# Innovator Sorting and Firm Size

by

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ABSTRACT

This paper examines the link between firm size and innovation. Given that innovation is highly reliant on human capital, the ability to attract, motivate, and retain high quality inventors is a key determinant of firm innovation. Firm size may affect these abilities, and small firms are known to account for a disproportionate share of aggregate innovation. I therefore investigate the role that sorting of inventors across firms plays in explaining this disparity. Talented inventors may find employment at a large firm less attractive due to the relative absence of growth options and a lower ability to link compensation to performance. Using inventor-level patent data, I construct employment histories for inventors at U.S. public firms. I find that the most productive inventors are disproportionately likely to move to small firms, while the least productive inventors disproportionately remain at large firms. These results cannot be explained fully by small firms' superior growth opportunities. In addition, productive innovators' turnover in small firms is sensitive to the level of option compensation. Taken together, this evidence is consistent with inventor sorting explaining part of the firm size innovation gap.

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Chapter 1

# INTRODUCTION

Small firms account for a disproportionate share of innovation, spawning debate on the optimal boundary of firms with respect to conducting innovative activity. While many studies emphasize large firms' comparative advantage in R&D competitions due to their ability to spread the cost of R&D investment on larger sets of output (Cohen and Levinthal, 1989; Cohen and Klepper, 1996a), others maintain that the scope of the firm can negatively affect incentives to take on risky, long-term investment (Rosen, 1991). Small firms may have the advantage to attract, motivate and retain valuable human capital that is crucial for the production of innovation.[1] Seru (2014) provides evidence that diversification in firm's activities can stifle innovation by weakening the incentives of the divisional managers. Further, Phillips and Zhdanov (2012) argue that large firms may find it disadvantageous to engage in an R&D race with small firms if they have the option to acquire the small firms through mergers and acquisitions.[2]

In this study, I consider whether and to what extent a firm's size is related to its ability to attract and retain high quality inventors who can contribute to innovation. Using inventor-level patent data from USPTO, I construct employment history for 165,896 inventors from 1980 to 2002 at U.S. public firms. I find that the most productive inventors are disproportionately likely to move to small firms, while the least productive inventors disproportionately remain at large firms. These results are not

[1]There is rising concern among practitioners on the importance of hiring the right talent. For example, the CEO and founder of Dropbox emphasizes the importance of hiring the most talented workers and hired Guido van Roussan, the father of Python. (Laskowski, 2014; Constine, 2012)

[2]Higgins and Rodriguez (2006) and Bena and Li (2014) also find evidence that support the "outsourcing" of innovation.

fully explained by differences in growth opportunities at the firms and are sensitive to the relative level of performance-sensitive equity compensation in small firms. Taken together, this evidence provides support for the notion of inventor sorting by firm size as a partial explanation for the firm size innovation gap.

The connection between the matching of innovative firms and innovators is at the heart of understanding the nature and origin of corporate innovation. Since the size of the firm may be closely associated with the ability of attracting and retaining valuable human capital, the sorting of innovators into firms of heterogeneous size can arise as a result of an endogenous matching process, generating disparity in the capacity to innovate between small and large firms.

It could be that a large firm is able to provide greater resources that complement the innovative skill of the individual and therefore increase his marginal productivity or probability of success, resulting in greater expected reward. Small and large firms differ in their ability to reward talent, however. A more talented individual who carries greater probability of success in developing innovation is more likely to capture the total value he creates in the a small firm than in a large for two reasons. First, because effort and talent are observed only imperfectly, larger firms may have difficulty identifying and rewarding talent. As firm size decreases, the cost of measuring individual performance decreases (Stigler, 1962; Garen, 1985), giving the small firms greater capacity to link pay and performance to arrive at outcomes closer to the optimal. Also, as the firm grows, the volatility of the output may increase and relate less to each inventor (Schaefer, 1998). Second, evidence also suggests that small firms are more successful in linking personal reward to performance (Zenger and Lazzarini, 2004; Andersson *et al.*, 2009). Because individual performance is difficult to measure (or for reasons such as to foster teamwork), firms often link pay with performance of the whole firm, using profit sharing or equity awards. Since high quality inventors are more likely to create value for the firm, they may prefer joining small firms where their expected compensation is greater (Lazear, 1986).[3] This may stem from a smaller firms better ability to attribute innovative output to individual performance or the fact that the value of the whole firm is more sensitive to the inventor's effort or ability in small firms when compensation is linked to firm performance.

The primary question is whether the presence of firms of different size results in segregation of innovative talent or, instead, whether workforce composition is similar across firm size (Haltiwanger *et al.*, 1999). To begin, I ask whether more productive inventors are more likely to change firm (Bishop, 1990; Hoisl, 2007). A priori, the presence of innovators and firm sorting is unclear. If the assignment of inventor's quality is random among firms, we should observe that the probability of an innovator changing his employment is independent of his quality. In the presence of sorting, one might observe both high and low quality workers separating from firms if they are under- or over-placed, respectively, since improved match quality between employer and employees may result in efficiency (Sattinger, 1975). However, as long as voluntary separations are more frequent than involuntary ones, which is a reasonable assumption, higher quality inventors who are overplaced will be more likely to separate from the firm. Therefore, the probability of leaving the firm should be positively related to the quality of the inventors. Further, if a firm is sufficiently small, it is less likely that free-riding will dominate in case where one must incur the full cost of effort but share rewards from effort with the whole firm.

The patent application data provides a rich set of measures to proxy for inventor productivity. I use both the cite-weighted patents and average citations per patent

[3]In addition, it is also possible that individual in small firms might derive utility from the autonomy in the innovative process. In the extreme case, the choice of joining a small firm is related to the choice of being in the status of entrepreneurship, see Vereshchagina and Hopenhayn (2009) and Moskowitz (2002) for the preference explanations that justify such choice.

generated by the inventor in the most recent five years as two benchmark measures of productivity. Consistent with the hypothesis, I find that the marginal probability for an inventor to leave his firm is positively related to his quality. An inventor ranked in the top 25% in terms of the benchmark quality measure is 1.2% to 1.4% more likely to leave the firm in the next 5 years, which is 17% to 20% increase from the average rate of employment change.

Next, I examine how the choice of employer's size is dependent on the inventor's quality ranking in terms of his past performance. For individual employees, the decision to change employment should depend upon the expected income between his current and potential future employer. Better inventors can be matched to large firms if the large firms can provide better resources that complements innovative talent. However, small firms can have better advantage in rewarding talent, especially if compensation is linked with equity of whole firm performance, as an inventor is more likely to capture a larger portion of the value he creates in the a small firm than in a large. If the later effect dominates, high quality inventors should be more likely to join the small firms.

Since there are mechanically more inventors that can be employed by large firms than by small firms, I compare the increase in probability for the high quality inventors to join large or small firms relative to the average rate. I find that high quality inventors disproportionately join small firms. An inventor ranked in the top 25th percentile is 32% more likely relative to the average rate (1.9%) to move to a small firm in the next 5 years, while the marginal probability to move to a large firm relative to the average increases by only 18%, which is about half the magnitude. In addition, conditional on moving, the top 25% inventors are 2.7% more likely to join small firms, which is 13.5% above the mean.

Inventor sorting by firm size implies that high quality inventors are more likely to leave large firms. By interacting the inventor's quality ranking with the size of the departing employer, I verify that the greater probability of separation of high quality inventors is not confined to those employed by small firms, where employee turnover is known to be higher (Oi, 1983; Topel and Ward, 1992; Kim and Marschke, 2005). Instead, I find that the lower quality inventors are less likely to leave irrespective of the employers' size. Intuitively, involuntary separation should also increase in low ability; therefore, the finding does provide support for the presumption that voluntary separation is more common in the sample.

In addition, the sorting of inventor quality by firm size also implies that high quality inventors should move from large to small firms. I observe that high quality inventors are more likely to join small firms regardless of the size of their previous employers; however, there is no evidence that the higher quality inventors move from small to large firms. Using the sample conditional on changes of employment, I also find support for top 25% inventors moving from large firms to small firms. That high quality inventors move across small firms is not inconsistent with the sorting hypothesis, as long as these inventors stay within the pool of small firms. Thus, the overall evidence supports the flow of high quality inventors from large to small firms, though top inventors move across small firms as well.

A natural concern is that high quality inventors are likely to be separated from firms with low growth opportunities, either because these inventors chase growth, where match quality is presumably higher, or because there is less demand for the high quality workers in such firms. Since firm size is closely related to growth opportunities, it is important to distinguish whether the finding that high quality inventors sort into small firms is mainly driven by selection into growth firms. If this is true, we should expect that the increasing probability of the high quality inventor joining a small firm is stronger for inventors previously employed in firms with a low level of growth opportunities. On the contrary, if we still observe a higher probability of high quality inventors moving from growth to small firms, it may suggest that the sorting on size does not fully correspond to sorting on growth.

First, in the main regressions, I include various controls that proxy for the growth opportunities, including Tobin's Q and firm age. Second, I also include both the R&D investment and the average quality of the innovation output of the firm to control for the fact that high quality inventors are likely to separate from firms that are less R&D intensive. Further, both these concerns are mitigated by including firm fixed-effects, which essentially compares the inventor's choice of employment relative to the pool of inventors that has been selected into the same firm.

To further disentangle firm size from growth opportunities, I show that although there is greater probability for high quality inventors to leave a firm with little growth opportunities, the marginal probability to join small firms is not significantly different for high quality inventors employed in firms with above or below median level of growth opportunities. For those who choose to join small firms, they are not more likely to come from the value firms, and this evidence mitigates the possibility that the sorting result is solely driven by talented inventors chasing growth opportunities. Nevertheless, because top inventors move from both value and growth firms, the evidence does not fully rule out the presence of sorting based on growth, but does suggest that the size of the firm plays an additional role.

Compensation difference may also play a role. Individual performance is difficult to measure, especially for innovation activities.[4] Therefore, firms often link pay with

[4]One may wonder if it is possible to write compensation contract based on observable output of individual innovation, such as number of patents or citations earned. First, the number of patents filed may be subject to firm's patenting strategy, which makes it an inadequate measure for individual performance. Although individual performance can be based on innovative output (i.e. citations)

performance of the whole firm by offering equity-linked compensation. Theoretically, in small firms, measuring cost is lower and individual effort is more closely related to the firm's overall performance. Small firms, especially start ups, are more likely to offer high-powered incentives (Zenger and Lazzarini, 2004; Andersson *et al.*, 2009), though it is still a common practice for large firms to offer such contracts as well, especially in technology-intensive industries.[5] Nevertheless, incentives offered by the contracts can vary by firm size, and the dilution of incentives from rewarding employees for increasing the value of the whole firm can be more substantial for large firms (Hochberg and Lindsey, 2010; Core and Guay, 2001; Oyer and Schaefer, 2005). Therefore, if the extent to which inventor sorts on firm size is related to how their talent is rewarded in small and large firms, the turnover of the high quality inventors should be more sensitive to the incentives offered in small firms than in the large firms.

I construct a proxy for firm's the value of options outstanding using the value of shares reserved for stock options outstanding as of the year end. Consistent with the hypothesis, I find that for small firms, a top 25% inventor is not more likely to leave when the firm tends to offer above-industry level of equity-linked compensation, measured as the average value of outstanding options, whereas he is about 5-6% more likely to leave if the level is low. However, this effect is not present for inventors working in large firms. The incentive provided by the large firms have negligible effect in retaining the high quality inventors, but the turnover of high quality inventors in small firms is strongly sensitive to the level of incentives offered.

through long-term contracts, citations may represent the economic value of the innovation but not necessarily the value created for the firm. For example, it may induce more entry to the technology field and increase competition. Thus, contracts based on innovative output instead of firm value may create perverse incentives for the R&D team that destroys firm value.

[5]One reason for broad-based equity compensation in large firms may be to index the wage to the market (Oyer, 2004).

Moving to a firm-level analysis, I examine whether firms benefit from hiring inventors of better quality and how this benefit differs across firm size. All else equal, an additional inventor should always have more impact on the future innovation in a small firm, since his additional invention constitutes greater portion of the firm's total output. In this case, for an additional hiring of any type of inventor, the increase in a firm's future innovation should be greater in small firms than in large firms. On the other hand, all else equal, a high quality inventor is expected to improve the future innovation of the firm, either through his own ability or knowledge spillover relative to a less competent inventor. In this case, for either type of firm, the impact on the firm's future innovation output should be proportional to the quality of the inventors hired. Taken together, the contribution to a firm's future innovation performance should be most significant for a high quality inventors newly hired by a small firm.

I aggregate the number of the inventors that change jobs at their destination firms and obtain the number of inventors hired by the firm each year. I find that a percentage increase in the hiring of top inventors relative to total hires increases the average citations of the firm by about 0.37% to 0.45%, and the increase is about 1.5 times greater in small firms than in large firms. Further, there is support for a monotonic relation between inventor quality and firm innovative output in small firms but not in large firms. The differential effect of small and large firms found in the relation between the quality of newly-hired inventors and firm future innovation is consistent with match quality being enhanced for top inventors at small firms.

Last, I perform a number of robustness checks to confirm the validity of my findings. The benchmark results are robust to different measures of inventor quality that put different weights in the quality and quantity of the patents, take into account the self-citing bias in large companies, and consider the lifetime quality instead of a dynamic ranking. In addition, the fact that the quality measure based solely on the quantity of patents does not yield the same results ensures that the benchmark result is not mechanically driven by the frequent patent filers.

The remainder of the paper is organized as follows. Chapter 2 presents how the paper is related to the literature. Chapter 3 describes the data and and assesses the potential impact that inventor quality sorting can have on the disparity in innovation between small and large firms. Chapter 4 presents the empirical investigation on the evidence of inventor sorting. Chapter 5 discusses the channels that may drive inventor sorting. Chapter 6 analyzes the relation of the newly hired inventors on the firm's future innovation productivity. Chapter 7 presents some robustness checks on the benchmark results and Chapter 8 concludes.

Chapter 2

# RELATED LITERATURE

My study lies on the intersection of the literature on matching and sorting of employees and the corporate literature on the evolution and quality of innovation. With respect to the former literature, my focus is on firm size and an employees ability to produce innovation. For the latter, my study relates to the large literature on employee incentive contracts and firm efficiency.

