure **??** 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 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 23 shows the average Herfindahl index for the sectors over their life cycle.[14] 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 17, 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 RD inertia by the concentration of the technological sector the firm is in.

If we examine concentration on the complementary proximity measure (see figure **??**, 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

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

suggests that the young firms in the highly concentrated sectors are innovating in complementary areas much more to differentiated themselves.

In relation to the firms' originality (Figures 18b and 18a), 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.[15] 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 **??** it looks like they also move away from complementary areas however in Figure **??**, they seem to be increasing for the first ten years.

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 original-

[15] See Shapiro (2012), Arrow (1962), etc.

ity firms remain at a high level of originality in terms of both the maximum and the average although the gap decreases over time.

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.

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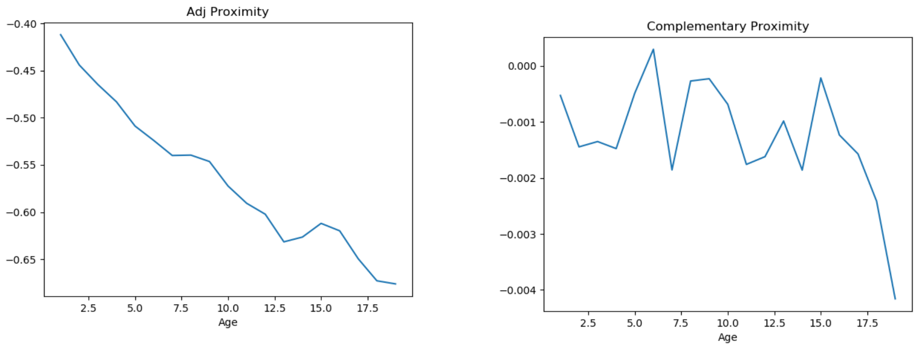
A Results and Figures

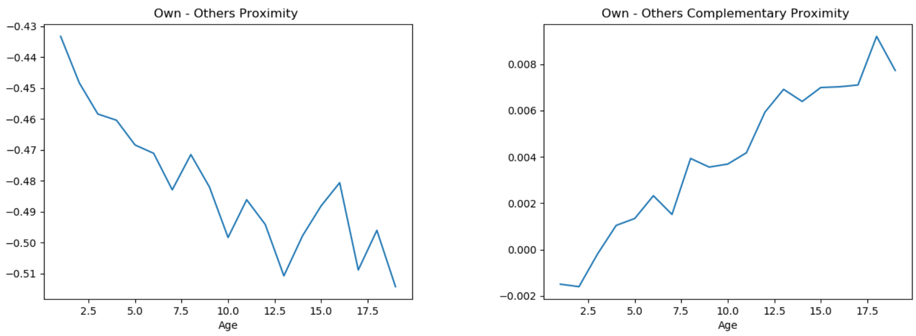
This section gathers the results that are referenced in the main text. The corresponding full regression results will be made available in an online appendix.



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

(b) By complementary proximity

Figure 3: 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 4: 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.

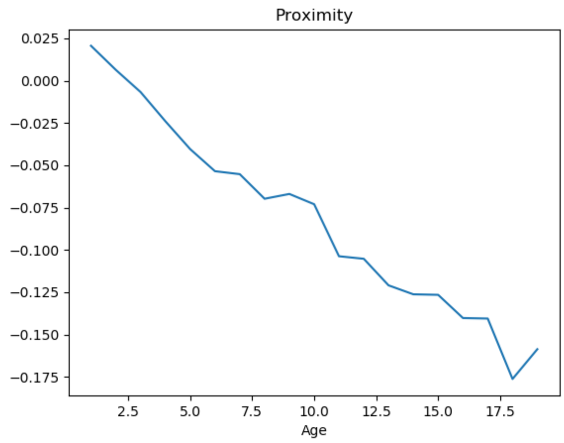
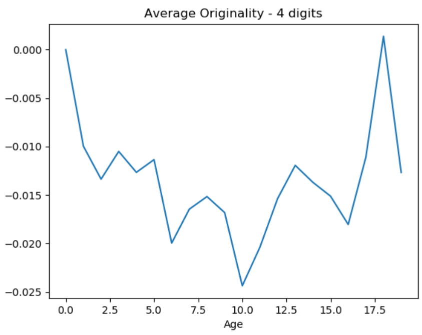


Figure 5: These figures plot the average proximity of the incumbent firms to the entrants initial position by firm age. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience, whether it first patented with other applicants and what the firm's initial originality groups is.



