Human Capital, Firm Capabilities, and Innovation[*,†]

Ajay Bhaskarabhatla
Erasmus School of Economics

Deepak Hegde
New York University

Thomas Peeters
Erasmus School of Economics

Feb 23, 2018

Abstract

Are differences in inventor productivity due to differences in inventors' skills or differences in the capabilities of the firms they work for? We analyze a 37-year panel that tracks the patenting of more than a million U.S. inventors and find strong evidence for serial correlation in inventors' productivity. We apply a modified fixed effects estimator and decompose the contributions of inventors' human capital, coinventors' human capital, and firm capabilities for productivity. Our estimates suggest inventors' human capital is 4-5 times more important than firm capabilities for explaining the variance in inventor productivity. High human capital inventors work for firms that have (i) other high human capital inventors, (ii) superior financial performance, and (iii) weak firm-specific invention capabilities. On the margins, managers should emphasize selecting talent rather than training workers to enhance innovation performance.

Key Words: Human Capital, Innovation, Inventor effects, Matching, Competitive advantage

JEL Codes: O30, O31, O32, J24

---

[*] Address for correspondence: bhaskarabhatla@ese.eur.nl (Bhaskarabhatla), dhegde@stern.nyu.edu (Hegde), and peeters@ese.eur.nl (Peeters).

[†] For their helpful comments and suggestions, we are grateful to conference and seminar participants at the INFORMS 2015 Annual Meeting, Academy of Management 2016 Annual Meeting, SMS Conference 2016, EARIE 2016 Conference, R&D Management Conference 2016, The 10th Workshop on The Organization, Economics and Policy of Scientific Research, Erasmus School of Economics, Indian Institute of Management, Bangalore, Saunders College of Business at Rochester Institute of Technology, Cox School of Business at Southern Methodist University, and New York University's Stern School of Business. All errors are our own.

I. Introduction

Inventors at Apple, Google, and Genentech have disrupted markets with a stream of new products since the companies were founded. Those at firms such as Webvan, Netscape and King Digital Entertainment created novel products, but failed to sustain their brilliant starts. Inventors' ideas at many other firms are abandoned before product development because they are not novel or useful enough.

Are inventors at some companies inherently more skilled, or do the companies make their employees more productive? Can inventors sustain their inventive sparks after they change employers and over their careers? How are inventors matched to firms, and what are the implications of matching for inventor productivity? The outcomes of inventive activity are notoriously unpredictable and these questions related to inventor productivity have immediate relevance for managers, as well as for research on the theory of the firm, human capital and competitive advantage. We study these questions here and empirically assess the roles of human capital and firm-specific capabilities in shaping inventors' productivity.

Disentangling human capital from firm-specific capabilities poses several measurement related challenges. First, tasks in most firms are performed by teams, making it hard to measure the human capital of individual workers. Second, firms deploy a combination of human capital and firm capabilities to tasks, and the two factors' contributions to task performance are difficult to separate. Third, worker productivity is a consequence of endogenously matched human capital and firm capabilities, complicating their identification through standard regression techniques.

We tackle these challenges by assembling data on all U.S. patents granted by the U.S. Patent and Trademark Office (USPTO) between 1973 and 2010. Patents record the identity of their inventors and owner-employers, allowing us to construct a 37-year panel of each patenting inventor's, and each patenting firm's, annual patenting output—our proxy for inventive performance. We retain only repeat inventors—that is, those who had a record of patenting in at least two years during the study period—since our estimations require at least two annual observations per inventor. The 1.2 million repeat inventors in our USPTO sample worked at about 117,000 unique firms. We merge this patent data with Compustat data on U.S. publicly listed companies. The merger retains about 336,000 inventors at 1,700 U.S. publicly listed firms, with detailed information on time-varying firm-capabilities, such as R&D investments, that influence inventor performance from 1978 to 2010. We leverage this Compustat sample to measure the inventive productivity of inventors, coworkers, and firms, tease apart their contributions to productivity, and thus address the empirical challenges listed above.

We begin by examining whether inventors sustain their productivity in the USPTO sample of 1.2 million repeat inventors. Under the null hypothesis of no persistence, inventors' past year patenting should not predict subsequent year output. However, we find that a percentage increase in an inventor's average number of patents over past years is associated with a 0.43-0.76 percent increase (at $p < 0.01$) in the inventor's patents in a subsequent year, after controlling for experience. To allay the concern that these estimates are driven by persistence in the propensity to file for patents rather than in inventiveness, we investigate persistence with other measures including citation-weighted patents, patent generality and originality, and confirm strong serial correlation in inventors' performance for each of these measures. Thus, it appears inventors' performance displays certain characteristics—in terms of innovation impact, breadth, and novelty—all of which persist strongly over time.

Estimates of inventor persistence could be biased if higher productivity inventors are more likely to be employed by firms with superior capabilities for invention. Controlling for observable firm characteristics (such as age, size, financial performance, R&D intensity and patent stock) and unobserved, time invariant, differences through firm-fixed effects does not diminish evidence for persistence. Evidence for persistence also remains robust to controlling for co-inventors' productivity. For inventors who change employers, persistence estimates drop in the immediate patenting year following their move, but recover in later years to be comparable to the estimates for inventors who did not move (0.32 v/s 0.39 respectively, both at $p<0.01$).

If, as these findings suggest, inventors can seamlessly repeat their performance, even after they change firms, then what role do firm-specific capabilities play in making inventors productive? Next, we attempt to measure the relative contributions of human capital and firm-specific capabilities to inventors' productivity by exploiting inventor movement between firms. A traditional fixed effects approach, used to identify capabilities that do not change over time in panel data, can estimate worker and firm fixed effects only for workers who move.[1] This would imply using observations on only about 30 percent of the sample inventors who changed firms. Instead, we use a method developed by Abowd, Kramarz, and Margolis (1999) (henceforth AKM) and further refined in Abowd et al (2002) that estimates employer and

[1] For example, in a pioneering study, Bertrand and Schoar (2003) use the traditional fixed effects approach with data on moving workers to identify CEO effects on firm policies.

employee effects, even for the non-movers. This method pins down the fixed effects of moving inventors and firms connected by the movers, and then uses this information to identify the fixed effects of non-movers.