In comparison to my study, the literature on sorting and matching of employees are concerned with the efficiency of the employment and the effect on wages or welfare. More importantly, it explores the stationary distribution of employees and employers in the analysis, which complicates identification. In contrast, my method exploits changes in employee quality. Due to the high uncertainty in the innovation process, an employee previously considered to be of low or average ability may become more successful in a short period of time and therefore become "mis-matched" with the employer. Instead of measuring the quality of fit or match, I attempt to measure the effect by looking at how employees respond to a change in their position.

While many studies attempt to uncover the relation between worker and firm matching as the answer provides both positive and normative insight on the efficiency of allocation (Sattinger, 1975), the evidence on both the presence and the direction of firm-worker matching is inconclusive. The most popular method to uncover matching is to analyze the correlation between firm and worker fixed-effects in the wage regressions as proposed by the seminal work of Abowd *et al.* (1999) (AKM, henceforth). The idea is that more productive firms pay higher wages than less productive firms for the same type of worker and therefore firm fixed-effects reflect the rank of the firm. They find either insignificant or negative correlation in the fixed-effects between worker and firm type, and this result has been established in many matched employer-employee data and for a number of countries. However, Eeckhout and Kircher (2011) point out that wage does not necessarily increase monotonically in firm type given the same type of worker, which means that wage cannot be linearly decomposed into firm and worker fixed effects. Therefore, the negative or insignificant results can be misleading. The AKM method uncovers the firm's rank at the expense of imposing structure on the relation of firm type and wage. In order to impose minimum conditions on the data generating process, Bartolucci and Devicienti (2012) propose the use of worker mobility to uncover sorting. The idea is that, in the presence of positive assortative matching, better workers are more likely to match with better firms when they change employment. However, the essential assumption for identification is that there is some mismatch in the equilibrium allocation of workers and firms, which is not unreasonable given the common frictions in the labor market such as the cost for firms to fill a vacancy. The identification strategy thus relies on the variation in types of workers moving across firms of different types. I employ a similar strategy, but am able to dynamically measure inventor quality.

An alternative method that alleviates the Eeckhout and Kircher (2011)'s criticism is to use individual output data in obtaining the worker and firm fixed effects. This is impossible when individual output data is not available,[6] but patent productivity available at the inventor level provides a parsimonious setting for the exercise, as recognized by Liu *et al.* (2016). With the availability of inventor-employer matched data, they replicate the AKM exercise using individual-level productivity as measured by the patent output by each inventor. However, the focus of their paper is on the value

[6] A number of paper use profit data in addition to wage data, for example, Haltiwanger *et al.* (1999) and Mendes *et al.* (2010); however, it is hard to attribute firm profit to each individual worker's output.

of human capital in the innovative sector rather than addressing the issue of inventor and firm match. Their findings suggest that the inventor fixed-effect plays a larger role in explaining a firm's innovation performance. Unlike previous studies that focus on general workers, Liu *et al.* (2016) present a direct evidence on the relation between inventor productivity and firm innovative productivity, which supports the conjecture that small firms' better innovation performance can potentially be attributed to their better inventor pool.

Workers sorting in different dimensions may have further implications. For example, Combes *et al.* (2008) studies worker sorting based on geography to explain the spatial wage disparities, and Ouimet and Zarutskie (2014) study the matching between firm age and employee to understand the driver of new firm creation and growth. This paper provides evidence for workers sorting based on firm size, which sheds light on the understanding of the innovation gap between small and large firms.[7]

Studies on knowledge transfer across firms or geographical areas often exploit the mobility of knowledgeable scientists. Surveying 2,697 German inventors active between 1977 and 2002, Hoisl (2007) finds that more productive inventors are less likely to move in the cross-section, which supports the notion that firms may retain valuable scientists with high cost. In a related study, Kaiser *et al.* (2015) find that mobile scientists with bachelor or master degrees contribute more to patenting activity than immobile ones. Marx *et al.* (2015) find that the enforcement of non-compete agreements may drive away talented inventors and lead to a regional disadvantage. And more recently, Akcigit *et al.* (2015) find that the migration of "super-star" inventors

[7]The finance literature also studies the matching between CEO talent and firm size (Terviö, 2008; Edmans *et al.*, 2009). However, these papers build on the complementarity of managerial talent and firm size in order to obtain the assignment that can potentially attribute the rise of CEO compensation to the growth in firm size. Therefore, both the focus and implications of these papers is very different from the firm-worker matching literature.

across countries is sensitive to the level of personal income tax, suggesting knowledge transfer away from countries with high personal taxation. This paper provides additional evidence on the relation between mobility and inventor productivity that contributes to this line of work.

Apart from inventor mobility, this paper adds a new dimension to the research on how firm boundaries shape corporate innovation. Earlier studies suggest that large firms are more efficient in generating innovation since they can spread their cost of R&D on larger sets of output, which put large firms in better position in R&D competition (Cohen and Klepper, 1996b; Cohen and Levinthal, 1989; Cohen and Klepper, 1996a). Recent studies, however, suggest that the cost of developing innovation in large firms can be high. Phillips and Zhdanov (2012) posit that large firms optimally may choose to invest less in R&D if they have the option to acquire small firms. And, Seru (2014) finds that complex organization structure in conglomerates may induce competition among divisions that may stifle the incentive to innovate in each division. However, this paper is not the first to consider the human factor in explaining innovation gap between small and large firms. Kim and Marschke (2005) suggest that firms' patenting decision can be shaped by the mobility of the inventors as firms may want to protect themselves from employees expropriating valuable research ideas. As a result, small firms high patent-R&D ratio can be explained by the greater turnover rate of its scientists. However, their findings cannot explain why small firms also have greater average citations per patent, which is the measure of quality in this paper.

The findings of this paper also provide additional support for theories on the classic free-riding problem (Alchian and Demsetz, 1972; Prendergast, 1999). Previous empirical studies on the effect of team size and performance find different results. In an experimental setting, Van der Heijden *et al.* (2009) find evidence for free-riding incentives undermining performance in revenue-sharing teams, but institutional remedies such as appointing a team leader may also solve the problem. Heywood and Jirjahn (2009) find that firm size is associated with reduced profit sharing use when the production technology is independent but not when interdependent. Other studies find either insignificant or even positive links between firm size and profit-sharing plans (Fitzroy and Kraft, 1987; Hamilton *et al.*, 2003), which instead gives support to theories on peer monitoring (Kandel and Lazear, 1992). Therefore, the finding that the turnover of high quality inventors is sensitive to the proxy of equity-linked compensation in the small firms but not in the large firms adds to evidence consistent with the free-rider theory in a different setting.

Last, this paper also contributes to the broad literature concerning the determinants of innovation. There are two main focus in this literature. One focus is on any firm or market characteristics that correlates with managerial incentive to take on risky investments such as innovation. Numerous finance studies have explore the link between innovation and these characteristics, including stock liquidity (Fang *et al.*, 2014), analyst coverage (He and Tian, 2013), banking competition (Cornaggia *et al.*, 2015), unionization (Bradley *et al.*, 2015), firm boundaries (Seru, 2014), corporate governance (Meulbroek *et al.*, 1990) and institutional ownership (Aghion *et al.*, 2013). Other studies along this line, however, focus on the form and use of incentive schemes that may affect innovation output. Manso (2011) shows that the optimal contract to motivate innovation should exhibit long-term incentive and tolerance of failure, which is supported by evidence in Tian and Wang (2014). Lerner and Wulf (2007) find that shifting compensation of the heads of corporate R&D has positive impact on the firms innovation. Kedia and Mozumdar (2003) find that granting options that retain key employees increases firm value. And, Chang *et al.* (2015) examine the effect of employee stock options on corporate innovation. With the exception of Kedia and Mozumdar (2003), these studies normally do not distinguish whether the improved innovation is a result of greater effort provision or the selection of better workers. A separate literature, pioneered by Lazear (1986), studies the self-selection (sorting) of workers into firms that offer different policies. These studies ask the question how different policies lead to variation in firms worker productivity. For example, when firms offer incentive contracts, the high type workers may choose the high-powered contracts. For example, Lazear (2000) finds that workers productivity increases when firms change from flat rate to piece-rate wage policy; Oriana *et al.* (2012) find that firms offering compensation contracts with tighter link between performance and effort may attract higher ability managers. The goal of this paper is not to provide direct evidence on the sorting effect of the firms' compensation policy on corporate innovation; nevertheless, the findings of the paper speak to the intuition that the sorting effect can vary with firm size through the compensation channel.

Therefore, this paper is closely related to Zenger (1994) and Zenger and Lazzarini (2004), where the effect of firm size and the sorting of workers is analyzed. The former surveys individual engineers in two large firms, and find that the engineers with higher educational background are more likely to leave the current employer for a smaller firm. The later surveys engineers in high-tech firms and obtain evidence that small firms are able to attract talented workers by offering high-powered incentive. Complementary to these findings, this paper finds evidence of talent sorting using a more direct measure of quality in a large-sample analysis of inventors.

Chapter 3

# DATA AND SAMPLE

The primary data source is the Harvard Business School (HBS) US Patent Inventor Database (Li *et al.*, 2014), which consists of unique matches of inventor-patent data from the U.S. Patent Office (USPTO) for the period 1975-2010. The HBS patent database contains inventors' disambiguated names and locations, which allows me to track both employment history and location of the inventors over time.[8] Each observation is a patent filing, with its application year, grant year, inventors, the location where the inventors reside, and its assignee name. The data contain 9.4 million worldwide inventor-patent matches filed in the USPTO, with 4.2 million granted patents and 3.1 million unique inventors, 51% of which are filed from the U.S.

I merge the data with the National Bureau of Economic Research (NBER) Patent citations Data File (Hall *et al.*, 2001) to obtain other patent information, which restricts the sample period from 1975 to 2006. In addition, to obtain information on the characteristics of the assignees, I merge the data with the Compustat data using the crosswalk provided by the NBER database.[9] Lastly, following Acemoglu *et al.* (2014), I end the sample in 2002 to minimize the potential truncation problem of patents' citations since patents filed at the later time period mechanically have fewer citations.

[8]The NBER patent data also maintain information on the inventors. However, it is difficult to uniquely identify each inventor. For example, it is difficult to tell whether two inventors with the same first and last names but different middle names refer to the same person. See Li *et al.* (2014) for the details of the disambiguation process.

[9]For details of the crosswalk, please see Hall *et al.* (2001).

## 3.1 Measuring Innovation

**Quality measures for inventors**: The patent data give a rich set of measures that can proxy for an inventor's quality. Citations received by the patent can be seen as an external validation of its economic value and technological significance (Trajtenberg, 1990; Kogan *et al.*, 2012; Abrams *et al.*, 2013; Akcigit *et al.*, 2015).[10] Following the convention in the literature, I use the citations received by the patent as the measure of the patent's quality. Given the patent output generated by the inventor, I construct four different inventor quality measures that place different weights on the quantity and quality of the of the inventor's patents as well as account for the distortion that may arise from the difference in the nature of patenting activities in small and large firms.

Following Akcigit *et al.* (2015), my benchmark measure is the citation-weighted patent count for the most recent 5 years, which balances the effect of quantity and quality. Let $P_{it}$ be the number of patents of the inventors filed in year $t$ and $p_{it}$ be the number of forward citations received by these patents. The citation-weighted patent count is denoted as:

$$\text{Cite-Weighted Patent Count}(q1_t^i) = \sum_{\tau=0}^{\tau=4} p_{i,t-\tau}. \tag{3.1}$$

However, an inventor in a large research team may work on multiple projects and thus have more patents filed in his name, whereas an inventor working in a small firm

[10] Abrams *et al.* (2013) argue that forward citation is not a perfect measure of the economic value of innovation as the relationship between lifetime forward citations and patent value exhibits an inverted U-shape, with fewer citations at the high end of value than in the middle. They posit that this is related to the use of strategic patents that deter subsequent entry (forward citations). Hence, the use of forward citations to evaluate inventors quality may actually underestimate some high quality inventors that have produced patents for strategic purposes. However, the use of a categorical instead of continuous rank for inventor quality may partially mitigate this concern.

may focus more intensively on a limited number of projects. One way to scale the effect of team size is to use the average citations per patent, which is defined as:

$$\text{Average Citation}(q2_t^i) = \frac{\sum_{\tau=0}^{\tau=4} p_{i,t-\tau}}{\sum_{\tau=0}^{\tau=4} P_{i,t-\tau}}. \tag{3.2}$$

The third measure is the raw number of patents. Although this measure is less preferable since it does not take into account invention quality and is more likely to be affected by patenting strategy,[11] it has the advantage of being considered as an immediately visible performance measure for the inventors. Promotions and bonuses can thus be contingent on the quantity of patents produced without relying on long-run valuation through the citations realized in future.

$$\text{Patent Count}(q3_t^i) = \sum_{\tau=0}^{\tau=4} P_{i,t-\tau}. \tag{3.3}$$

Lastly, large firms are likely to have a larger patent stock and therefore tend to cite their own patents more often then small firms, which may inflate the citations received by patents filed in a large firm. Thus, I also consider the above quality measures by excluding the self-citations, which are denoted as $q4_t^i$ and $q5_t^i$.

Based on these innovation measures, we can obtain the distribution of inventor quality in each year. A top 25% inventor is thus defined as an inventor who outranks his peers in his quality measure by being on the top 25th percentile of the quality distribution in the given year. The notation bottom 25% is defined accordingly. I use both $q1$ and $q2$ as my benchmark measures since they capture inventor quality in

[11]Citations are also likely to be affected by the firm's patenting strategy if the firm chooses to patent invention of good quality; however, conditional on patenting, the level of citations received outside the firm may still reflect the degree of the patent's quality compared to other inventions.

different aspects, while the results for the non-benchmark measures are discussed in Section 7.

**Innovation output for firms**: In subsequent analysis, I also control for the firm innovation output as one of the firm characteristics, where the different measures of innovation are computed at the firm level. In addition, in Section 3.4, to compare the innovation capacity between small and large firms, I also construct the "tail innovation index" as in Acemoglu *et al.* (2014), which is defined as the ratio of number of patents by a firm with citations above the 99th percentile divided by the number of patents by the firm with citations above the median. This measure captures the tendency to generate patents with very high citations, presumably patents with greatest "hit," controlling for "average" innovation output.

## 3.2 Employment History of the Inventors

In the U.S., the employment contract normally requires that the right to the patent developed during the course of employment be assigned to the employer.[12] Therefore, in most cases, the assignee of the patent corresponds to the employer of the inventor. By making use of the panel nature of the patent database, I construct the employment history of the inventors in U.S. public firms and identify inventor mobility whenever there is a change in the patent assignee of the inventor's patent application.[13]

Specifically, the employment of an inventor is observed whenever the inventor files a patent with the firm. Suppose an inventor files a patent with firm A in year $t$

[12]Some states, including California, Minnesota and Utah, restrict the employer claim to ownership of its employee's invention under some circumstances.