(a) Average Originality

(b) Max Originality

Figure 6: 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 7: 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.

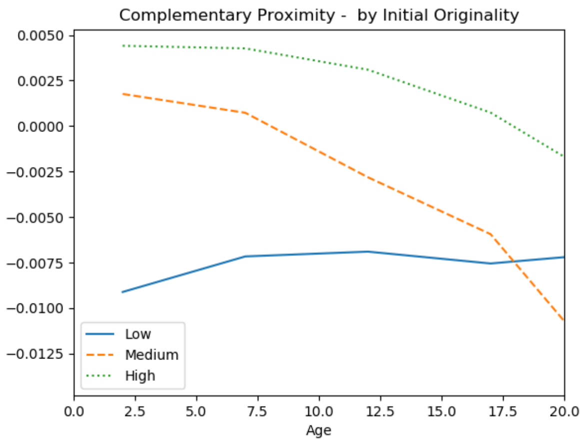
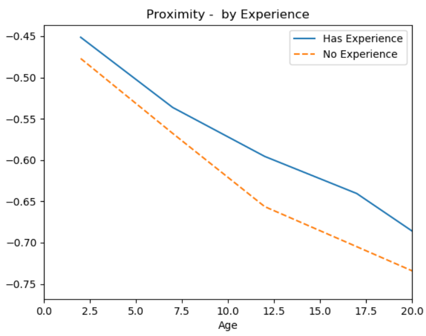


Figure 8: This figure plots the average entrant complementary proximity by initial originality category. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.

(a) Average Originality

(b) Max Originality

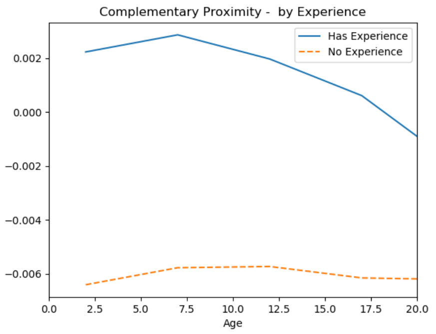
Figure 9: These figures plot the entrant's originality built from 4-digit IPC codes grouped by firms' initial originality. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, whether it has previous experience and whether it first patented with other applicants.



(a) Entrants' Jaffe Proximity

(b) Difference in Proximity between Entrants and Incumbents

Figure 10: 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

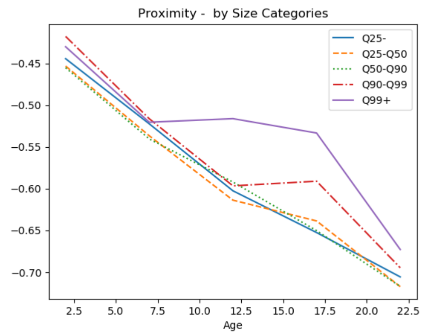
(b) Difference in Proximity between Entrants and Incumbents

Figure 11: 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.

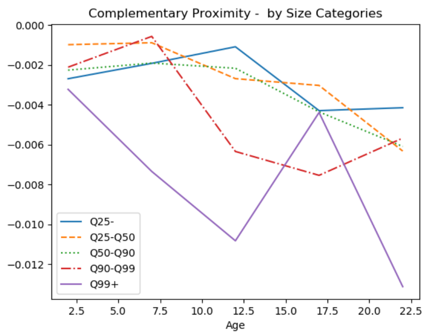
(a) Average Originality

(b) Max Originality

Figure 12: 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.