The following example, adapted from Graham et al (2012), illustrates the AKM approach. Suppose there are three inventors and two firms. Inventor A works for firm X and has two patents. Inventor C works for company Y and has three patents. Inventor B works for company X first, producing four patents, and then moves to company Y to produce six patents. The AKM method treats inventors A, B, and C and firms X and Y as connected through movements. Since B produces two more patents after moving to firm Y, Y's fixed effect (net of other determinants not modelled here) is to generate two more than X's. If firm X's fixed effect is the benchmark and is set to zero, firm Y's fixed effect is two. A's and B's inventor fixed effects can then be obtained by subtracting firm X's fixed effect (0 patents) from A's and B's patenting in firm X, and therefore are equal to two and four patents respectively. Similarly, subtracting firm Y's fixed effect (two patents) gives inventor C's fixed effect as one patent (3-2).

Applying the AKM method to our sample reveals that inventor fixed effects explain 23- 29 percent of the observed variance (58-63 percent of the model variance) in inventors' patenting performance. In contrast, only 3-5 percent of the overall variance in performance (8-13 percent of the model variance) is explained by firm fixed effects (net of the effect of observed firm-level variables such as age, size, patent stock and R&D intensity). These results suggest inventor-specific human capital underlies much of the variance in inventor productivity.

The AKM method refines the fixed-effects estimator, which is commonly used in economics and management research, and provides the most robust method we are aware of for extracting the time-invariant effects of employer and employee capabilities (see Iranzo et al 2008, Ewens and Rhodes-Kropf 2015, and Graham et al 2012, for applications of the approach to other contexts). Yet, a drawback of the AKM method is that it treats workers' and firms' capabilities as fixed, and thus does not permit examination of how capabilities influence mobility or how mobility affects the capabilities of inventors or employers (Abbowd et al 1999, Abbowd et al 2017).

We explore the question of how inventor ability and employer capabilities affect mobility and matching by implementing a novel "rolling window" strategy for AKM estimations. That is, we estimate AKM fixed effects for inventors and firms in progressive time windows, allowing the estimates to vary across the windows. For example, we first limit the AKM estimation sample to a 10-year window from 1978 (the first year of our estimation sample after including lagged explanatory variables for periods t-2 and t-1) through 1987 and estimate the firm and inventor effects based on movements within this window. These estimates are not contaminated by changes to inventors and firms after 1987 and we use them to examine how the "fixed effects" predict movements in 1988. Next, we draw a new subsample of 10 years—by rolling the window one year—from 1979 through 1988, and estimate AKM firm and inventor effects based on moves within this new window. These estimates are used to examine how the "fixed effects" predict movements in 1989, and so on.

The rolling window technique reveals a negative correlation between inventor human capital and firm capability, and a positive correlation between inventor and coworkers' human capital. Inventors with lower human capital, and those with colleagues who have lower human capital, are more likely to move, indicating inventor mobility may be due to voluntary and involuntary separations. Highly skilled inventors are more likely to move to firms which employ other high-skilled inventors and to firms with low firm-specific inventive capabilities. Worker human capital and coworker human capital appear to be strategic complements, while human capital and firm capability are strategic substitutes.

The contributions of our study are four-fold. First, the result that inventors' human capital is transferrable across tasks, projects and firms provides some of the first large-sample evidence for the general nature of human capital, even when applied to non-repetitive tasks like invention. The finding implies intense competition for inventive talent in labor markets and that to gain advantage, managers should hire the best and brightest talent. Of course, this advantage may be fleeting if talented workers appropriate away the firm's rents or leave for better-paying firms (Becker 1962, Lazear 2009).

Second, a large body of scholarship focuses on investigating how firm characteristics, such as incentive schemes or organizational culture, affect innovation and firm performance (e.g., Wernerfelt 1984, Rumelt 1984, Barney 1986, Nelson and Winter 1984, Klein 1998, Bloom et al 2013, Martinez et al 2015). This research suggests that the majority of variance in firm performance remains unexplained even after accounting for the effects of firms' characteristics such as industry, business segment, and corporate structure (McGahan and Porter 1997, 2002). Our results suggest that differences in the human capital embedded in firms may account for a substantial portion of the unexplained variance, and serve as a complement to the growing body of research on worker characteristics and human resource management (e.g., Agrawal et al 2014, Wright et al 2014, Campbell et al 2012, Mayer et al 2012, Coff and Kryscynski 2011, Groysberg 2010, Jones 2009, Lazear 2009, Groysberg et al 2008, Rothaermel and Hess 2007, Wuchty et al 2007, Huckman and Pisano 2006, Hatch and Dyer 2004). For managers, our findings imply firms should invest at least as much effort in selecting employees as they do in post-recruitment training.

Third, we provide suggestive evidence for positive assortative matching based on human capital but negative assortative matching between human capital and firm capabilities. This result implies managers' actions to wrest competitive advantage by developing firm-specific capabilities, such as strong management processes and training programs, may turn off highly inventive workers. Instead, a better approach to augment innovation performance may be to build an organization that serves as a platform for highly talented workers.

Finally, our analyses contribute to empirical methodology by combining AKM with the rolling window technique to partially recover changes to individuals and firms in a long time-series. Using this approach generally, attributes such as capabilities that have yet been treated as fixed can be allowed to vary, and incorporate influences such as learning on firms and workers. Of course, this methodology does not remedy the biases induced by endogenous mobility, but allows one to descriptively explore the endogenous matching of firms and workers by estimating capabilities using the information in rolling windows prior to matching.

The rest of the paper is organized as follows. Section II situates our study in current literature. Section III describes our data, sample construction, and variables of interest. Section IV investigates persistence in inventor performance. Section V measures the importance of inventor skill and firm capabilities for inventors' performance. Section VI explores inventor-coinventor and inventor-firm matching. Section VII concludes by discussing the limitations and implications of our analyses.