[13]By surveying a stratified random sample of German inventors, Hoisl (2007) finds that 92% of the questioned inventors are employed with the applicant of the patent. In addition, Agrawal *et al.* (2006), Nakajima *et al.* (2010) also use this approach to track the career path of inventors.

and is observed again to file a patent with firm B in year $t + k$. It is very likely that he changes his employment from firm A to firm B during the period $t$ to $t + k$. However, the fact that the inventor files patents with different firms does not necessarily mean that the inventor makes an employment choice. Involuntary job changes due to bankruptcy or corporate transactions may contaminate the analysis of the employment decision. In order to make inference on the employment choice, I further impose the following restrictions in identifying employment changes. First, I exclude involuntary job changes due to firm bankruptcy by requiring the firm where the inventor leaves (firm A in the above example) continues to stay in the sample after the inventor leaves the firm in year $t$, i.e. firm A has to file at least one other patent after year $t$. This restriction also makes the identified job changes less likely to result from changes in generic corporate policy that cut down internal innovations or eliminate the research personnel. Second, I exclude any "job changes" resulting from M&A and spin-off transactions. I obtain information on M&A and spin-off transactions from SDC. Including these types of job flows significantly overestimates the number of employment changes in the sample. Therefore, I exclude any inventor job changes between an acquire-target (parent-target) pair that involves in an M&A or spin-off transaction.[14] Third, strategic alliances between the firms may result in the patents being assigned to two parties simultaneously, which also gives rise to spurious job changes. When a patent is assigned to multiple firms and thus an inventor is matched with multiple assignees in a given year, I first check previous years for employment for one of these assignees. If there is no match, I check the

[14]However, this procedure does not track inventor flows between two public firms that involve transactions through a private entity. For example, General Motors spun-off Hughes Research Lab as "HRL Laboratories, LLC" in 1997, with GM and Raytheon as co-owners. As a result, 283 inventors in the sample are being transferred from GM to Raytheon around the mid 90s. To minimize the probability of including such transactions, I further exclude all inventor job flows between firm-pairs having more than 10 inventors moving from one to the other throughout the sample.

subsequent years. If none of the employers are found in the previous or subsequent years, I randomly assigned one of the firms as the employer of the inventor of the year.[15] The final sample consists of 448,728 inventor-years matched with Compustat firms from 1980-2002 whose employer in the next period can be observed. In the sample, there are 16,843 employment changes between two Compustat firms, which represents 3.75% of the inventor sample.[16], [17]

There are several limitations to the sample. First, the structure of the dataset does not allow me to identify the exact time of the job switch, which can take place any time between year $t+1$ and $t+k$ in the above example. Therefore, firm size of the old and new employer are compared at different years if the inventor does not file patents in the two consecutive years. However, it is unlikely that a firm changes its position in the size distribution very often. Moreover, the average gap, $k$, is about 4.3 years in the sample, which is relatively a short period for a firm to dramatically grow in size. Second, the inventor drops out of the sample if he does not file patents anymore. Therefore, the number of job changes is likely to be underestimated if the inventors change jobs but do not file a patent again. For example, engineers who have good records may change to a managerial position overseeing research activity. On the other hand, the sample does successfully capture the mobility of inventors who

[15]The results are robust to excluding these observations. In addition, reported results also exclude 28 inventors who have moved more than 5 times in the sample period who also happen to have common names. Results are robust to their exclusion.

[16]Chung *et al.* (2014) estimate the annual quit rate in the U.S is around 1-2.5% for the period 1990-2014. The separation rate of 3.75% is higher in my sample since this figure is based on the denominator that only includes inventors for whom I can observe their employers in any subsequent year.

[17]Using the whole sample that include the private firms, the employment changes between public firms represent about 15.52% of the entire job flows (public firms constitute about 12% of the sample firms). While this proportion may seem small, job changes across the private firms are identified through changes in assignee number, which is very likely to over-count since a large portion of these changes in the inventor-firm match results from corporate transactions.

patent frequently, presumably those that have greater impact in generating innovation. Nevertheless, the limitations should be considered when making inferences from the results.

### 3.3 Sample Characteristics

I consider US patents assigned to US corporations filed between 1980 to 2002. The sample contains 2,324,336 patents matched to inventors. Aggregating at the inventor level, the sample consists of 1,440,064 inventor-years, with 58% of the inventor-years matched to Compustat firms. I further restrict the final sample to inventors who file patents in any subsequent year so that I can identify whether they change employment as well as the characteristics of their new firms. Panel A of Table 1 presents the summary statistics of the sample. In general, inventors who work in Compustat firms have more patents and higher citations per patent than the average. An average inventor generates 1.72 patents in a year and generates 5.4 patents throughout the sample period, Thus, he patents about 3.14 times during the sample period. The number of years between his first and last patent is about 5.4 years. The average citations per patent is 10.14 and average citations per patent over the most recent 5-year period is 11.95. Panel B shows the summary statistics for the sample inventors whose employer can be observed in any subsequent year. The average number of patents filed is 1.98, and the average total citations received is 23.67. Both numbers are slightly greater compared to the sample without restriction, which may reflect the fact that these inventors have to stay in the data for a longer period for the employment changes to be observed. Also, the average citations per patent is higher because inventors that are more productive are more likely to stay in the data for longer periods. Panel B also reports the statistics on the various measures that are used to rank the inventors. An average inventor receives 70.42 citations in the most recent 5 years, which is about 5.16 citations per patent. The average rate of separation from an employer in a five year window is 6.9%, out of which about 27% join small firms and 73% join large firms.

Table 2 shows the frequency of job changes. There are 165,896 inventors in the sample, of which 8.84% have changed job at least once, and 88.31% of the movers change jobs only once. Panel A of Table 3 reports the summary statistics of the inventor characteristics of "movers" and "non-movers" at the inventor-year level. For the movers, the variables are measured at the last year in the prior firm. Univariate comparison shows that movers have higher average citations, but not raw and citation-weighted patents. However, after excluding self-citations from the same firm, the movers have greater citation-weighted patents than non-movers. This observation thus emphasizes the importance of taking into account firm characteristics in the analysis. Panel B reports the characteristics of the "old firm" and "new firm." The "new firms" are smaller in size, have greater growth opportunities measured by Tobin's Q, are more R&D intensive and have a greater inventor to employee ratio. Also, it should be noted that large firms mechanically have a greater number of employees than small firms. About 80% of the inventors are employed by big firms, while only about 20% are employed by small firms. This asymmetry in employment has to be taken into account when interpreting the economic magnitude of employer size choice.

### 3.4 The Effect of Inventor Sorting

In this section, I first illustrate the stylized disparity between firm size and innovation that has been documented in the earlier studies and then assess the impact inventor sorting may have on this disparity, via a thought experiment. The sample consists of Compustat firms that have at least one patent in a given year. I sort all patenting firms into size quintiles based on the number of employees each year.

Panel A of Table 4 presents the summary statistics of firm characteristics. The mean and median of the book assets of patenting firms in the sample is about 3,609 and 219 million, respectively. Comparing to the mean of all Compustat firms (2,402.20), patenting firms tend to be the larger ones among all U.S firms. An average patenting firm has 22.2 patents and employs 30 inventors in a given year, which comprise only about 2.3% of its total employees. Panel B shows the statistics within each size quintile. The average book assets of the firms in the lowest quintile (the small firms) is about 25 million while that of the large firms is about 16 billion. Small firms have higher Tobin's Q, are younger and have higher R&D spending relative to book assets. Although small firms generate far fewer patents on average, the quality of the patents are on average better, as measured by either the average citations per patent, or the tail index. In addition, about 37% of the innovators are categorized as talented (i.e. top quartile) in the quintile 1 firms, which is 35% above the average portion of talented employees (27.4%) among all U.S. public firms, in contrast, only about 24% of the innovators are categorized as talented among the pool of large firms.[18]

Figure 1a shows the proportion of high quality patents that an average firm has in each size quintile. Out of the patents that have citations above the top 10 percentile in the year, the average quintile 1 (small) firm has 9% of these patents that earn extremely high citations ranking in the top 1%, while the average quintile 5 (large) firm has 6% of similar quality patents. Panel A in Figure 1b shows the average citations per patent for firms across size quintiles throughout the sample period. The average citations per patent of the bottom-quintile firms is almost 50% greater than that of the top-quintile firms. Panel B shows the same figure for the "tail index," which captures the tendency to generate patents with very high value given that it

[18] The average percentage of talented inventors in the sample is above 25%, which reflects the fact that inventors work in Compustat firms are of better quality then the those in the private firms sector.

has generated at least one above average patent. An average small firm seems to be more likely to generate more extremely cited patents. Panel C shows the difference in patenting efficiency in terms of every 10 million dollars spent. It seems that an average large firm spends more than 10 times on generating a patent compared to an average small firm. It is known that large firms spend a great proportion of R&D expenditures on incremental innovation which support its production processes and generates relatively fewer patents (Cohen and Klepper, 1996a). However, suppose that an average large firm shares the same cost of patenting as an average small firm, which is about $182,615 dollars per patent. Given that the average large firm generates 84.98 patents in a given year, the total cost spent on patenting would be about 15 million. Panel B of Table 4 lays out the statistics of firm characteristics by employee size. The average quintile 5 firm spends 630.79 million on R&D, suggesting only about 2.4% of its R&D expenditure is directed to innovations that result in patenting. In other words, the average quintile 5 firms either are burdened with higher cost to generate a patent, or they have disproportionately low spending on investment that targets patentable innovation, which implies a loss in innovation efficiency as measured by patents in either case.

To illustrate the effect of sorting, I calculate the average citations for each firm by adding back the potential loss of patents and citations from the leavers, and subtract the gain from the inventors who newly join the firm. If top innovators do not move from one firm to another, does this reduce the gap of average citations between large and small firms? The potential loss from a leaver is computed by adding up all the citations and patents generated by the leaver after he leaves the firm. The gain from a newly hired inventor is computed by adding up the citations and patents during his tenure in the new firm. Notice that a “leave” or a “new hire” is defined only when this inventor moves between two sample firms, and does not include inventors who newly enter or exit the labor market nor the employment flow between public and private firms.

Figure 2a shows the hypothetical average citations assuming no inventor mobility between the sample firms. The actual difference in the average citations between the quintile 5 and quintile 1 firm, 4.9, is reduced by about 30% to 3.3. Figure 2b further shows the effect in time-series. The dashed line is uniformly below the solid line for quintile 1 firms, and the dashed line is slightly above the solid line for quintile 5 firms.[19] In addition, the gap between the solid and dashed line is larger for the small firms. Because large firms have a very large pool of inventors, i.e. there are 113.8 inventors in an average quintile 5 firm but only 4.13 for an average quintile 1 firm, a change in one inventor can affect overall productivity for the small firms much more than for the large firms.

[19] That both lines trend downward and almost converge to zero at the end of the sample period reflects the fact that citations are truncated at the end of the sample period.

Chapter 4

# INVENTOR SORTING

## 4.1 Inventor Quality and Propensity to Leave

I begin by investigating the effect of inventor quality on his propensity to leave his employer. The results are reported in Table 5. A linear probability model is used to estimate the likelihood that an inventor leaves the firm in the next 5 years.[20] The dependent variable is whether the inventor changes his employer in the next 5 years. The variable of interest is inventor quality, i.e. top 25% and bottom 25% for the highest quality pool and lowest quality pool respectively. I define a firm as "small" if its size lies in quintile 1 to quintile 3 of the firm size distribution, and a firm as "big" if its size lies in quintile 4 or 5.[21] The size of the firm is measured at the year in which the inventor is observed to join a new firm. To capture other reasons for inventor departure, I control for the career stage ($careeryr$) and job tenure ($jobyr$). $Careeryr$ is the number of years passed since an inventor filed his first patent, which is used as a proxy for an inventor's age. $Jobyr$ is the number of years that the inventor has

[20] It is known that OLS is frequently a biased estimator and almost always an inconsistent estimator for binary outcomes (Horrace and Oaxaca, 2006). However, the size of the sample and the inclusion of high-dimension fixed effects makes it very difficult to use a nonlinear method of estimating the probability. I compare the result of LPM and logit regression that allows for across-firm variations and obtain qualitatively and quantitatively similar results.

[21] The cutoff for Big and Small firms is chosen for two reasons: first, 80% of the inventors come from the 40% large firms in the top 2 quintile. Therefore, using median (1,783 employees) as the cutoff results in few inventors moving to the small firms and significantly reduces the power of the test. On the other hand, economically, Hochberg and Lindsey (2010) find that the positive relation between non-executive stock options and firm performance is concentrated in firms with number of employees below median, which is 4.9 thousand in their IRRC sample. In my sample the quintile 3 firms have 1.96 thousand employees on average and a maximum of 5.5 thousand employees, while the quintile 4 firms have 7.1 thousand employees on average. Therefore, I believe classifying firms as "Big" by the last two quintiles is an appropriate measure.

worked for the current employer, which is used to capture the intuition that a worker is less likely to quit the longer he stays with the employer (Burdett, 1978). As controls for firm-level characteristics, I include the firm's intensity in innovation as captured by its investment in R&D, and innovation quality, measured as average citations per patent excluding the contribution of the inventor of interest. Also, a firm's growth opportunities, as measured by Tobin's Q, is likely to affect the inventor's decision. Other control variables include firm size as measured by the size of employment, the leverage ratio, firm age, profitability as measured by ROA and year fixed effects.

The first specification exploits variation across firms and years. In this case, the regression includes 2-digit industry and year fixed effects in addition to the controls mentioned above. Column 1 shows that the probability of departing from a firm is statistically significant and positively related to an inventor's quality ranking. The coefficients on the characteristics of the employer suggest that the inventors are more likely to leave from firms that are smaller and have little growth opportunities, even though the firm invests more in research and development. As for the individual level controls, the significance and the direction of the coefficients on *careeryr* and *jobyr* suggest that an inventor is more likely to change employment at the later stage of his career, but at the earlier years of employment. The specification in Column 2, by including firm and year fixed effects, essentially estimates the probability of a top 25% inventor leaving relative to the pool of inventors in the same firm. Firm fixed effects not only capture the correlation of productivity among inventors working in the same firm, but also takes into account other time-invariant characteristics of the firm that can affect the inventor's decision to depart. The results are very similar in both columns. Inventors at the top quartile are 17% to 20% more likely to leave the firm in the next 5 years relative to the average rate of employment change in the next 5 years (6.9%), while inventors at the bottom quartile are less likely to leave the firm relative to the average. Columns 3 and 4 report the estimation using the average citations per patent as the measure of inventor quality ($q2$). The result is qualitatively similar but the effect of inventor quality on the propensity to leave the firm in the next 5 years becomes asymmetric for the top and bottom inventors in terms of magnitude. The top quartile inventors are about 7 to 9% more likely to leave the firm in the next 5 years while the bottom quartile inventors are almost twice as likely to stay.