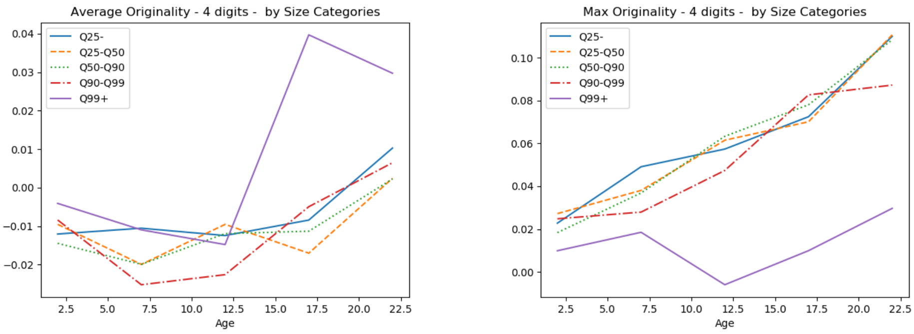


(a) Jaffe Proximity



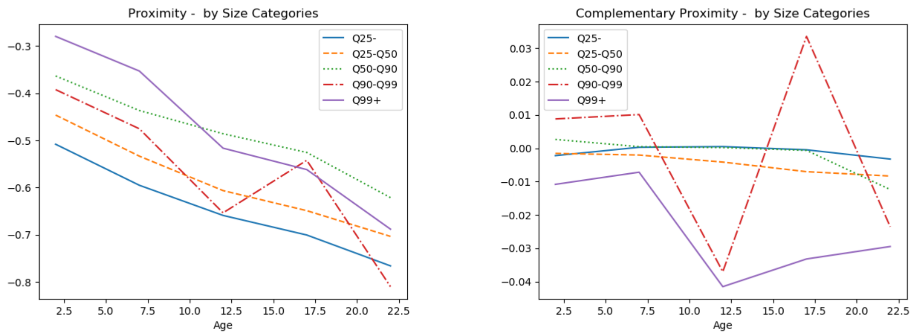
(b) Complementary Proximity

Figure 13: This figure 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.



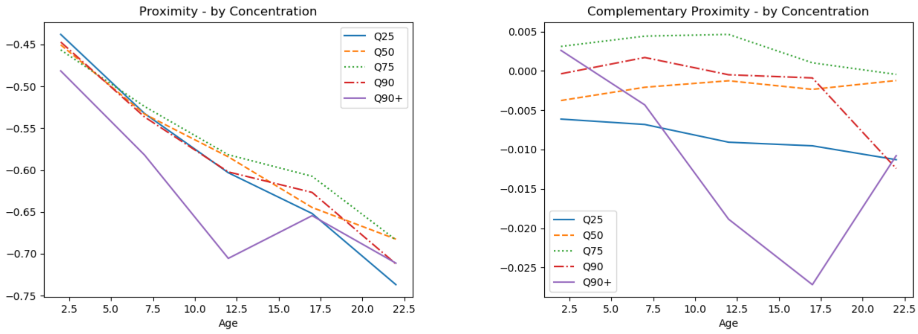
(a) Average Originality (b) Max Originality

Figure 14: 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 15: This figure 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 16: This figure plots 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.

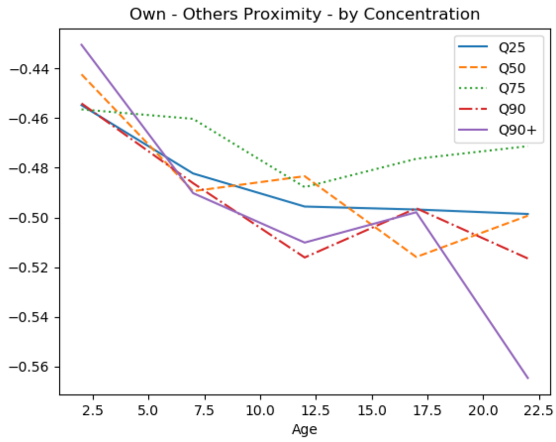
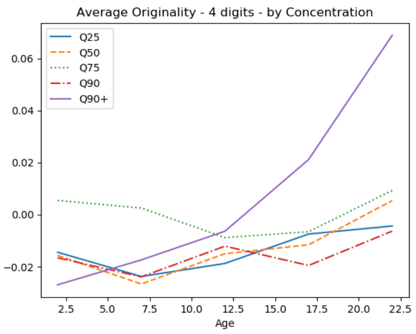
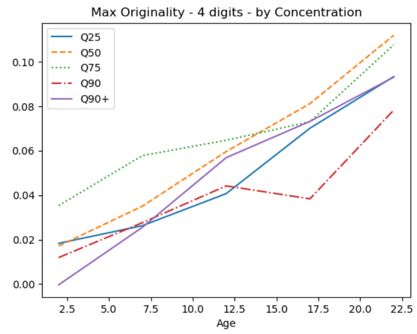


Figure 17: This figure plots the average entrant Jaffe proximity with the incumbent trends removed by its dynamic sector concentration quantile. The additional controls are year, the firm's primary 4 digit IPC code, its initial size quantile, its initial originality category, whether it has previous experience and whether it first patented with other applicants.