II. Related Literature

Previous studies have assessed the effects of individual- and firm- characteristics on innovation performance or performance persistence. But a survey of past work does not help adjudicate to what extent human capital, rather than firm capability, drives innovation. Previous literature is also silent on the related question of how employers and employees are matched as a function of their inventive capabilities.

Several scholars have established that firm characteristics including size, age, ownership structure, and R&D intensity effect innovation performance (e.g., Cohen et al 1987, Belenzon and Berkowitz 2010, Bernstein 2015). Researchers have also examined the persistence of innovation performance at the firm level and reached different conclusions: Peters (2009) provides evidence consistent with the persistence of firm-specific advantages, Raymond et al

(2010) reports persistence only in high-tech industries, Cefis (2003) for firms that cross a threshold of innovation output, and Geroski et al (1997) find no evidence for persistence.

Related work that examines inventor productivity suggests a small number of highly productive individuals—stars and superstars—contribute disproportionately to innovation and entrepreneurship (Agrawal et al 2014, Azoulay et al 2010, Oettl 2012). Other studies suggest the modern inventor, burdened by the necessity to master an ever-increasing body of knowledge to come up with something new, is finding it harder to invent independently and thus works in larger teams, suggesting a decline in the importance of individual inventors (Singh and Fleming 2010, Jones 2009, Wuchty et al 2007).

The debate over the relative importance of inventors and firms notwithstanding, hiring and retaining talent is now seen as a key source of competitive advantage for organizations (Grigoriou and Rothaermel 2014, Wright et al 2014, Felin et al 2012, Campbell et al 2012, Coff and Krysczynski 2011, Castanias and Helfat 2001, Coff 1997, Bartlett and Ghoshal 2002). Several studies have concluded that mobile inventors contribute to knowledge flows between organizations (Singh and Agrawal 2011, Groysberg et al 2008, Oettl and Agrawal 2008, Moen 2005, Corredoira and Rosenkopf 2010). Heightened competition over scarce talent has resulted in the enforcement of noncompete agreements that limit inventor mobility (Marx et al 2009).

Despite the acknowledged importance of talented workers, few studies have attempted to empirically evaluate whether productive inventors are intrinsically skilled or whether their productivity is due to their employers' capabilities. Related studies have addressed matching between companies and academic inventors (Agarwal and Ohyama 2013, Mindruta 2013, or the role of collaborators on scientists' productivity (Bikard et al 2015), but without examining matching as a function of inventor and firm capabilities.

The questions we address, and the empirical approach we adopt, are closest in spirit to a small set of recent studies that assess the importance of individuals versus organizations on firm performance (Mollick 2012, Ewens and Rhodes-Kropf 2015, and Liu et al 2017). Mollick (2012) finds that the human capital of individual designers and middle managers are as important as organizational capabilities in explaining sales performance in the video game industry. Ewens and Rhodes-Kropf (2015) apply the AKM technique to separate the contributions of venture capital partners and firms to the success of portfolio companies. Liu et al (2017), in a contemporaneous working paper, apply the AKM technique to parse out inventor and firm effects on innovation rate and "style" (exploration versus exploitation). Their working estimates of the importance of human capital are substantially larger in magnitude than ours. While our paper proceeds to explore matching between firms and individuals, Liu et al (2017) examine the determinants of inventor productivity and style.

III. Data Description

III.1. Sample Construction

We start with the population of U.S. patents granted during the years 1973-2010, obtained from the U.S. Patent and Trademark Office (USPTO). Limiting the last patent grant year to 2010 allows us at least five years to observe forward citations, our measure of innovation impact, to the latest patents without truncation. We disambiguate inventor names recorded by the USPTO using the procedure outlined in Li et al (2013), and standardize assignee names using the procedure in Hall et al (2001). This yields a dataset of 2.9 million unique inventors and 261,825 firms. Of these, 1.25 million inventors had records of patenting in at least two years and we retain only these repeat inventors in our USPTO analytical sample, since identifying whether inventor performance persists from one year to the next and estimating inventor fixed-effects requires observing inventor patenting in at least two different years. Of these repeat inventors, 82.2 percent are always affiliated with a firm, 4.8 percent always appear in the sample as individual inventors, and 13 percent appear as independent inventors on some patents, and as employees on others. Overall, the sample inventors are associated with 164,361 unique firms. We consider patent application year as the year in which the inventor produced the invention. Hence, inventor productivity during a year is measured as the number of successful applications filed by the inventor in that year. This USPTO data yields a sample of 3.9 million inventor-firm-year observations during 1973-2010.

To investigate persistence of inventors' productivity, we draw subsamples corresponding to the second, sixth and tenth years during which we observe each inventor's patenting. This allows us to compare persistence among inventors who were active patentees for the *same* number of years, circumventing the problem of inventor attrition biasing persistence estimates. We subsequently examine the relationship between the inventors' productivity during each year and her productivity during previous years. Table 1 lists the number of assignees, inventors and patents in each subsample of our USPTO sample. Not surprisingly, the number of inventors with patenting records in six or ten years is lower than those with patenting records in two years of our 37-year sample span.

Insert Table 1 around here

Among unique assignees of patents in the USPTO sample, 45 percent are U.S. companies and 45 percent are foreign. The remaining are individual inventors and other assignee types (universities, non-profits and government institutions). In order to incorporate firm characteristics, we match the USPTO sample to Compustat data on publicly listed U.S. companies using the procedure described in Bessen (2009). The matching procedure is based on patent grants from 1976 and accounts for changes in patent ownership due to mergers, acquisitions, and spinoffs as of 2006, which we extend to 2010. This yields a Compustat sample of 351,967 inventors and 1,888 firms with more than a million inventor-firm-year observations during 1976-2010.

As before, we draw subsamples corresponding to the second, sixth, and tenth year observations from this sample to examine persistence of inventor productivity. The middle panel of Table 1 describes the subsamples resulting from the Compustat sample. We retain information on important Compustat variables, including firm age, the existence of R&D expenditures, R&D intensity, capital intensity, sales, changes in operating income and the number of employees.