Sorting predicts high quality inventors leaving large firms. If large firms cannot retain better employees and attract only the less competent ones, the positive relation between the probability of leaving the firm and the quality of the inventors should be observed primarily for inventors in the large firms. To test this prediction, I interact the size dummy of the current employer with the quality ranking of the inventors.

Columns 5 to 8 report the results using different specifications or alternative measures to rank the inventors. In Column 5, the interaction with the large firm dummy is positive and significant for the top quartile inventors, and negative and significant for the bottom quartile. The same is true across the four specifications. In three of the four columns, there is no statistical significance for the coefficient on the top 25% indicator interaction with small firm. However, controlling for firm unobserved heterogeneity, Column 6 seems to indicate that there is also an enhanced probability of leaving for inventors employed by small firms. Moreover, the interactions between firm size and the bottom 25% inventors are almost always negative and significant for either size firm. Several studies have noted that the job turnover rate is significantly higher among workers in small firms (Topel and Ward, 1992; Oi, 1983); therefore, it is unrealistic to expect that high quality inventors leave big firms exclusively. The evidence suggests that the positive relation between the propensity to change jobs and an inventor's quality is not confined to small firms, where turnover rates are normally higher. Overall, these results are consistent with the sorting hypothesis that the assignment of inventor to firm is not random as inventors move to seek a better match with employers following good performance, particularly if they are employed by larger firms.

### 4.2 Inventor Quality and New Firm Size

Next, I investigate whether high quality inventors are more likely to move to small firms. Table 6 presents estimates of probability of joining a small or large firm as a function of inventor quality. The dependent variable, "to small" is an indicator variable equal to 1 if the inventor moves to a small firm in the next 5 years and 0 otherwise, i.e. either he stays with the current employer or moves to a big firm. The dependent variable "to big" is defined accordingly. All specifications include year and firm fixed-effects. As shown in Column 1, the coefficient on top 25% is positive and statistically significant at 1% level. An inventor in the top 25th percentile is more likely to move to a small firm in the next 5 year by about 32% relative to the average rate (1.9%). Column 2 uses average citations (q2) as the measure of inventor quality; the coefficient is still positive and significant although the magnitude is smaller.

As mentioned in the previous section, one concern is that the flow of inventors to small firms is driven by the high job turnover rate within the pool of small firms, i.e. inventors are likely to change their jobs from a small firm to another small firm. Column 3 and 4 suggest that this may not be the case. In Column 3, the coefficients on both interaction terms for the top 25% inventors are positive and significant, but cannot be statistically distinguished from each other, while in Column 4, where inventors are ranked by the average citations of their past invention instead of total citation counts, only the coefficient on the interaction term with large firm is statistically significant. The results thus suggest that there is no statistical difference in the relation between inventor quality and the likelihood to change jobs related to the size of the original firm.

Alternatively, inventors can choose to join large firms. However, it is worth noting that, mechanically, more inventors can be employed by the large firms relative to small firms since about 80% of the inventors are employed by large firms in the sample. Taking into account the mechanical asymmetry, I compare the increase in probability for the top 25% inventors to join large or small firms relative to the average rate. The sorting hypothesis implies that high quality inventors disproportionately join small firms, which suggests that the economic magnitude of the marginal probability of joining small firms should be larger. Column 5 reports the same specification, with the dependent variable indicating whether the inventor moves to a big firm in the next 5 years as opposed to staying with the current employer or moving to a small firm. The coefficient on the top 25% indicator is positively significant, but its magnitude relative to the mean is lower by almost half (18%). In addition, the coefficient is no longer significantly different from zero when the quality measure is replaced by the inventors' average citations in Column 6. Column 7 and 8 then interact the size of the old employer with the inventors' quality indicator. Interestingly, comparing Column 3 and 7, while there is substantial evidence that the high quality inventors are more likely to move to small firms regardless of the size of their previous employers, there is no evidence that the high quality inventors that previously were employed in small firms are more likely to move to big firms than average. This result thus further strengthens the sorting hypothesis.

Table 7 reports the estimation results using only the inventor-years that consist of changes in employment. In other words, the question here is whether high quality inventors are more likely to be re-hired by small firms conditional on changing employment. This specification thus moves away from the decision to leave or stay, but instead focusing on the size of the new employer conditional on changing jobs. The dependent variable is an indicator variable that equals to 1 if the inventor joins a small firm. Again, results are reported for specifications that include industry or firm fixed effects. Column 1 shows that, conditional on changing his job, the top 25% inventors are 2.7% more likely to join small firms, which is a 13.5% increase from the mean. However, there is no significant evidence showing that the bottom quality inventors are more likely to join the large firms. The coefficients on *careeryr* and *jobyr* indicate that, conditional on moving, the inventors that choose to join a small firm are younger but have stayed with the previous employers for longer periods. In addition, the coefficients on both Tobin's Q and R&D expenditures are positive and significant, indicating that the inventors that choose to join small firms are more likely to come from firms that have greater growth opportunities and that invest more in R&D on average. Column 2 reports the estimates with firm fixed effects, the coefficient on top 25% is slightly lower but still positive and statistically significant. However, after controlling for unobserved heterogeneity of current employers, the coefficients on both Tobin's Q and R&D expenditures are not statistically different from zero, suggesting that effects are related to fixed firm characteristics. Columns 3 and 4 report the estimates using an alternative inventor quality variable. The coefficients on top 25% are stronger, but those on the bottom 25% inventors become positive and not distinguishable from zero.

Column 5 to 8 investigate the interaction between inventor quality and old employer's size on the choice of the new employer size. The coefficients are positive and significant for the interaction term between top 25% and the large firm indicator for three out of the four specifications, but positive and insignificant for the interaction with the small firm indicator. The evidence thus supports the flow of high quality inventors from large to small firms, though not ruling out the possibility that inventors move among small firms as well. Nevertheless, high quality inventors moving within the pool of small firms is not inconsistent with the sorting hypothesis as long as there is sufficient flow of high quality inventors from large to small firms. Overall, this evidence is largely consistent with the conjecture that small firms have higher quality innovators on average and that these employees may contribute to its disproportionate share in generating high quality innovation.

# Chapter 5

# CHANNELS OF INVENTOR SORTING

Next, I explore two channels that may contribute to inventor sorting. Talented personnel may chase growth opportunities. It is possible that sorting on size is driven by the correlation between size and growth opportunities since talented innovators move out of firms with little growth options. Second, firm size may limit the mechanisms available for effective compensation of top talent, particularly if equity awards are common.

## 5.1 Inventor Quality and Firm Growth Opportunities

To begin, I ask whether there is an increased probability of high quality inventors leaving firms with low growth opportunities. Table 8 presents the estimates on the probability of an inventor leaving the firm as a function of the interaction between an inventor's quality and the level of growth opportunities in his current employer. A firm is classified as a "growth" firm if its Tobin's Q is above the median in the given year, and is classified as "value" otherwise. The specification is similar to Column 5 in Table 5 with the interaction terms replaced by the growth firm and value firm indicators.

Columns 1 to 4 report the first set of results, controlling for either industry or firm fixed effects. In Column 1, the coefficients of both interaction terms between top 25% and the growth or value firm indicators are positively significant; however the coefficient for the later is almost twice as large. Similarly, no differential effect can be found for the bottom 25% inventors in the growth or value firms. Controlling for firm heterogeneity, the estimation is qualitatively similar in Column 2. Column 3 and 4 replicate the the specifications in Column 1 and 2 using the average citations per patent to rank the inventors. Only the interaction with the value firm dummy is positive and significant for the top 25% inventors, which suggests that high quality inventors are more likely to leave firms with low growth opportunities. The coefficients on the interaction terms of the bottom 25% inventors show no significant difference between the two interaction terms, reflecting that inventors who have poor past performance are less likely to leave the current employer regardless of the type of the firm. These results are consistent with the intuition that talented inventors may chase growth opportunities.

However, the question is whether this drives the sorting result. I examine whether the high quality inventors moving to small mainly come from firms with low growth opportunities in Columns 5 to 8. All four specifications include year and firm fixed-effects. Columns 5 and 6 report the results from the same specification as in Column 3 and Column 4 in Table 6, with the interaction terms replaced by the growth/value firm dummy. If sorting to small firms is driven by the fact that high quality inventors chase growth opportunities, then we expect that these inventors should mostly come from firms with little growth opportunities. In both columns, the interactions between the top quality inventor indicator and either firm type are positive and significant; however, they are not distinguishable from each other. High quality inventors who choose to join small firms are not more likely to come from value firms, and this evidence mitigates the possibility that the sorting result is driven by talented inventors chasing growth opportunities.

Also, if we can observe any positive probability that the high quality inventors moving from growth to small firms conditional on changing their jobs, it may suggest that the sorting on size does not correspond to sorting on growth. Column 7 and 8 report the test using the sample conditional on all the inventor-years that consist of changes in employment. In Column 7, the coefficient on the top 25% indicator is only statistically significant for inventors that come from value firms, but insignificant for those from growth firms. Nevertheless, the magnitude of the coefficient mean is large for both interaction terms and are very close in magnitude. Moving to the alternative measure of inventor quality, the coefficients on both interaction terms for the top 25% inventors become positive and significant, and still not significantly distinguishable from each other. These results thus hint at the conclusion that the sorting results are not purely driven by differences in growth opportunities across different sized firms.

### 5.2 Inventor Quality and Performance Compensation

The above results suggest that inventor sorting cannot be explained fully by small firms' superior growth opportunities. I next explore to what extent differences in incentives may play. Individual performance for innovative activities is difficult to measure, and, firms often link pay with performance of the whole firm by offering equity-linked compensation. However, small and large firms may differ in their ability to fairly reward talent. High quality inventors may sort into small firms because small firms are more able to reward his ability. I examine this hypothesis by comparing the use of equity-linked compensation in small and large firms. If the ability of the employer to link the inventor's expected compensation with his performance decreases in firm size, turnover of the high quality inventors should be more sensitive to the incentive offered in small firms than in the large firms.

Ideally, one would like to measure incentives in terms of the percentage increase in employee's wealth with respect to firm value or productivity. Since data on employee compensation is not available at individual level, I construct a proxy for the value of options outstanding using the shares reserved for stock options outstanding as of the year multiplied by the firm's stock price at the year end. I then scale this value by the total number of employees, which reflects the extent to which average individual compensation varies with firm's value. The shares reserved for stock options outstanding is taken from the Compustat variable "Common Shares Reserved for Conversion Stock Options (CSHRSO)."[22] Since its revision in 2004, SFAS 123 requires that an employer's financial statements include certain disclosures about stock-based employee compensation arrangements regardless of the method used to account for them. Therefore, firms were not required to disclose information on employee stock options prior to 2004. However, for the 757 firm-years that have voluntarily disclosed the information before 1996, which is the last year CSHRSO is reported, I find that the correlation between the variable "Options Outstanding (OPTOSEY)" and "CSHRSO" is 94%. Also, I perform a check using Edgar filings, and find that the item does represent the number of stock options outstanding as of the year end. This Compustat variable is preferred to the more detailed IRRC data on employee stock options for two reasons. First, my sample only overlaps with the IRRC data for the five-year period from 1997 to 2002. And second, Compustat covers the universe of all listed firms, while the IRRC data only contains information on the S&P 1500 firms and some patenting firms can be too small to be covered by the IRRC data.

Results for tests concerning incentive pay are reported in Table 9. To estimate the effect of equity compensation on inventor turnover in big and small firms, I adopt the specification that interacts inventor quality with the employer's size and the proxy for the level of average value of stock options shared by the employees. A firm is

[22] Compustat defines the variable as follows: Prior to August 22, 1996, this item included: 1) shares subject to shareholder approval, and 2) stock appreciation rights attached to or associated with stock options. This item represents shares reserved for stock options outstanding as of year-end plus options that are available for future grants. This variable excludes stock appreciation rights not specifically attached to stock options or associated with stock options. This item is not available for banks, utilities, or property and casualty companies. This item was no longer collected by Compustat after August 22, 1996, therefore the sample for this section is restricted from 1980 to 1996.

classified as "High" if the value of per employee stock options outstanding is greater than the industry median in the given year, and the opposite definition applies to the variable "Low." As shown in Column 1, there is no significant difference in the magnitude of the coefficients between the top 25% inventors in large firms that pay more and firms that pay less than the industry median. The top 25% inventors in large firms are about 1.5 to 1.9% more likely to leave the firm regardless of the level of equity-linked compensation offered. In contrast, the coefficient on "top 25% $\times$ small $\times$ low" is significantly positive while the coefficient on "top 25% $\times$ small $\times$ high" is not significant with almost zero effect in magnitude. A top 25% inventor in small firm that offers an average incentive contract higher than the industry benchmark is not more likely to leave his employer than the average, while a top 25% inventor in small firm that offers incentive contract lower than the industry benchmark is about 6% more likely to leave the firm than an average inventor. Column 2 shows the result after controlling for time-invariant firm heterogeneity, and the estimation is similar in magnitude. Columns 3 and 4 report the results using average citations to rank the inventors. The first two coefficients are positive in both columns but not statistically distinguishable from each other, indicating that the top 25% inventor is not less likely to leave the large firm even when the firm has a policy that tends to grant employee stock option above the industry median. In Column 3, the coefficient is statistically significant at the 10% level for the interaction term "top 25% $\times$ big $\times$ low," but insignificant for "top 25% $\times$ big $\times$ high"; however, both coefficients are still not statistically distinguishable from each other. In Column 4, both coefficients become insignificant. The results suggest that there is no statistical difference in the probability of high quality inventors leaving between large firms that tend to pay more equity and large firms that tend to pay less than the industry median. In contrast, the coefficient on "top 25% $\times$ small $\times$ low" is not only significant and positive, but statistically different from the coefficient on "top 25% $\times$ small $\times$ high." Also, the estimate is large in magnitude compared to the rest.