(a) Average Originality



(b) Max Originality

Figure 18: 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 Lee (2020)Lee (2020). 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[16]. 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 [17]. 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 Lee (2020)Lee (2020), 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.

[16] 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

[17] See Aghion et al. (2016)Aghion et al. (2016)

As such, I can look at the citing patents and determine whether they are in the same primary 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.

B.1 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[18]. 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.

[18]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 19 shows the number of observations that I have by firm age and Figure 21 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 20 and 22). This gap years measure provides a summary of patenting frequency.

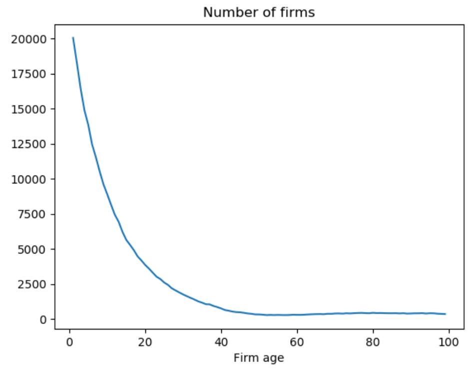


Figure 19: This figure shows the number of firm observations I have per firm age. The observations are based on patent application filings, not a stock of patents, therefore the lines are not necessarily decreasing.

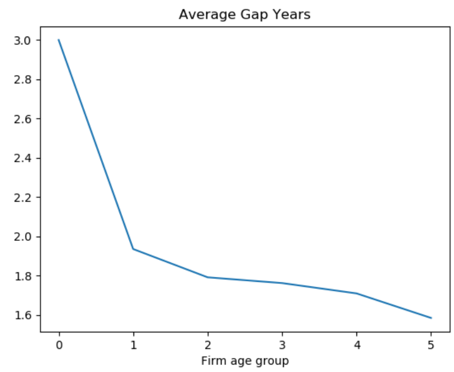
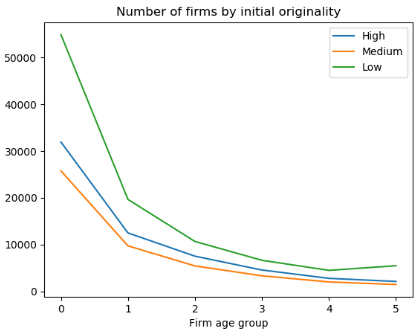
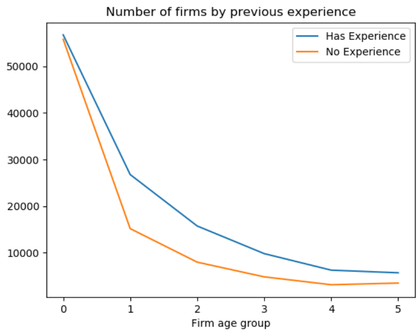


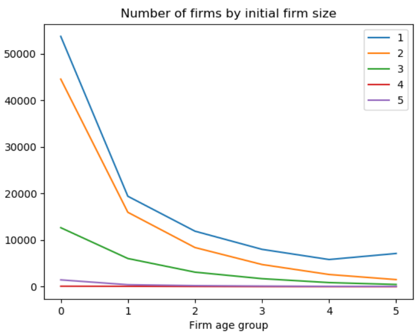
Figure 20: This figure plots the average number of years before the next patent filing.