For the AKM analyses, we restrict our Compustat sample to include inventors with at least four unique patent-year observations as is necessary to reliably identify inventor fixed effects through the AKM regressions. The AKM estimation sample is constructed by identifying firms connected through mobile inventors. The subsample of the largest connected network not only contains mobile inventors but also non-mobile inventors at firms in the network and encompasses over 99 percent of all inventor-firm-year observations formed by inventors with at least four patent-year observations who work for Compustat firms.[2] The bottom panel of Table 1 describes the "AKM sample" characteristics.

III.2. Sample Selection

In an ideal world, we would apply our identification strategies to a sample that included data on all inventors and their full employment and invention histories. Instead, we are forced to work with a second-best sample: the U.S. patenting records of inventors and their employment histories inferred from the records. The Compustat sample of inventors at U.S. publicly listed firms and the AKM sample of inventors belonging to firms connected through movements narrows our estimation samples even further. It is *a priori* not clear whether or how these selection criteria bias our estimates of inventor or firm capabilities.

[2] We cannot use data from the 1% of observations not part of the largest connected network in our estimations since there will be no basis to normalize the estimated fixed effects to a reference firm or inventor across unconnected networks.

First, we examine potential selection biases induced by the AKM sample, by comparing AKM sample characteristics to USPTO sample characteristics. The AKM sample, by construction, excludes firms without a moving inventor and includes only Compustat companies. Accordingly, one can expect AKM firms to have a larger number of movers. Indeed, 89 percent of the 1,760 AKM firms have at least two movers, whereas only 46 percent of the 164,361 USPTO firms (which includes AKM firms) have two or more movers. However, both AKM and USPTO samples have a nearly identical fraction of inventors who have never moved (about 70 percent of all inventors), moved once (16 percent versus 14 percent), moved twice (6.8 percent versus 6.2 percent), and so on.[3] Hence, other than having a greater absolute number of movers due to a larger employee base, AKM firms do not seem to be associated with a higher or lower probability of moving than the broader sample of patenting inventors.

Second, our samples have observations for inventors only during the years in which they filed at least one successful U.S. patent. Thus, the samples are unbalanced panels and one could argue the productivity of inventors who do not file patents in any year should be treated as zero during the year. We confirm the robustness of our all of our results after estimating each regression in extended samples that fill out zeros for the productivity of inventors during the years (between the years of the inventors' first and last patent in the samples) in which the inventor does not file a patent.[4]

Third, where possible, we check the sensitivity of our estimates to the samples used (for example, we examine inventor performance persistence in both the USPTO sample and the Compustat sample). These checks help ensure our findings are not an artifact of sample selectivity, and can be generalized at least to the important population of U.S. patentees.

III.3. Variable Description

Table 2 describes the variables we use to measure innovation performance, inventor characteristics and firm characteristics. For each inventor i at firm j in year t, we measure: (i) the total number of patents granted; (ii) the total number of patents weighted by forward citations (excluding self-citations) over the first five years after patent publication; (iii) the mean originality over patents; and (iv) the mean generality over patents. In the USPTO sample, 42 percent of the patents have one inventor, 26 percent have two inventors, 15 percent have three inventors, and the remaining 17 percent have four or more inventors. Similarly, in the

[3] Table A1, Panel A of the Appendix shows number of moves by inventors in the USPTO and AKM samples.

[4] We assume that the first year we observe an inventor patent at a firm is the year in which the inventor moved. Our findings are further robust to filling gaps in inventive activity by assuming that the year of move occurs at the mid-point of inactive years in an inventor's patenting history.

Compustat sample, 32 percent of the patents have one inventor, 27 percent have two inventors, 18 percent have three inventors, and the remaining 23 percent have four or more inventors. We correct for teamwork by dividing the first two measures by the number of co-inventors on each patent. To calculate mean originality and generality, we apply weights proportional to the inverse number of inventors. While (i) measures inventors' patenting intensity, (ii) weights inventors' patenting productivity by impact. (iii) and (iv) denote important characteristics of inventors' inventions. Taken together, the measures can be used to test whether inventors differ systematically in their inventive productivity and impact.

Insert Table 2 around here

The Compustat and AKM samples include an array of variables which control for correlates of inventors' performance (see Table 2). In most specifications, we control for coworker inventiveness by the mean contemporaneous performance of the inventor's co-workers, i.e., the set of inventors filing patents for the same assignee (firm j) in year t. We also calculate and include a measure of each inventor's patenting experience as the difference between the application year and the year the inventor filed her first patent application after 1975. Following prior literature (Hall and Ziedonis 2001), in specifications estimated using the Compustat sample, we control for firm age, the existence of R&D expenditures, R&D intensity, capital intensity, sales, changes in operating income, and the number of employees. We also control for the effects of firms' knowledge stocks on inventor productivity with a measure of firm j's patent stock in year t.

A last set of variables pertains to the overall financial performance of the organizations in our data set. Here we consider firm j's net income and Tobin's Q as calculated from its financial Compustat data for year t.

IV. Inventor Performance Persistence

IV.1. Empirical specification and baseline results

We investigate persistence in inventors' innovation performance by estimating a model that predicts inventor i's inventive output in year t as a function of past performance.

$$y_{it} = \delta \frac{1}{n} \sum_{k=1}^{n} y_{it-k} + \gamma_t + \beta_x X_{it} + \varepsilon_{it}. \text{ (Equation 1: persistence model)}$$

where y_{it} is a variable drawn from the set of innovation output measures defined in Table 2 for inventor i in year t. We are interested in the coefficient estimate for δ, which picks up the impact on inventor output in t of a change in the inventor's past performance averaged over past n years. A positive and significant estimate would suggest persistence in inventor performance.