Taken together, these results indicate incentives from the large firms are diluted if the employees have to share the reward from his own talent or effort with more employees, which prevents the large firms from attracting the best employees even if performance sensitive pay in the form of equity is offered. Turnover is more sensitive to the incentive offered in small firms than in large firms, which supports the argument that high quality inventors are likely to move to places where ability or effort can be fairly rewarded.

## Chapter 6

## INVENTOR HIRING AND FIRM PERFORMANCE

The previous findings suggest that high quality inventors are matched with small firms. It is thus straightforward to examine whether firms benefit from hiring inventors of better quality and how this benefit differs across firm size. The sorting hypothesis suggests that the contribution to a firm's future innovation performance should be most significant for high quality inventors newly hired by a small firm. Therefore, in this section, I move to investigate how the quality of newly hired inventors is related to the firm's future innovation performance.

I now turn to firm-year level data. The sample firms are the same as in Section 3. I aggregate the number of the inventors hired by each firm in every year. For firm-years I do not see any inventors hired, the number of newly hired inventors is zero. I compute the number of newly employed inventors within each quality category, and then scale the number by the total number of inventors that work for the firm in each year as the key independent variable. The dependent variable is the future innovation productivity of the firm, measured as the number of citations per patent for the firm in the future three or five years. Firms are categorized as "big" if their size is above the median of the sample and as "small" otherwise. Also, firm fixed-effects are included in all specifications to control for time-invariant unobserved factors that may affect future innovation as well.

Table 10a first shows the evidence on the relation between the quality of newly hired inventors and future innovation. Column 1 and 2 categorize the inventors by the total citation counts (q1) he produced in the most recent 5 years, while Column 3 and 4 categorize inventors by the average citations per patent (q2) produced in the most recent 5 years. Comparing the coefficients on the number of newly hired inventors among the quality categories, it is noticeable that only the hiring of inventors in the top 25th percentile and the middle categories have positive and significant impact on the future innovation performance, while there is no evidence showing that the inventors categorized in the bottom 25th percentile are associated with future innovation. With the exception of Column 4, the coefficients between the top and middle categories of the newly hired inventors are not statistically distinguishable from each other, though the point estimate for the top inventors is larger in magnitude than that of the medium inventors across all specifications. A percent increases in the hiring of top inventors increase the average citations of the firm by about 0.37% to 0.45% (Column 1 and Column3). The effect of the quality of newly hired inventors is even twice as strong on the innovative performance in the next 3 years, as shown in Columns 2 and 4.

However, the fact that high quality inventors sort into small firms implies a matching efficiency between these workers and small firms, which further suggests that the positive relation between the number of newly hired top 25% inventors and firm innovation should be the strongest in small firms. In Table 10b, I interact the scaled number of newly hired inventors with a firm size dummy that indicates whether the size of the firm is above or below the median of the sample. Comparing the first two rows in Column 1, the coefficient on the number of newly hired inventors is significantly positive for small firms, but indistinguishable from zero for the large firms. In addition, the mean of the estimates of the small firms is almost always significantly greater than that of the large firms. Holding all other variables constant, a one percent increase in the high quality inventors increases the firm's average citations by 0.55% in the next 5 years, which is about 1.5 times the effect in previous analysis.

Moving down the column, the coefficients on "newhire2 $\times$ big" and "newhire2 $\times$ small" indicate the effect of additional hiring of inventors at the medium level for both the large and small firms. While it may seem strange that hiring the medium inventors improves future innovation for the large firms, but hiring the top quality inventors does not, this can also reflect the fact the hiring of new inventors in the large firms concentrates in the medium quality pool. Column 2 reports the estimate of the same specification with the dependent variable measuring the innovation performance in the next 3 years. The inference for the impact of newly hired top inventors is similar to that of Column 1, but greater in magnitude. Also, for the medium inventors, the coefficients are positive and significant for both large and small firms, however the magnitude is very close and not distinguishable from each other. In fact, in all of the specifications, there is no significant difference in the coefficients for large firms across inventor quality, whereas for small firms there is support for a monotonic relation between inventor quality and firm innovation output. Column 3 and 4 report the same estimates as in Column 1 and 2 using measure q2 to categorize the inventors and the results yield similar inference.

Last, I interact quality of hires with firm size. Comparing the effect of the same quality inventors in the same type of firm, the coefficient monotonically decreases in the quality of the newly employed inventors for small firms but not for the large firms across all columns. In fact, for the large firms, in 3 out of the 4 specifications, the coefficients for each quality pool are not distinguishable from each other, even between the best and the worst pool of inventors. While the results suggest a positive relation between the quality of newly hired inventors and future innovation performance, this result does not preclude the possibility that firms target higher quality workers when anticipating potential innovation opportunities. Nevertheless, the emphasis is on the differential effect of newly-hired inventor quality between large and small firms, which supports the hypothesis that the high quality inventors have a larger impact in small firms.

Chapter 7

# ROBUSTNESS

In this section, I present the robustness checks on the benchmark results. Since how inventor ability is captured is central to the analysis, I explore how changes in the measure for inventor quality can affect the results . The results are reported in Table 11. Panel A reports the estimates using the specification in Column 2, Table 5 and Panel B reports the estimates from the specification in Column2, Table 7.

Since inventors who patent more frequently are more likely to be observed to move, one concern is that the result can be mechanically driven by the frequent patent filers. In Column 1, I use raw patent count in the most recent 5 years ($q3$) to rank the inventors and the the probability of inventors leaving a firm is still higher for inventors that rank in the top 25% as shown in Panel A. However, I find no evidence that these inventors have a greater propensity to join small firms conditional on changing their jobs. The coefficients on the top 25% and the bottom 25% inventors in Panel B are both small and not distinguishable from zero. This result supports the intuition that it is unlikely that quality measure based solely on the quantity of patents produced capture the variation in inventors' abilities and reassures that the benchmark result is not mechanically driven by the frequent patent filers. Another concern is that large firms are more likely to cite their own patents, and since patent stock increases in firm size, it is possible that the number of citations for patents developed in large firms, and thus the measure of inventor quality used in the analysis, are more likely to be inflated. Column 2 and 3 measures inventor quality by excluding the citations coming from the same company when computing both the citation-weighted patent count ($q1$) and the average citations per patent ($q2$). The results are very similar to the benchmark analysis in both cases.

Following Akcigit *et al.* (2015), I also consider a measure that reflects the inventor's lifetime quality. The measure used in the previous analysis has assumed a dynamic ranking that changes over time, which also assumes that the inventor's recent performance is indicative of his ability. However, one can imagine the case where a talented inventor does not have any past record but knows about his potential, he may want to move to places where his ability is rewarded. I redefine an inventor's quality over the course of his life in the sample as in Akcigit *et al.* (2015). A top 25% inventor is one who has ever been in the top 25% but never been in the bottom 25%, and a bottom 25% inventor is one who has ever been in the bottom 25% but never been in the top 25%. The result is reported in Column 4. The estimates in Panel A are qualitatively similar to the benchmark, except that the point estimate for the bottom 25% inventors becomes much smaller. A possible reason is that inventors that have low life-time quality are more likely to drop out of the data if he does not continue to produce, and therefore it is less likely to see him move. Conditioning on the inventors who change their employment, Panel B shows that these bottom 25% inventors are about 2% less likely to join small firms, which is about 15% relative to the mean; however, the propensity for the top 25% inventors to join small firms is much smaller and becomes insignificant based on having ever been in the top 25%, perhaps suggesting a noisier measure. Last, I explore the possibility of various permutations on variable definitions and the results are robust to different definitions of firm size and to whether I compare the size of the new and old employers at the time the inventors leave the old firms or join the new firms when there is a gap in between.

Chapter 8

# CONCLUSION

The belief that small firms are more innovative is prevalent among practitioners and financial economists. This paper provides evidence related to the fact that small firms have a more productive, innovative work force on average. I exploit the panel nature of the patent database to construct the employment histories of each individual inventor and show that high quality inventors disproportionately join small firms. Although there is evidence that talented innovators exit from firms that suffer the loss of growth opportunities, the intuition that high quality inventors tend to chase growth opportunities cannot fully account for the findings on inventors sorting disproportionately to small firms.

The question arises as to why large firms may be inefficient in retaining or attracting high quality inventors. One explanation is that firm size is associated with the degree that the firm can reward talent. An individual's contribution to the firm is measured with less noise in small firms, and compensation can therefore be more closely linked to individual performance. Further, equity awards will be less diluted in smaller firms. Although in practice we still observe large firms offering compensation in the form of equity to employees, these incentives are argued to have no incentive effects (Oyer, 2004; Oyer and Schaefer, 2005), which suggests that large firms have a disadvantage in retaining human capital. In contrast, if high expected reward is a key mechanism that drives the high quality inventors to join small firms, we should observe that turnover of high quality inventors is sensitive to the portion of compensation offered in the form of equity for the small firms, which is supported by the findings of this paper.

This paper bridges the gap between the large literature concerned with the matching or sorting of workers to firms and the studies exploring innovation as a function of firm characteristics, which contributes to the greater innovation efficiency found in small firms and highlights on the effectiveness of employee incentive contracts on output across firm size.

**Table 1:** Summary Statistics: Inventor Characteristics

The unit of analysis is inventor-year. The sample period is from 1980-2002. Panel A presents summary statistics for all US inventors that can be matched to Compustat firms. Panel B presents summary statistics for the sample inventors who file patents in any subsequent year so that I can identify whether they change employment. *Patents* is the number of patents for which the inventor applies in the given year. *Citations* is all forward citations for the patents from the application data. *Citations (excl. self-cites)* is *Citations* excluding self-citation from the same firm. *Cpatent* is average citations per patent for which the inventor applies in the given year and *Cpatent (excl. self-cites)* is the average citations per patent excluding self-citations from the same firm. *Total patents* refers to the total number of patent for which an inventor applies throughout the sample period. *Total citations* is the total number of citations received by the inventor throughout the sample period. *Total year* is the average number of years an inventor stays in the sample. The prefix *p5yr* refers to the same variable computed at the most recent 5-year window. *Leave* is an indicator variable on whether the inventor leaves the current employer in the next 5 years. *Tosmall* is an indicator variable on whether the inventor moves to a small firm in the next 5 years. *Tobig* is an indicator variable on whether the inventor moves to a big firm in the next 5 years.

Table 1 continued.

| Panel A: All Inventors | | | | | | |
|---|---|---|---|---|---|---|
| Variables | N | mean | std | p50 | p1 | p99 |
| Inventor-year | | | | | | |
| Patents | 838,344 | 1.720 | 1.944 | 1.000 | 1.000 | 9.000 |
| Citations | 838,344 | 17.580 | 37.214 | 7.000 | 0.000 | 157.000 |
| Citations (excl. self-cites) | 838,344 | 14.585 | 30.098 | 6.000 | 0.000 | 133.000 |
| Cpatent | 838,344 | 10.608 | 17.499 | 5.000 | 0.000 | 81.000 |
| Cpatent (excl. self-cites) | 838,344 | 9.019 | 15.564 | 4.000 | 0.000 | 72.000 |
| Inventor | | | | | | |
| Total patents | 367,195 | 5.399 | 10.013 | 2.000 | 1.000 | 44.000 |
| Total citations | 367,195 | 53.062 | 148.784 | 15.000 | 0.000 | 578.000 |
| Total years | 367,195 | 5.404 | 5.893 | 3.000 | 1.000 | 23.000 |
| Panel B: Sample | | | | | | |
| Inventor-year | | | | | | |
| Patents | 448,728 | 1.981 | 2.294 | 1.000 | 1.000 | 10.000 |
| Citations | 448,728 | 23.665 | 45.750 | 11.000 | 0.000 | 196.000 |
| Citations (excl. self-cites) | 448,728 | 19.016 | 35.871 | 8.000 | 0.000 | 160.000 |
| Cpatent | 448,728 | 12.777 | 18.994 | 7.000 | 0.000 | 88.500 |
| Cpatent (excl. self-cites) | 448,728 | 10.497 | 16.463 | 5.500 | 0.000 | 77.000 |
| P5yrcitations (q1) | 448,728 | 70.422 | 147.599 | 30.000 | 0.000 | 606.000 |
| P5yrcpatent (q2) | 448,728 | 14.301 | 18.116 | 9.000 | 0.000 | 85.000 |
| P5yrpatents (q3) | 448,728 | 5.160 | 7.645 | 3.000 | 1.000 | 33.000 |
| P5yrcitations (excl. self-cites) (q4) | 448,728 | 56.013 | 114.356 | 23.000 | 0.000 | 487.000 |
| P5yrcpatent (excl. self-cites) (q5) | 448,728 | 11.728 | 15.723 | 7.050 | 0.000 | 73.333 |
| Leave | 448,728 | 0.069 | 0.253 | 0.000 | 0.000 | 1.000 |
| To small | 448,728 | 0.019 | 0.136 | 0.000 | 0.000 | 1.000 |
| To big | 448,728 | 0.051 | 0.221 | 0.000 | 0.000 | 1.000 |

**Table 2:** Frequency and Characteristics of Employment Changes

The unit of analysis is an inventor who have files at least one patent between 1980-2002. This table reports the frequency that an inventor changes his employment during the sample period 1980-2002. *Non-mover* refers to the number of inventors that have never changed employment during the sample period. *Mover* refers to the number of inventors that have ever changed jobs.

| | Freq. | Percent |
|---|---|---|
| Non-mover | 151,170 | 91.16 |
| Mover | | |
| 1 | 13,004 | 11.78 |
| 2 | 1,416 | 1.35 |
| $\geq 3$ | 306 | 0.29 |
| Total number of inventors | 165,896 | |
| Total number of moves | 16,843 | |

**Table 3:** Difference between Movers and Non-movers

The unit of analysis is an inventor-year between 1980-2002. Panel A reports the difference in mean between the inventor-years that consist of changes in employment (*Mover*) and those that do not (*Non-movers*). *Careeryr* is the number of years past since the inventor filed his first patent. *Jobyr* is he number of years that the inventor has been employed by the firm since his first patent with the firm. All other inventor-related variables are defined in Table 1. Panel B reports the characteristics of the "old" and "new" firms of the inventor-years that consist of changes in employment. All other variables are defined in Table 4.