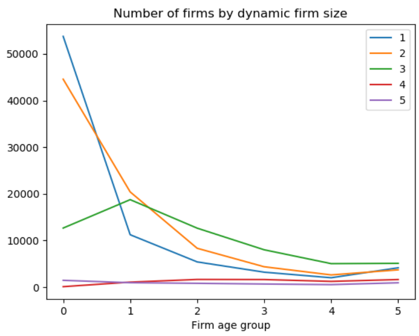
(a) By initial originality group



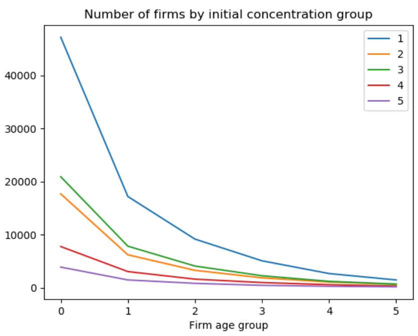
(b) By previous experience



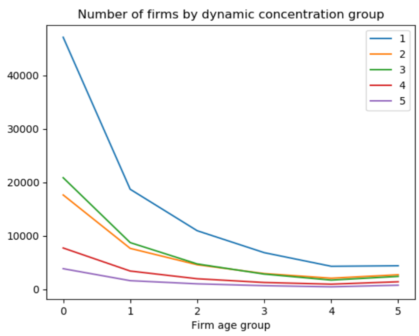
(c) By initial firm size group



(d) By dynamic firm size group

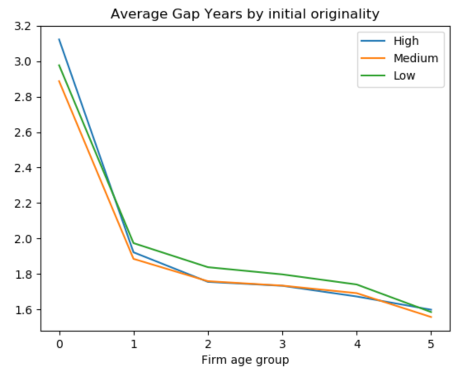


(e) By initial concentration group

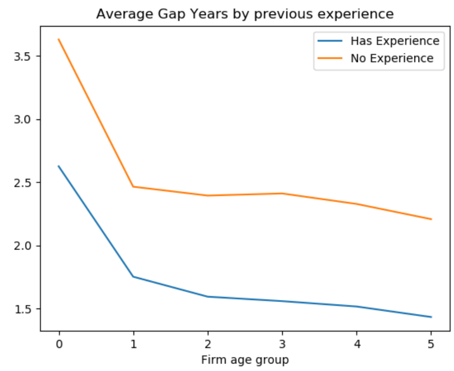


(f) By dynamic concentration group

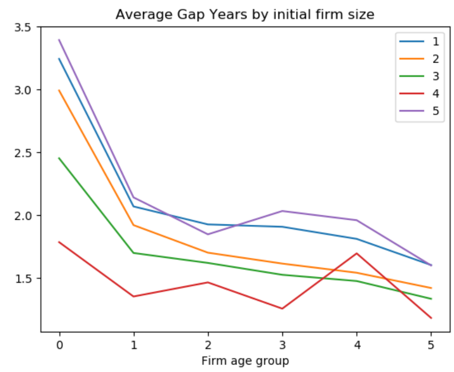
Figure 21: Number of observations



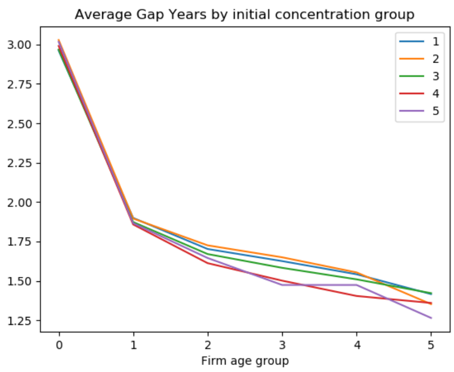
(a) By initial originality group



(b) By previous experience



(c) By initial firm size group



(d) By initial concentration

Figure 22: Average number of years between patent applications

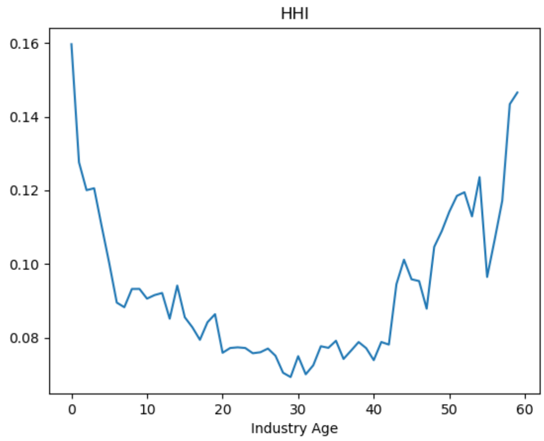


Figure 23: This figure shows the median 4 digit technology sector Herfindahl index where the Herfindahl index is calculated based on firm discounted knowledge stock measures on patent counts. Only