Our sample is an unbalanced pool and has gaps for the years in which an inventor did not apply for a patent. The specification nevertheless treats all past performance the same, regardless of whether the performance occurred in the past year (that is, in t-1) or much before, with or without gaps. To absorb the effect of varying lengths of time between t and t-1, we include a variable that measures the difference, in years, between an inventor's first patent application and current year t.[5] We also include a vector of year fixed effects (γ_t), a vector of control variables (X_{it}), and an inventor-year-specific error term ε_{it}. When estimating on the full USPTO sample, X_{it} has only the variable measuring inventors' patenting experience. When we estimate Equation (1) with the Compustat data sample, we add the firm-level control variables defined in Table 2, as well as firm or industry (NAICS two digit) fixed effects.

A positive estimate of δ provides support for the persistence hypothesis, but the estimate may be biased in favor of persistence if successful inventors are more likely to stay in the sample and repeat their patenting performance over multiple years. To address this attrition bias we run the estimation three times, each time predicting the effect of past performance on inventor performance in the second, sixth, or tenth year in which the inventor has a record of patenting.[6] These specifications vary the number of past years considered for past performance (n) to be one, five, and nine respectively. That is, we predict inventors' innovation performance in their second year of patenting using their performance during the first year, in their sixth year using performance in their past five years (averaged), and so on. Examining performance persistence among inventors who have records of patenting in the same number of years alleviates concerns that our estimates are contaminated by attrition.

Table 3 shows OLS estimates of equation (1) obtained from the USPTO subsample. The first three columns report results for the (log) number of patents and the next three columns for (log) number of citation weighted patents as measures of inventors' innovation performance. The remaining six columns present results obtained by using the (yearly mean) generality and (yearly mean) originality as measures of inventors' innovation performance. For each measure, we derive estimates from three subsamples, each predicting the second, sixth, or tenth year innovation performance of inventors as a function of past performance.

---

[5] In alternative estimations, we create additional observations for gap years with corresponding year innovation output measures set to zero and obtain similar results.
[6] Table A2 in the Appendix reports descriptives for the two-, six-, and ten-year subsamples.

We find strong evidence for positive serial correlation in inventor performance (all serial correlation coefficients are significant at $p<0.01$). For example, focusing on annual patent productivity, the estimates suggest that a percentage increase in past year patents is associated with a 0.43-0.76 percent increase in current year patents. Of course, one could argue that patent counts measure inventors' patenting propensity rather than true inventive performance. The next three columns of Table 3 show that a one percent increase in past citation-weighted patents per year, predicts a 0.30-0.62 percent increase in current year citation-adjusted patents. We emphasize that these estimates cannot be explained by attrition of less successful inventors from the sample—even among comparably "long-lived" inventors (those who have patent applications in ten or more years in the sample) a one percent increase in past citation-weighted patents per year is associated with a 0.62 percent increase in current year output. Thus, evidence for persistence increases with inventor longevity.

Originality and generality are not logged and take on values in [0, 1]. Our coefficient estimates confirm strong positive serial correlation for these innovation characteristics as well. All results are obtained after controlling for year fixed effects and inventor patenting experience measured by years since first patent application.[7,8] Thus, it appears inventors display a strong propensity to replicate their performance, regardless of whether performance is measured by the number of patents, patent impact, generality or originality.

Insert Table 3 here

IV.2. Firm and co-inventor effects

The USPTO sample allows for broad coverage of inventors and their patents, which renders the estimates of persistence reported in Table 3 representative of the population of repeat U.S. patentees. However, the USPTO sample incorporates little information on firm characteristics which one can expect to be correlated with inventors' performance. For example, top inventors may be more likely to be matched with, and remain in, R&D-intensive firms and thus persistently produce more patents. Similarly, financially rich companies may be more likely to

[7] At first sight, the negative sign on experience may appear counter-intuitive. However, since all data points in these subsamples refer to the 2nd, 6th or 10th observation of all inventors, this variable also captures the gap between inventors' patenting years. The negative sign thus suggests that inventors for whom a longer spell elapsed between their patents have inferior innovation performance during any given year, all else constant.

[8] We confirm evidence for serial correlation after creating additional observations for gap years with corresponding year innovation output measures set to zero. In these models the persistence coefficients range from 0.51 to 0.62, i.e., they are higher than the estimates tabulated here.

attract and retain teams of top inventors and thus contribute to their employees' performance persistence. To test whether firm-specific factors bias estimates of inventor persistence, we restrict our attention to our Compustat sample.

Compustat firms are publicly listed and tend to be larger, better capitalized and more professionally managed than their unlisted counterparts. They may also be more likely to employ efficient, firm-specific processes and routines that drive innovation performance as compared to unlisted family-owned firms, start-ups, spin-offs and individual inventors. These differences may render results obtained from the Compustat sample unrepresentative of inventors at large. Hence, we proceed after ascertaining that the persistence estimates obtained from the USPTO sample reported in Table 3 are statistically identical to those obtained by running the same specifications on the Compustat sample.[9]

Having established that evidence for persistence is not sensitive to the innovation measure used, we henceforth only report results obtained from specifications that use yearly citation-weighted patents to proxy for innovation performance. We re-estimate equation (1) after adding the firm characteristics detailed in Table 2 and industry fixed effects as controls. Since inventors produce patents in teams and higher productivity inventors may be more likely to work with similar others, we add a control variable which measures the contemporaneous impact-weighted patent productivity of the focal inventor's coworkers. The results, reported in the first three columns of Table 4, show that a one percent increase in past year performance is associated with a 0.27-0.53 percent higher output in the current year. The coefficient estimate on coworker innovation output is positive and significant, indicating that productivity is positively correlated for workers in the same firm. The results of firm fixed effects models (reported in columns 4-6 of Table 4) reveal that even within firms, inventors' performance is highly persistent. Thus, even after one accounts for time-invariant firm characteristics and coworker productivity, the past productivity of inventors strongly, positively, predicts their future productivity (again, all serial coefficients are significant at $p<0.01$).