Panel A: Difference in Movers and Non-Movers

| | Non-movers | | Movers | | |
|---|---|---|---|---|---|
| Variables | N | Mean | N | Mean | Diff. |
| Patents | 431,885 | 1.994 | 16,843 | 1.662 | 0.332*** |
| p5yrpatents | 431,885 | 5.190 | 16,843 | 4.396 | 0.794*** |
| p5yrcitations | 431,885 | 70.64 | 16,843 | 64.97 | 5.664*** |
| p5yrcpatents | 431,885 | 14.25 | 16,843 | 15.60 | -1.352*** |
| p5yrcitations (excl. self-cites) | 431885 | 55.90 | 16843 | 58.81 | -2.903*** |
| p5yrcpatent (excl. self-cites) | 431885 | 11.63 | 16843 | 14.34 | -2.711*** |
| Total years | 431,885 | 11.56 | 16,843 | 13.54 | -1.979*** |
| Career year | 431,885 | 6.174 | 16,843 | 5.900 | 0.274*** |
| Job year | 431,885 | 3.934 | 16,843 | 2.896 | 1.038*** |

Table 3 continued.

| Panel B: Difference in Old and New Firms | | | | | |
|---|---|---|---|---|---|
| | New | | Old | | |
| Variables | N | Mean | N | Mean | Diff. |
| Total Assets (Mil.) | 16,843 | 18,190.440 | 16,843 | 28,391.450 | -10,201.010*** |
| Employees ('000) | 16,843 | 55.427 | 16,843 | 77.728 | -22.301*** |
| Market Equity | 15,946 | 24,788.750 | 16,520 | 30,255.570 | -5,466.821*** |
| Tobin's Q | 15,753 | 2.689 | 16,163 | 2.207 | 0.481*** |
| Firm age | 16,843 | 25.558 | 16,843 | 34.467 | -8.908*** |
| R&D ratio | 16,211 | 0.101 | 16,454 | 0.077 | 0.024*** |
| Leverage ratio | 16,810 | 0.204 | 16,830 | 0.229 | -0.025*** |
| ROA | 16,406 | 0.125 | 16,811 | 0.132 | -0.007*** |
| Cpatent | 16,838 | 9.850 | 16,838 | 8.584 | 1.266*** |
| Tail invention | 16,120 | 0.018 | 16,192 | 0.015 | 0.004*** |
| Number of Inventors | 16,843 | 307.583 | 16,843 | 405.460 | -97.877*** |
| Proportion of Inventors | 16,835 | 0.023 | 16,840 | 0.012 | 0.011*** |

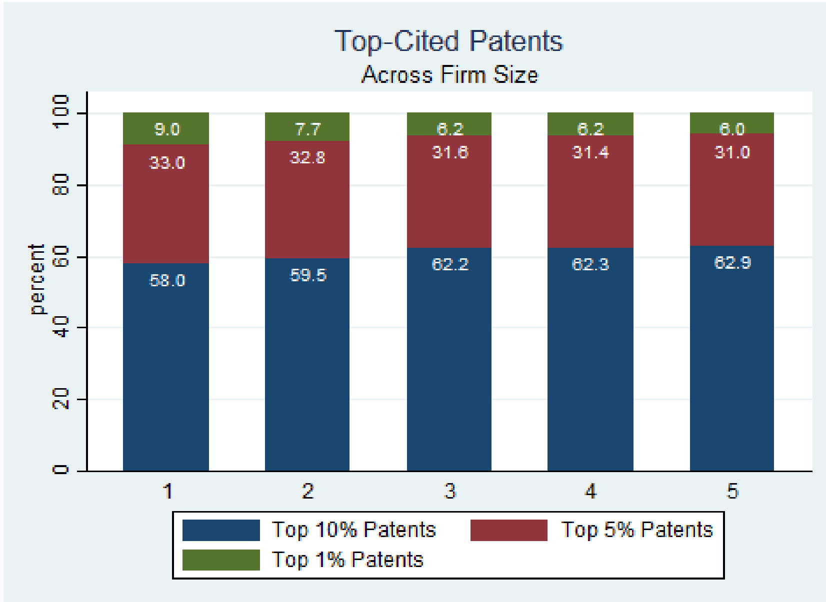


**Figure 1a:** Proportion of Top-Cited Patents

The figure plots the average proportion of highly cited patents for firms within each size quintile. Quintile 1 represents the smallest firms as measured by employee size, and quintile 5 the largest.

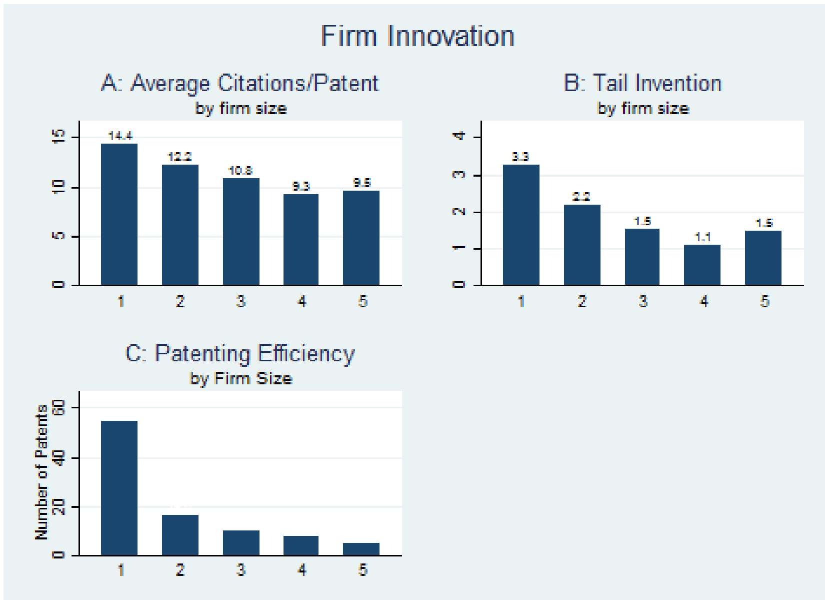


**Figure 1b:** Innovation Performance by Firm Size

The figure plots the average innovation performance for firms within each size quintile. Panel A shows the average quality of innovation output measured by the average citations. Panel B shows the average tail index, which is the ratio of number of patents by a firm with citations above the 99th percentile divided by the number of patents by the firm with citations above the median. Panel C shows the average patenting efficiency measured as number of patents every 10 million dollars spent.

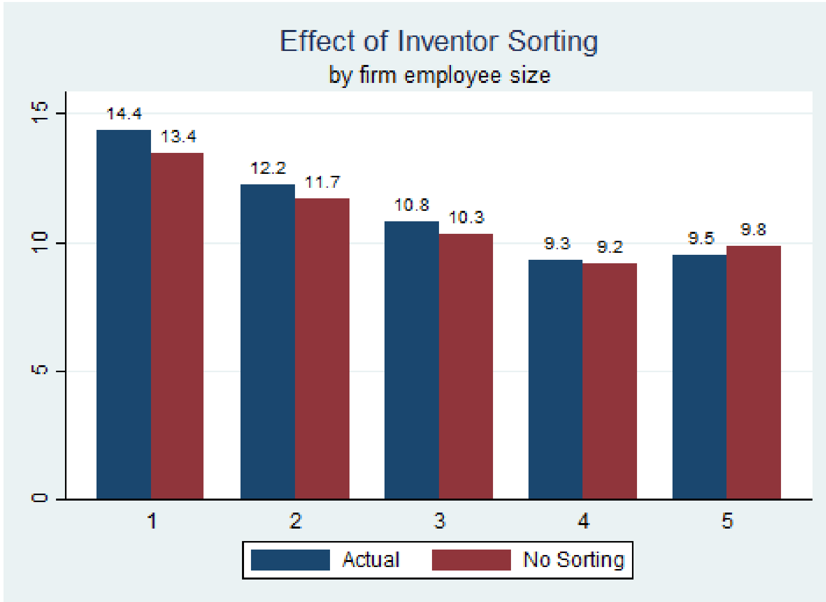


**Figure 2a:** Effect of Inventor Sorting

The figure compares the actual average citations for firms within each quintile to the average citations obtained by the firms assuming there is no inventor flow among the sample firms.

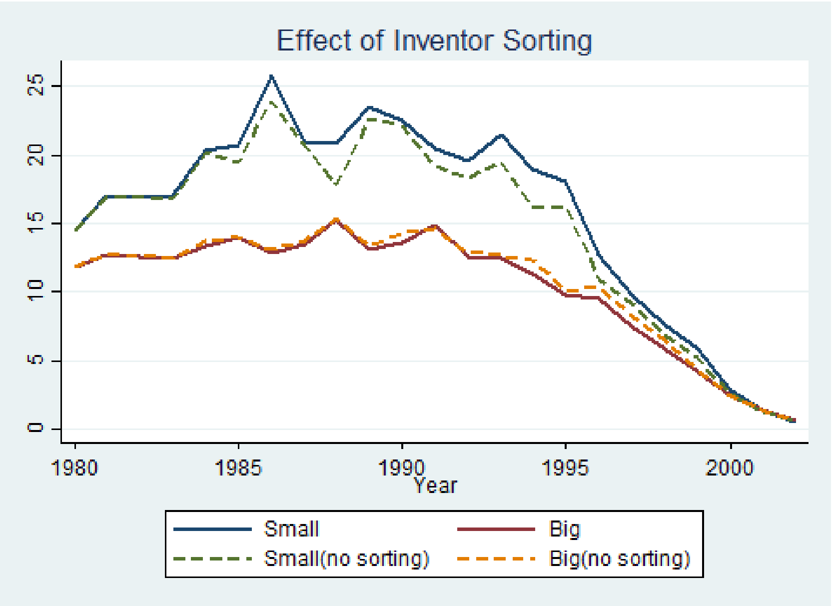


**Figure 2b:** Effect of Inventor Sorting by Year

The figure plots time series comparison of the actual and the hypothetical average citations between firms in the lowest (small) and highest (big) quintile, assuming there is no inventor flow .

**Table 4:** Summary Statistics: Firm Characteristics

The unit of analysis is a firm-year. The sample consists of all Compustat firms that have applied for patents in the given year between 1980-2002. *Total Assets* is total book assets. *Employees* is the number of employees. *Firm age* is the number of years since firm first appears in Compustat. *Market Equity* is the market value of equity the firm at the end of calendar year (csho $\times$ prcc_c). *Tobin's Q* is the ratio of market value of assets divided by book value of assets. *R&D ratio* is the research and development expenditure divided by the firm's total asset. *Patents* is the number of patents that the firm applies in the given year. *Citations* is all forward citations from the patents that the firm applies in the given year. *Cpatent* is average citations per patent that the inventor applies in the given year. *Tail invention* is the ratio of number of patents by a firm with citations above the 99th percentile divided by the number of patents by the firm with citations above the median. *Patents per 10 mil. R&D* is the number of patents divided by every 10 million of R&D expenditure. *Number of Inventor* is the number of inventors in the firm. *Number of top 25% Inventors* is the number of inventors that is in the top 25th percentile in the year. *Proportion of inventors* is the number of inventors as a portion of total number of employees. *Proportion of top 25% Inventors* is number of top 25% inventors as a percentage of total number of inventors.

Table 4 continued.

| Panel A: All Patenting Firms | | | | | | |
|---|---|---|---|---|---|---|
| Variables | N | mean | sd | p50 | p1 | p99 |
| Total Assets (Mil.) | 27,188 | 3,609.177 | 20,246.459 | 218.978 | 1.490 | 57,100.000 |
| Employees (000) | 27,188 | 14.167 | 44.890 | 1.783 | 0.011 | 186.800 |
| Firm Age | 27,188 | 18.707 | 14.007 | 14.000 | 1.000 | 51.000 |
| Market Equity | 25,457 | 3,137.470 | 14,993.263 | 234.903 | 2.081 | 56,291.823 |
| Tobin's Q | 24,601 | 2.264 | 2.204 | 1.489 | 0.652 | 13.957 |
| R&D ratio | 22,552 | 0.118 | 0.318 | 0.055 | 0.000 | 0.998 |
| Patents | 27,164 | 22.281 | 97.202 | 3.000 | 1.000 | 373.000 |
| Citations | 27,164 | 219.829 | 1,051.598 | 24.000 | 0.000 | 3,815.000 |
| Cpatent | 27,164 | 11.227 | 15.399 | 7.250 | 0.000 | 74.000 |
| Tail invention | 20,336 | 0.018 | 0.102 | 0.000 | 0.000 | 0.500 |
| Patents per 10 mil. R&D | 21,670 | 19.154 | 157.006 | 5.019 | 0.077 | 204.082 |
| Number of Inventors | 27,188 | 30.249 | 126.286 | 5.000 | 1.000 | 510.000 |
| Proportion of Inventors | 27,171 | 0.023 | 0.094 | 0.003 | 0.000 | 0.281 |
| Proportion of Top 25 inventors | 27,188 | 0.274 | 0.316 | 0.178 | 0.000 | 1.000 |

Table 4 continued.

| Panel B: Firm Characteristics by Size | | | | | |
|---|---|---|---|---|---|
| Firm Size (in Quintile) | 1 | 2 | 3 | 4 | 5 |
| Total Assets (Mil.) | 25.359 | 102.147 | 342.362 | 1364.572 | 16174.200 |
| Employees (000) | 0.116 | 0.587 | 1.964 | 7.056 | 60.973 |
| Market Equity | 73.693 | 244.768 | 581.246 | 1462.831 | 13361.210 |
| Tobin's Q | 3.565 | 2.395 | 1.984 | 1.738 | 1.743 |
| Firm Age | 7.915 | 11.730 | 16.897 | 24.382 | 32.546 |
| R&D ratio | 0.277 | 0.126 | 0.073 | 0.047 | 0.039 |
| Patents | 2.728 | 4.004 | 6.061 | 13.360 | 84.979 |
| Citations | 39.161 | 46.735 | 65.586 | 135.859 | 809.264 |
| Firm Cpatent | 14.358 | 12.240 | 10.772 | 9.263 | 9.524 |
| Tail invention | 0.033 | 0.022 | 0.015 | 0.011 | 0.015 |
| Patents per 10 mil. R&D | 54.759 | 15.977 | 10.217 | 7.581 | 4.769 |
| Number of inventors | 4.130 | 5.902 | 8.422 | 18.764 | 113.771 |
| Number of top 25% Inventors | 1.594 | 2.166 | 2.961 | 5.657 | 33.834 |
| Proportion of inventors | 0.086 | 0.018 | 0.006 | 0.003 | 0.002 |
| Proportion of top 25% inventors | 0.368 | 0.312 | 0.252 | 0.219 | 0.238 |