Insert Table 4 here

IV.3. Movers analysis

The above analysis provided evidence for inventors' performance in a sample that included inventors who stayed at the same firm, and those who changed employers. Here, we move

[9] Table A3 of the Appendix shows that persistence estimates obtained from the Compustat sample are not qualitatively different from those obtained from the larger USPTO sample.

closer towards addressing whether the observed persistence can be causally attributed to inventors' human capital by investigating persistence among inventors who change employers. To accomplish this, we split the USPTO sample of inventors, consisting of two observations per inventor, into two: (i) non-movers, or those who file patents for the same firm in both their yearly observations, and (ii) movers, or those who file patents from a different firm in their second observation. While we find significant evidence for persistence in both samples, the performance of movers is far less persistent than that of non-movers (serial correlation coefficient of 0.06 versus 0.27; both at $p<0.01$).

We investigate whether this estimated drop in persistence for movers is permanent or transitory, by examining a sample containing the third observation for each inventor. Here we can distinguish between inventors who never moved, those who switched firms between their first and second observation (movers in the second observation sample) and those who switched between observations two and three. For this last group, persistence estimates are similar to those obtained from the sample of second observations, i.e., persistence exists, but is weaker than for non-movers (coefficient estimate of 0.09 versus 0.39; both at $p<0.01$). However, focusing on inventors who moved after their first observation, we find the persistence estimate recovers for the third observation (and is statistically no different than the persistence estimate for the third observation in the non-mover subsample, i.e., 0.32 versus 0.39; both at $p<0.01$). Thus, the negative effect of moving on performance persistence, while significant, appears to be transitory. Inventors replicate their productivity at their new employers after an initial adjustment period.

We return to the USPTO sample, which includes observations on individual inventors, to examine whether inventors' productivity is affected by their employment at firms. We find that estimated persistence is highest for inventors who remain independent throughout (0.34; $p<0.01$) and lowest for independent inventors who join firms (0.22; $p<0.01$).[10] Persistence estimates are similar for inventors who remain at firms throughout (0.3; $p<0.01$) and those who drop out of firms to invent independently (0.32; $p<0.01$). Thus, inventors' ability to repeat their productivity does not appear to be enhanced by employment at the average firm.

[10] Table A4 tabulates corresponding estimates.

V. Human Capital and Firm Capability

V.1. The AKM methodology

The analysis so far suggests inventors repeat their invention performance over the course of their careers, even after they change employers. However, the estimates of persistence could be biased if high ability inventors are more likely to work for more innovative firms or inventors within firms are rewarded with more resources to invent upon their initial success, leading to persistence. Assessing whether the persistence is driven by human capital, or by assortative matching of high ability inventors and firms, requires disentangling the contributions to inventor performance of inventor- and firm-specific capabilities.

Previous studies have tried to disentangle the contributions of industry, corporate structure or top management to firm performance with variance decomposition techniques (see e.g., Quigley and Hambrick 2015; McGahan and Porter 2002). While these techniques help identify the aggregate contributions of the variables to differences in firm performance, we seek to isolate the contribution of inventor skills and firm capabilities for inventor productivity. To accomplish this objective, we employ the “AKM” methodology, developed by Abowd et al (1999) and further refined in Abowd et al (2002). This method supplies an identification strategy to estimate large sets of individual-specific dummy variables (individual effects) across several dimensions, e.g., firms and workers, alongside time-varying factors. For our purpose, the dependent variable of interest is the yearly innovation output of an inventor. We introduce individual dummies along two dimensions: the individual inventors and the firms they work at. We include, as before, the set of time-varying contributors to innovation defined in Table 2 and estimate a model of the form:

$$y_{ijt} = \beta_x X_{it} + \beta_z Z_{jt} + \gamma_t + \alpha_i + \phi_j + \epsilon_{ijt}. \quad \text{(Equation 2: innovation output model)}$$

Here, y_{ijt} refers to the log number of citation weighted patents of inventor (i) at firm (j) in year (t). The vectors X_{it} and Z_{jt} represent time-varying inputs related to the inventor (X_{it}) and firm (Z_{jt}). The vectors γ_t, α_i and ϕ_j contain sets of year, individual inventor and firm fixed effects, respectively. ϵ_{ijt} denotes an inventor-firm-year-specific error term.

The AKM methodology is, in essence, a large-scale fixed effects estimator, and its identification strategy relies on variation in performance within inventors and organizations. In our AKM sample, inventors are always assigned to a firm and identifying both inventor and firm effects requires variation in the match-up of inventors and firms. This variation is supplied by mobile inventors, i.e., inventors who have filed patents for at least two separate firm-assignees. Intuitively, the individual effect of a mobile inventor is determined as her average innovation performance across firms, net of other contributing factors which are explicitly included in the estimating equation. The firm-specific effects can then be gauged through the average over- or under-performance of all mobile inventors during their spell at the firm, relative to their average career-long performance. This logic pins down the fixed effects of non-mobile inventors by calculating their average inventive performance in the data, net of time-varying inputs and firm effects inferred from the mobile inventors' performances. To allow interpreting all inventor and firm effects with reference to a common baseline, the AKM method requires that all firms and inventors in the estimation sample belong to a "network" connected by mobile inventors.

The AKM technique uses inventor movement to pin down inventor and firm-fixed effects, but it is unlikely that inventor movement across firms are random. Still, exogenous mobility has been the maintained assumption in several AKM applications (e.g., Graham et al 2016, Ewens and Rhodes-Kropf 2015). We acknowledge this limitation and interpret our findings here as suggestive rather than definitive. In Section IV.3, we introduce a dynamic AKM estimation strategy to investigate the endogeneity of inventor movements and inventor-firm matching.

V.2. Baseline AKM results

We use AKM regressions to adjudicate the contributions of inventor and firm-specific effects on inventors' performance. To this end, we calculate the covariance of annual innovation output with the inventor, firm- and year-fixed effects, divided by the variance of the dependent variable, i.e., $\frac{\mathrm{Cov(y,inventor\ FE)}}{\mathrm{Var(y)}}$, $\frac{\mathrm{Cov(y,firm\ FE)}}{\mathrm{Var(y)}}$ and $\frac{\mathrm{Cov(y,year\ FE)}}{\mathrm{Var(y)}}$. These ratios calculate the fraction of the total R^2 attributable to inventor-specific, firm-specific and year-specific factors respectively. The measures can be interpreted just as the outputs of a variance decomposition analysis, as they estimate the contribution of each fixed effect to the overall explanatory power of the model. In addition, we are also interested in the joint significance of the inventor and firm effects, which we assess with an F-test of the estimated coefficients.

We estimate the AKM model in equation (2) using the user-written STATA command FELSDVREG (Cornelissen 2008) and report the results in Table 5. Column (1) reports the results from the AKM sample for the regression with all firm characteristics (Z_{jt}) and inventor observables (X_{it}). Our results indicate that the contributions of inventor and firm effects to innovation performance are highly significant. Inventor heterogeneity explains 27 percent and firm heterogeneity 4.4 percent of the total variance in inventors' innovation performance.[11] In relative terms, inventor effects are by far the most important factor contributing to innovation performance. Although not immediately relevant to our objective, we note that year-effects subsume the influence of factors such as the macroeconomic environment or patent law changes that commonly affect the patenting intensity of all inventors in the sample, and account for about 11 percent of the explained variance in patent performance in our panel. Inventor fixed effects, firm fixed effects and year fixed effects are all jointly significant at $p<0.01$.

Insert Table 5 here

V.3. Robustness checks

Columns (2)-(4) of Table 5 report the results of robustness checks. Column (2) repeats the analysis in Column (1), but without any observed firm or inventor characteristics. This assures that the estimated importance of inventor-fixed effects relative to firm-fixed effects reported in Column (1) is not because we included a large battery of firm characteristics and only a few inventor characteristics as controls.

Our AKM sample is selected with the requirements that (a) each inventor in the sample has patented in at least four different years to facilitate the identification of inventor-fixed effects, and (b) firms are connected through a network formed by inventor moves. These requirements allow us to compute the fixed effects of both mobile and immobile inventors in connected firms. Of course, mobile inventors may be systematically different from inventors who have never changed firms and one may question AKM's imputation of fixed effects for non-mobile inventors. Column (3) reports the importance of inventor and firm effects obtained by estimating equation (2) on a subsample of mobile inventors alone (as in Bertrand and Schoar, 2003). Despite the blip in inventive productivity suffered by inventors immediately after their move, this subsample of movers yields estimates of inventor-fixed effects quite close in importance to the ones obtained from the full AKM sample (0.27 v/s 0.24).

In column (4), we re-estimate the model after selecting a sample of inventors with at least ten-year observations (instead of four). This allows more observations, and hence more degrees of freedom, to identify each individual effect. It also addresses concerns that inventor effects calculated with data on a short window of inventors' careers may be noisy. As a further

[11] Since the model explains 43 percent of the overall variation in inventor performance, inventor heterogeneity and firm heterogeneity account for 62.7 percent (27/43) and 10.2 percent (4.4/43) of the variance explained by our model.

robustness check, we identify the fixed effects after filling in zeros for the years in which inventors do not patent and report the results in column (5). Finally, we exclude observations of firms that change ownership due to mergers and acquisitions of entities in column (6). These three specifications suggest inventor-specific skill explains 23.9-28.8 percent of the variance in their inventiveness.[12]

The results in Table 5 indicate that inventor effects are far more important in explaining innovation than firm effects. This finding cannot be attributed to the choice of firm-level observables we include, systematic differences between mobile and immobile inventors or between those with short and long patenting careers. It is also not an artifact of not observing inventor activity during certain years or firm-ownership changes injecting noise to our imputation of inventor movement.

V.4. Distribution of inventor and firm effects

Here we examine heterogeneity among inventors and firms in their estimated inventive capabilities. As a given inventor (firm) fixed effect should be interpreted relative to all other inventor (firm) fixed effects in the sample, we follow the common practice of rescaling the estimated effects by the distribution mean. Rescaling centers the distributions of fixed effects at zero. Figures 1 and 2 display the distribution of inventor- and firm-fixed effects obtained from the regression model in Column 1 of Table 5, which uses log citation-weighted patents as the dependent variable. After rescaling, the average fixed effect equals 0 for both firms and inventors. The standard deviation of inventor- and firm-fixed effects are 0.65 and 0.73 respectively. The median inventor has an estimated effect of -0.08, i.e., slightly the population average, while the first and third quartile stand at -0.44 and 0.33 respectively. This leftward shift with respect to the population average is caused by the relatively long right tail of the distribution. As can clearly be seen in Figure 1, the left tail of "underperforming" inventors is fairly short relative to the right tail suggesting the presence of star inventors. By comparison, the distribution of firm effects is more balanced. Here the median estimated effect is 0.01 with the first and third quartiles at -0.40 and 0.41 respectively. Figure 2 confirms this observation, as it shows no apparent skew in the distribution of firm effects. Hence, star firms seem less common than star inventors.

Insert Figure 1 and Figure 2 around here

[12] Table A5 of the Appendix also reports pairwise correlation coefficients among inventor- and firm-fixed effects obtained from the different estimations described above. The coefficients are all higher than 0.85 suggesting robustness of our findings to the different specifications and samples.

V.5. Technology field differences

Previous research suggests important technology field- and industry-level differences in the importance of firm-specific capabilities, as well as the organization of innovative activities (e.g., Pavitt 1984, Levin et al 1987, McGahan and Porter 1997, Malerba 2005). We explore technology field differences by estimating the baseline AKM specifications, with the complete set of covariates, for each of the six technology fields defined in Hall et al (2001). The results, shown in Table 6, suggest inventor-fixed effects are the dominant contributor to innovation performance in all industries.[13] The regressions, however, unmask heterogeneity among fields in the importance of firm capabilities on inventor productivity: in the traditional fields of Chemicals, Drugs and Medical Instruments, and Mechanical, firm capabilities explain 3-5 percent of the variance in inventor performance. Firm capabilities are significantly less important, and explain only 1.5 percent of the variance in inventor productivity, in the more modern fields of Electrical & Electronics and Computers & Communications. Thus, in modern fields inventor skills are even more important relative to firm capabilities. While establishing the reasons behind this finding is beyond the scope of this study, the finding is consistent with portrayals of information technology fields as highly dynamic, with intense competition for high-skilled labor and porous boundaries across firms (Saxenian 1994, 2006).