**Table 5:** Inventor Quality and Propensity to Leave

This table reports estimation from the linear probability model. The unit of observation is an inventor-year. The sample period is 1980-2002. The dependent variable is *Leave*, which equals to 1 if the inventor leaves the firm in the next 5 years. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. Column (1), (2), (5) and (6) reports the estimates using measure q1 as defined in Section 3.1, and Column (3), (4), (7) and (8) report the estimates using quality measure q2. *Big* is a dummy variable that equals to 1 if the firm's size lies in quintile 4 and 5 in the given year, and *small* is a dummy variable equals to 1 if the firm's size lies in quintile 1 to 3 in the given year. All other firm characteristics variables are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Leave | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Top 25% | 0.012*** | 0.014*** | 0.006** | 0.005** | | | | |
| | (0.002) | (0.002) | (0.002) | (0.002) | | | | |
| Bottom 25% | -0.012*** | -0.012*** | -0.010*** | -0.010*** | | | | |
| | (0.001) | (0.001) | (0.002) | (0.002) | | | | |
| Top 25% × big | | | | | 0.013*** | 0.014*** | 0.006** | 0.006** |
| | | | | | (0.002) | (0.002) | (0.003) | (0.002) |
| Top 25% × small | | | | | 0.008 | 0.014** | 0.007 | 0.005 |
| | | | | | (0.006) | (0.006) | (0.006) | (0.006) |
| Bottom 25% × big | | | | | -0.012*** | -0.012*** | -0.010*** | -0.011*** |
| | | | | | (0.001) | (0.001) | (0.002) | (0.002) |
| Bottom 25% × small | | | | | -0.012** | -0.009* | -0.019*** | -0.006 |
| | | | | | (0.005) | (0.005) | (0.007) | (0.006) |

Table 5 continued.

| | Leave | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Big | | | | | 0.025*** | 0.000 | 0.025*** | 0.000 |
| | | | | | (0.009) | (0.007) | (0.009) | (0.007) |
| Careeryr | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Jobyr | -0.006*** | -0.005*** | -0.006*** | -0.005*** | -0.006*** | -0.005*** | -0.006*** | -0.005*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm Size | -0.009*** | 0.000 | -0.009*** | 0.000 | -0.012*** | 0.000 | -0.012*** | 0.000 |
| | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) | (0.004) |
| Tobin's Q | -0.003*** | -0.001 | -0.003*** | -0.001 | -0.003*** | -0.001 | -0.003*** | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Firm age | -0.000 | -0.050 | -0.000 | -0.049 | -0.000 | -0.050 | -0.000 | -0.049 |
| | (0.000) | (0.050) | (0.000) | (0.049) | (0.000) | (0.050) | (0.000) | (0.050) |
| Leverage | 0.006 | 0.015 | 0.006 | 0.015 | 0.009 | 0.015 | 0.009 | 0.015 |
| | (0.013) | (0.017) | (0.013) | (0.017) | (0.013) | (0.017) | (0.013) | (0.017) |
| ROA | -0.016 | -0.021 | -0.017 | -0.022 | -0.025 | -0.021 | -0.025 | -0.022 |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.015) | (0.016) |
| R&D | 0.072** | 0.008 | 0.074** | 0.008 | 0.078** | 0.008 | 0.083** | 0.008 |
| | (0.034) | (0.020) | (0.034) | (0.020) | (0.033) | (0.020) | (0.033) | (0.020) |
| Firm Cpatent | -0.006* | -0.002 | -0.006* | -0.002 | -0.006* | -0.002 | -0.006* | -0.002 |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) |
| Constant | 0.158*** | 1.197 | 0.158*** | 1.183 | 0.147*** | 1.197 | 0.148*** | 1.185 |
| | (0.012) | (1.105) | (0.012) | (1.088) | (0.012) | (1.106) | (0.011) | (1.089) |
| Observations | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 |
| R-squared | 0.021 | 0.048 | 0.020 | 0.047 | 0.021 | 0.048 | 0.021 | 0.047 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Firm FE | No | Yes | No | Yes | No | Yes | No | Yes |

**Table 6:** Inventor Quality and New Firm Size

This table reports estimation from the linear probability model. The unit of observation is an inventor-year. The sample period is 1980-2002. The dependent variable in Column (1) to (4) is *To small*, which is a dummy variable which equals to 1 if the inventor moves to a small firm in the next 5 years. The dependent variable in Column (5) to (8) is *To big*, which is a dummy variable equals to 1 if the inventor moves to a big firm in the next 5 year. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. *Big* is a dummy variable that equals to 1 if the firm's size lies in quintile 4 and 5 in the given year, and *small* is a dummy variable equals to 1 if the firm's size lies in quintile 1 to 3 in the given year. Column (1), (3), (5) and (7) reports the estimates using cite-weighted patent(q1), and Column (2), (4), (6) and (8) report the estimates using average citations(q2). All other firm characteristics variables are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | To small | | | | To big | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw. | Avg. | Cw. | Avg. | Cw. | Avg. | Cw. | Avg. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Top 25% | 0.006*** | 0.003*** | | | 0.009*** | 0.002 | | |
| | (0.001) | (0.001) | | | (0.002) | (0.002) | | |
| Bottom 25% | -0.003*** | -0.002*** | | | -0.009*** | -0.008*** | | |
| | (0.001) | (0.001) | | | (0.001) | (0.001) | | |
| Top 25% × big | | | 0.005*** | 0.003*** | | | 0.009*** | 0.003 |
| | | | (0.001) | (0.001) | | | (0.002) | (0.002) |
| Top 25% × small | | | 0.014*** | 0.005 | | | 0.002 | -0.002 |
| | | | (0.004) | (0.004) | | | (0.004) | (0.005) |
| Bottom 25% × big | | | -0.003*** | -0.002** | | | -0.010*** | -0.009*** |
| | | | (0.001) | (0.001) | | | (0.001) | (0.001) |
| Bottom 25% × small | | | -0.008** | -0.007* | | | -0.002 | -0.000 |
| | | | (0.003) | (0.004) | | | (0.004) | (0.005) |

Table 6 continued.

| | To small | | | | To big | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw. | Avg. | Cw. | Avg. | Cw. | Avg. | Cw. | Avg. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Big | | | 0.001 | -0.001 | | | -0.000 | 0.000 |
| | | | (0.004) | (0.004) | | | (0.005) | (0.005) |
| Careeryr | 0.001*** | 0.001*** | 0.001*** | 0.001*** | 0.002*** | 0.003*** | 0.002*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Jobyr | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.004*** | -0.004*** | -0.004*** | -0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm size | -0.004** | -0.004** | -0.004** | -0.004** | 0.004 | 0.004 | 0.004 | 0.004 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Tobin's Q | -0.001** | -0.001** | -0.001** | -0.001** | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Firm age | -0.026 | -0.025 | -0.025 | -0.025 | -0.018 | -0.018 | -0.019 | -0.018 |
| | (0.023) | (0.022) | (0.023) | (0.022) | (0.031) | (0.030) | (0.031) | (0.030) |
| Leverage | 0.006 | 0.006 | 0.006 | 0.006 | 0.008 | 0.008 | 0.008 | 0.008 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.013) | (0.013) | (0.013) | (0.013) |
| ROA | -0.001 | -0.002 | -0.001 | -0.002 | -0.020 | -0.020 | -0.020 | -0.020 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.013) | (0.014) | (0.013) | (0.013) |
| R&D | 0.005 | 0.005 | 0.005 | 0.005 | 0.004 | 0.004 | 0.004 | 0.003 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.015) | (0.015) | (0.015) | (0.015) |
| Firm Cpatent | 0.000 | 0.000 | 0.000 | 0.000 | -0.002 | -0.002 | -0.002 | -0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Constant | 0.607 | 0.601 | 0.599 | 0.597 | 0.466 | 0.457 | 0.473 | 0.464 |
| | (0.497) | (0.490) | (0.499) | (0.492) | (0.674) | (0.663) | (0.672) | (0.661) |
| Observations | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 | 406,770 |
| R-squared | 0.034 | 0.034 | 0.034 | 0.034 | 0.037 | 0.036 | 0.037 | 0.036 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 7:** Inventor Quality and New Firm Size (Conditional)

This table reports estimation from the linear probability model. The unit of observation is inventor-year. The sample period is 1980-2002. The dependent variable is *To small*, which is a dummy variable which equals to 1 if the inventor moves to a small firm. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. *Big* is a dummy variable that equals to 1 if the firm's size lies in quintile 4 and 5 in the given year, and *small* is a dummy variable equals to 1 if the firm's size lies in quintile 1 to 3 in the given year. Column (1), (2), (5) and (6) reports the estimates using measure q1, and Column (3), (4), (7) and (8) report the estimates using quality measure q2. All other firm characteristics variables are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | To small | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Top 25% | 0.027*** | 0.020** | 0.038*** | 0.030*** | | | | |
| | (0.009) | (0.010) | (0.010) | (0.010) | | | | |
| Bottom 25% | -0.011 | -0.009 | 0.006 | 0.013 | | | | |
| | (0.008) | (0.009) | (0.009) | (0.010) | | | | |
| Top 25% × big | | | | | 0.025** | 0.016 | 0.042*** | 0.030*** |
| | | | | | (0.010) | (0.010) | (0.010) | (0.010) |
| Top 25% × small | | | | | 0.036 | 0.051 | 0.015 | 0.034 |
| | | | | | (0.029) | (0.035) | (0.025) | (0.028) |
| Bottom 25% × big | | | | | -0.010 | -0.011 | 0.010 | 0.012 |
| | | | | | (0.008) | (0.009) | (0.010) | (0.010) |
| Bottom 25% × small | | | | | -0.019 | 0.021 | -0.026 | 0.016 |
| | | | | | (0.027) | (0.030) | (0.030) | (0.036) |

Table 7 continued.

| | To small | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Big | | | | | -0.018 | 0.051 | -0.033 | 0.038 |
| | | | | | (0.031) | (0.034) | (0.031) | (0.036) |
| Careeryr | -0.003*** | -0.003*** | -0.002*** | -0.002** | -0.003*** | -0.003*** | -0.002*** | -0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Jobyr | 0.005*** | 0.004*** | 0.006*** | 0.005*** | 0.005*** | 0.004*** | 0.006*** | 0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Firm size | -0.008 | -0.036*** | -0.008 | -0.034*** | -0.006 | -0.041*** | -0.006 | -0.040*** |
| | (0.005) | (0.012) | (0.005) | (0.012) | (0.007) | (0.013) | (0.007) | (0.013) |
| Tobin's Q | 0.011*** | -0.005 | 0.011*** | -0.005 | 0.011*** | -0.005 | 0.011*** | -0.005 |
| | (0.003) | (0.005) | (0.003) | (0.005) | (0.003) | (0.005) | (0.003) | (0.005) |
| Firm age | -0.000 | -0.064* | -0.000 | -0.063* | -0.000 | -0.064* | -0.000 | -0.063* |
| | (0.001) | (0.036) | (0.001) | (0.036) | (0.001) | (0.035) | (0.001) | (0.035) |
| Leverage | -0.039 | 0.017 | -0.037 | 0.016 | -0.040 | 0.021 | -0.037 | 0.019 |
| | (0.041) | (0.043) | (0.042) | (0.042) | (0.041) | (0.043) | (0.041) | (0.043) |
| ROA | -0.008 | 0.021 | -0.008 | 0.017 | -0.003 | 0.021 | -0.006 | 0.018 |
| | (0.044) | (0.074) | (0.045) | (0.073) | (0.044) | (0.074) | (0.045) | (0.073) |
| R&D | 0.409*** | -0.006 | 0.406*** | -0.010 | 0.409*** | -0.005 | 0.409*** | -0.007 |
| | (0.088) | (0.111) | (0.087) | (0.111) | (0.087) | (0.110) | (0.087) | (0.110) |
| Firm Cpatent | 0.014 | -0.013 | 0.012 | -0.013 | 0.014 | -0.013 | 0.013 | -0.014 |
| | (0.009) | (0.011) | (0.009) | (0.011) | (0.010) | (0.011) | (0.010) | (0.011) |
| Constant | 0.260*** | 1.757** | 0.251*** | 1.723** | 0.266*** | 1.725** | 0.271*** | 1.710** |
| | (0.038) | (0.719) | (0.038) | (0.718) | (0.039) | (0.718) | (0.039) | (0.712) |
| Observations | 15,545 | 15,545 | 15,545 | 15,545 | 15,545 | 15,545 | 15,545 | 15,545 |
| R-squared | 0.035 | 0.144 | 0.036 | 0.144 | 0.035 | 0.144 | 0.036 | 0.144 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | No | Yes | No | Yes | No | Yes | No |
| Firm FE | No | Yes | No | Yes | No | Yes | No | Yes |

**Table 8:** Inventor Quality and Firm Growth Opportunities

This table reports estimation from the linear probability model. The unit of observation is inventor-year. The sample period is 1980-2002. The dependent variable in Column (1) to (4) is *Leave*, which is a dummy variable which equals to 1 if the inventor leaves the firm in the next 5 years. The dependent variable in Column (5) to (6) is *To small* that equals to 1 if the inventor moves to a small firm in the next 5 year. Column (7) and (8) reports estimates from the sample conditional on the movers, the dependent variable is whether the inventor moves to a small firm. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. *Growth* is a dummy variable which equals to 1 if the firm's Tobin's Q is above the median of the year and *Value* is defined in the opposite way. Column (1), (2), (5) and (7) reports the estimates using measure q1, and Column (3), (4), (6) and (8) report the estimates using quality measure q2. All firm characteristics variables are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | Leave | | | | To small | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Top 25% × growth | 0.009*** | 0.012*** | 0.002 | 0.003 | 0.005*** | 0.003* | 0.019 | 0.029** |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.001) | (0.001) | (0.014) | (0.014) |
| Top 25% × value | 0.017*** | 0.016*** | 0.010*** | 0.009*** | 0.007*** | 0.004*** | 0.021* | 0.031** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.001) | (0.001) | (0.013) | (0.013) |
| Bottom 25% × growth | -0.008*** | -0.009*** | -0.008*** | -0.010*** | -0.003*** | -0.003** | -0.017 | 0.005 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.012) | (0.015) |
| Bottom 25% × value | -0.014*** | -0.014*** | -0.010*** | -0.009*** | -0.002*** | -0.002* | -0.001 | 0.020* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.011) | (0.012) |

Table 8 continued.

| | Leave | | | | To small | | | |
|---|---|---|---|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | | Cw-patents(q1) | | Avg.-citations(q2) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Careeryr | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.001*** | 0.001*** | -0.003*** | -0.002** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| Jobyr | -0.006*** | -0.005*** | -0.006*** | -0.005*** | -0.001*** | -0.001*** | 0.004*** | 0.005*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) | (0.002) |
| Growth | -0.013*** | -0.002 | -0.012*** | 0.000 | -0.000 | -0.000 | 0.003 | 0.002 |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.001) | (0.001) | (0.014) | (0.014) |
| Firm size | -0.006*** | 0.001 | -0.006*** | 0.001 | -0.004** | -0.004** | -0.036*** | -0.034*** |
| | (0.002) | (0.004) | (0.002) | (0.004) | (0.002) | (0.002) | (0.013) | (0.013) |
| Tobin's Q | -0.002*** | -0.001 | -0.002** | -0.001 | -0.001** | -0.001** | -0.005 | -0.005 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.005) | (0.005) |
| Firm age | 0.000 | -0.050 | -0.000 | -0.049 | -0.026 | -0.025 | -0.064* | -0.063* |
| | (0.000) | (0.050) | (0.000) | (0.049) | (0.022) | (0.022) | (0.037) | (0.037) |
| Leverage | 0.000 | 0.013 | 0.001 | 0.014 | 0.006 | 0.006 | 0.016 | 0.014 |
| | (0.013) | (0.017) | (0.013) | (0.017) | (0.005) | (0.005) | (0.043) | (0.043) |
| ROA | 0.019 | -0.016 | 0.018 | -0.017 | -0.000 | -0.001 | 0.022 | 0.019 |
| | (0.013) | (0.015) | (0.013) | (0.015) | (0.006) | (0.006) | (0.074) | (0.074) |
| R&D | 0.072*** | 0.008 | 0.073*** | 0.007 | 0.005 | 0.005 | -0.005 | -0.008 |
| | (0.025) | (0.017) | (0.026) | (0.017) | (0.008) | (0.008) | (0.111) | (0.111) |
| Firm Cpatent | 0.004 | -0.001 | 0.005* | -0.001 | 0.000 | 0.000 | -0.013 | -0.013 |
| | (0.003) | (0.002) | (0.003) | (0.002) | (0.001) | (0.001) | (0.011) | (0.011) |
| Constant | 0.115*** | 1.170 | 0.114*** | 1.149 | 0.588 | 0.581 | 1.761** | 1.731** |
| | (0.010) | (1.069) | (0.010) | (1.051) | (0.479) | (0.472) | (0.740) | (0.740) |
| Observations | 417,982 | 417,982 | 417,982 | 417,982 | 417,982 | 417,982 | 15,545 | 15,545 |
| R-squared | 0.018 | 0.050 | 0.017 | 0.049 | 0.035 | 0.034 | 0.144 | 0.144 |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | No | Yes | No | No | No | No | No |
| Firm FE | No | Yes | No | Yes | Yes | Yes | Yes | Yes |

**Table 9:** Inventor Quality and Performance Compensation

This table reports estimation from the linear probability model. The unit of observation is at inventor-year level. The sample period is 1985-1995. The dependent variable is *Leave*, which is a dummy variable which equals to 1 if the inventor leaves the firm in the next 5 years. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. *Big* is a dummy variable that equals to 1 if the firm's size lies in quintile 4 and 5 in the given year, and *small* is a dummy variable equals to 1 if the firm's size lies in quintile 1 to 3 in the given year. *High* is an indicator variable that equals to 1 if the firm's per employee value of outstanding stock options (cshrso $\times$ prcc_c) is above the industry median in the given year, while *low* is defined accordingly. Column (1) and (2) reports the estimates using measure q1, and Column (3) and (4) report the estimates using quality measure q2. All firm characteristics variables are defined in Table 4. All firm characteristics control are included but not reported. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 continued.

| | Leave | | | |
|---|---|---|---|---|
| | Cw-patents(q1) | | Avg.-citations (q2) | |
| | (1) | (2) | (3) | (4) |
| Top 25% × big × high | 0.019*** | 0.019*** | 0.004 | 0.005 |
| | (0.005) | (0.004) | (0.004) | (0.004) |
| Top 25% × big × low | 0.015*** | 0.015*** | 0.008* | 0.006 |
| | (0.004) | (0.004) | (0.005) | (0.005) |
| Top 25% × small × high | -0.001 | 0.009 | 0.005 | 0.010 |
| | (0.010) | (0.009) | (0.009) | (0.009) |
| Top 25% × small × low | 0.061*** | 0.050*** | 0.052*** | 0.034** |
| | (0.019) | (0.018) | (0.017) | (0.017) |
| Bottom 25% × big × high | -0.011*** | -0.011*** | -0.009*** | -0.012*** |
| | (0.003) | (0.004) | (0.003) | (0.004) |
| Bottom 25% × big × low | -0.016*** | -0.015*** | -0.010*** | -0.010*** |
| | (0.002) | (0.002) | (0.003) | (0.002) |
| Bottom 25% × small × high | -0.017 | -0.011 | -0.020* | -0.004 |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| Bottom 25% × small × low | -0.011 | -0.016 | -0.002 | -0.007 |
| | (0.015) | (0.015) | (0.018) | (0.017) |
| Careeryr | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Jobyr | -0.008*** | -0.007*** | -0.008*** | -0.007*** |
| | (0.001) | (0.000) | (0.001) | (0.000) |
| Observations | 196,488 | 196,488 | 196,488 | 196,488 |
| R-squared | 0.018 | 0.048 | 0.017 | 0.047 |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | No | Yes | No |
| Firm FE | No | Yes | No | Yes |

**Table 10a:** Inventor Quality and Firm Performance

This table reports estimation from OLS. The unit of observation is a firm-year. The sample period is 1980-2002. The dependent variable is the log of the average citations per patent computed for the future 5 years in Column (1) and (3) and for future 3 years in Column (2) and (4). *Newhire1* is the number of top 25% inventors joined the firm divided by the total number of inventors in the current year. *Newhire3* is the number of bottom 25% inventors joined the firm divided by the total number of inventors in the current year. *Newhire2* is the number of the medium 50% inventors joined the firm divided by the total number of inventors in the current year. *Big* is a dummy variable that equals to 1 if the firm's size is above the median in the given year, and *small* indicates whether the firm's size is below the median. *Patent stock* is the total number of patents the firm has as of the end of the year. Column (1) and (2) reports the estimates using measure q1, and Column (3) and (4) report the estimates using quality measure q2. All other firm characteristics variables are defined in Table 4. All firm characteristics are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10a continued.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Cw-patents(q1) | | Avg. Citations(q2) | |
| Firm Avg. Citations | 5yr | 3yr | 5yr | 3yr |
| Newhire1 | 0.370** | 0.626*** | 0.452*** | 0.738*** |
| | (0.178) | (0.169) | (0.162) | (0.149) |
| Newhire2 | 0.265** | 0.406*** | 0.196* | 0.271** |
| | (0.114) | (0.122) | (0.117) | (0.129) |
| Newhire3 | 0.126 | 0.088 | 0.131 | 0.178 |
| | (0.119) | (0.195) | (0.130) | (0.207) |
| Tobin's Q | 0.007 | 0.004 | 0.007 | 0.004 |
| | (0.008) | (0.006) | (0.008) | (0.006) |
| Firm age | -0.011 | 0.003 | -0.011 | 0.004 |
| | (0.121) | (0.139) | (0.121) | (0.139) |
| Firm Size | 0.045* | 0.051** | 0.045* | 0.051** |
| | (0.027) | (0.025) | (0.027) | (0.025) |
| R&D | -0.044 | -0.033 | -0.044 | -0.032 |
| | (0.113) | (0.088) | (0.113) | (0.088) |
| Leverage | 0.049 | -0.027 | 0.048 | -0.028 |
| | (0.086) | (0.085) | (0.086) | (0.085) |
| ROA | 0.055 | 0.038 | 0.054 | 0.037 |
| | (0.089) | (0.077) | (0.089) | (0.077) |
| Patent stock | -0.204*** | -0.251*** | -0.203*** | -0.249*** |
| | (0.025) | (0.023) | (0.025) | (0.023) |
| Constant | 3.259*** | 3.110*** | 3.252*** | 3.099*** |
| | (1.183) | (1.136) | (1.183) | (1.136) |
| Observations | 14,361 | 16,771 | 14,361 | 16,771 |
| R-squared | 0.674 | 0.665 | 0.674 | 0.665 |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes |

**Table 10b:** Inventor Quality, Firm Performance and Firm Size

This table reports estimation from OLS. The unit of observation is a firm-year. The sample period is 1980-2002. The dependent variable is the log of the average citations per patent computed for the future 5 years in Column (1) and (3) and for future 3 years in Column (2) and (4). *Newhire1* is the number of top 25% inventors joined the firm divided by the total number of inventors in the current year. *Newhire3* is the number of bottom 25% inventors joined the firm divided by the total number of inventors in the current year. *Newhire2* is the number of the medium 50% inventors joined the firm divided by the total number of inventors in the current year. *Big* is a dummy variable that equals to 1 if the firm's size is above the median in the given year, and *small* indicates whether the firm's size is below the median. *Patent stock* is the total number of patents the firm has as of the end of the year. Column (1) and (2) reports the estimates using measure q1, and Column (3) and (4) report the estimates using quality measure q2. All other firm characteristics variables are defined in Table 4. All firm characteristics are defined in Table 4. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Cw-patents(q1) | | Avg. Citations(q2) | |
| Firm Avg. Citations | 5yr | 3yr | 5yr | 3yr |
| Newhire1 × big | -0.008 | 0.263 | 0.259 | 0.462** |
| | (0.179) | (0.177) | (0.199) | (0.230) |
| Newhire1 × small | 0.545** | 0.792*** | 0.519** | 0.840*** |
| | (0.234) | (0.225) | (0.208) | (0.179) |
| Newhire2 × big | 0.383*** | 0.462*** | 0.241 | 0.305** |
| | (0.149) | (0.169) | (0.153) | (0.145) |
| Newhire2 × small | 0.175 | 0.362** | 0.160 | 0.249 |
| | (0.164) | (0.167) | (0.159) | (0.182) |
| Newhire3 × big | 0.230 | 0.304 | 0.268 | 0.422 |
| | (0.149) | (0.264) | (0.165) | (0.268) |
| Newhire3 × small | 0.034 | -0.096 | -0.051 | -0.109 |
| | (0.176) | (0.260) | (0.206) | (0.304) |

Table 10b continued.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Cw-patents(q1) | | Avg. Citations(q2) | |
| Firm Avg. Citations | 5yr | 3yr | 5yr | 3yr |
| Tobin's Q | 0.007 | 0.004 | 0.007 | 0.004 |
| | (0.008) | (0.006) | (0.008) | (0.006) |
| Firm age | -0.011 | 0.004 | -0.010 | 0.004 |
| | (0.122) | (0.139) | (0.122) | (0.139) |
| Big | 0.049 | 0.012 | 0.049 | 0.013 |
| | (0.037) | (0.038) | (0.038) | (0.038) |
| Firm size | 0.036 | 0.049* | 0.035 | 0.049* |
| | (0.028) | (0.027) | (0.028) | (0.027) |
| R&D | -0.038 | -0.029 | -0.041 | -0.031 |
| | (0.113) | (0.088) | (0.113) | (0.088) |
| Leverage | 0.049 | -0.030 | 0.048 | -0.031 |
| | (0.086) | (0.085) | (0.086) | (0.085) |
| ROA | 0.062 | 0.041 | 0.059 | 0.038 |
| | (0.089) | (0.077) | (0.089) | (0.077) |
| Patent stock | -0.205*** | -0.251*** | -0.204*** | -0.250*** |
| | (0.025) | (0.023) | (0.025) | (0.023) |
| Constant | 3.245*** | 3.106*** | 3.236*** | 3.100*** |
| | (1.188) | (1.138) | (1.188) | (1.139) |
| Observations | 14,361 | 16,771 | 14,361 | 16,771 |
| R-squared | 0.674 | 0.665 | 0.674 | 0.666 |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes |

**Table 11:** Robustness

This table reports estimation from the linear probability model. The unit of observation is an inventor-year. The sample period is 1980-2002. Panel A reports the estimates using the specification as in Column 2, Table 5 The dependent variable in Panel A is *Leave*, which is a dummy variable that equals to 1 if the inventor leaves the firm in the next 5 years. Panel B reports the estimates from the specification as in Column2, Table 7. The dependent variable is *To small*, which is a dummy variable that equals to 1 if the inventor move to a small firm. *Top 25%* is a dummy variable that equals to 1 if the inventor ranks at the top 25th percentile in the given year. *Bottom 25%* is a dummy variable that equals to 1 if the inventor ranks at the bottom 25th percentile in the given year. Column (1), (2) and (3) reports the estimates using measure q3, q4 and q5 respectively. Column (4) reports the estimates using the life-time measure: an inventor is considered as top 25% if he has ever been in the top 25% but never been in the bottom 25%, and he is considered as bottom 25% if he has ever been in the bottom 25% but never been in the top 25%. All other control variables are included but not reported. Standard errors are clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11 continued.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Patent | Citations (excl. self-cite) | Cpatent (excl. self-cite) | Life-time |
| | | Panel A: Leave | | |
| Top 25% | 0.013*** | 0.019*** | 0.014*** | 0.019*** |
| | (0.002) | (0.002) | (0.003) | (0.003) |
| Bottom 25% | -0.011*** | -0.016*** | -0.016*** | -0.004*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| Observations | 406,770 | 406,770 | 406,770 | 406,770 |
| R-squared | 0.048 | 0.049 | 0.048 | 0.048 |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes |
| | | Panel B: To small | | |
| Top 25% | 0.002 | 0.016* | 0.029*** | 0.007 |
| | (0.010) | (0.009) | (0.009) | (0.009) |
| Bottom 25% | -0.001 | -0.010 | 0.013 | -0.021** |
| | (0.008) | (0.009) | (0.010) | (0.008) |
| Observations | 15,545 | 15,545 | 15,545 | 15,545 |
| R-squared | 0.143 | 0.144 | 0.144 | 0.144 |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No |
| Firm FE | Yes | Yes | Yes | Yes |

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