Insert Table 6 here

VI. Employee-Firm Matching

VI.1. Time-varying inventor and firm effects

If human capital is the most important contributing factor for inventor performance, and inventors can easily replicate their innovative success at a different employer, then attracting and retaining high-skill inventors is critical for firms' innovative advantage. How can firms secure, and profit from, this advantage? A deeper understanding of the matching process between firms and high-skilled workers is essential to address this question, and also to explain why some firms are persistently more innovative than others. Understanding matching will also help inform how endogeneity of matching and inventor mobility affects inferences derived

[13] Table A6 of the Appendix confirms similar levels of persistence in inventor performance across all six technology fields.

from our previous estimations. In this section, we focus our attention on exploring matching between human capital and firm capabilities.

The standard AKM estimates reported in Section IV are not useful to study matching between inventors and firms. To illustrate why, suppose we are interested in relating an inventor's movement between two employers in year t to her individual ability, as estimated by AKM. When individual effects are estimated on the full sample, an inventor's effect is constructed from her average innovation output across all her employers, net of observable inputs and firm capabilities. This includes observations both before and after year t, and as such, these estimates are "contaminated" by the firms to which the inventor has not yet moved in year t (but will do so in a later year in the sample period). If we were to use these estimates to analyze the inventor's move in year t, it would be impossible to disentangle whether an inventor with a high (low) estimate moved to a firm with greater (lower) ability, or whether the inventor's estimate is high (low), because it is partly derived from her time working at a firm with greater (lower) ability. The same holds true for estimates of firm capabilities.

To address this issue, we propose a novel "rolling window" procedure that derives partially time-varying estimates of inventor and firm effects through the AKM methodology. To implement the procedures, we begin by limiting the sample to a 10-year period from 1978 through 1987. Then, we estimate equation (2) on the largest network in this subsample to obtain firm and inventor effects. Crucially, these estimates are not contaminated by how the inventor and firm effects change as a result of inventor moves after 1987. Next, we draw a new subsample of 10 years by rolling the window by one year, from 1979 through 1988. We again estimate equation (2) on this sample. We continue this rolling procedure till we arrive at the end of our main sample in 2010. Since the effects in different windows may be estimated in comparison to different benchmark inventors (firms), we standardize the estimated inventor (firm) effects by subtracting the mean and dividing by the standard deviation of all inventor (firm) effects in the same subsample. We thus end up with a set of standardized time-varying estimates for firm and inventor effects. These are, in our view, best interpreted as time-varying measures of an inventor's (firm's) relative innovation ability, compared to the distribution of contemporary inventor (firm) abilities (i.e., those active in the past 10 years). We repeat this procedure for rolling windows that span five years as a robustness check.

VI.2. Which inventors move?

We first use the individual effects estimated through the rolling window algorithm to investigate which inventors are likely to move to another firm in the future as a function of their current human capital and current firm's capabilities (estimated through rolling window

AKM). To this end, we define a mobility indicator y_{it}, which equals 1 in year t for inventor i at firm j if the next patent, filed at any time in the subsequent five years by inventor i is filed at a different firm than firm j. We set this indicator to equal 0 if all patents filed by inventor i in year $t+1$ are filed at firm j and code the variable value as missing if the inventor does not reappear in the sample after year t. We then estimate a regression model to relate this indicator to the estimates of inventor and firm effects obtained from the window ending in year t. Our model takes the form:

$$y_{ijt} = \beta_0 + \beta_1 \hat{\alpha}_{it} + \beta_2 \hat{\varphi}_{jt} + \beta_3 E[\hat{\alpha}_{ct}]_{jt} + \beta_4 x_{ijt} + \gamma_t + \sigma_j + \varepsilon_{it}$$

(Equation 3: mobility model)

In equation (3), $\hat{\alpha}_{it}$ denotes the current estimate of inventor i's individual effect, $\hat{\varphi}_{jt}$ represents the estimated firm effect and $E[\hat{\alpha}_{ct}]_{jt}$ stands for the average estimated inventor effect for all inventors c, filing patents at firm j in year t. We further report specifications where we add the current tenure of inventor i at firm j (x_{ijt}), and a set of year (γ_t) and NAICS two-digit level fixed effects (σ_j). We vary the estimated firm and inventor effects used by sourcing them from the rolling windows with ten- or five-year timeframes respectively. We use a linear probability model with bootstrapped standard errors to estimate Equation (3), such that the coefficients are interpreted as marginal probabilities.

Insert Table 7 around here

Table 7 reports the corresponding estimates. We find the inventor's individual effect is negative and significant in all specifications predicting mobility. An increase of one standard deviation in the estimated inventor ability is associated with a 3 percent decrease in the probability that the inventor moves. Given that the unconditional probability of an inventor moving in a particular year stands at 7.3 percent in the data, this is considerable. Recall that the baseline is made up of inventors reappearing as patentees at their current employer and not those who leave the labor market. Hence, even among high-skilled inventors, firms appear to retain more capable inventors longer. For the estimated firm effects, we find a significant negative coefficient, although the effect size is very close to zero. This suggests firms with more innovative capabilities are slightly less likely to experience inventor exits. In addition, inventors at firms with high average inventor effects (average calculated after leaving out the productivity of the focal inventor) are also less likely to move to a different firm in the next year. Here, an increase of one standard deviation in estimated ability again coincides with a decrease of around 2-3 percent in exit probability. In all models, we find inventors are less likely to move with experience.

VI.3. Human capital and firm matching

Next, we study matching between firms and inventors as a function of their capabilities derived from the rolling window procedure. In particular, we test whether high-skilled inventors are attracted to (a) firms with superior firm-specific inventive capabilities, (b) firms with other high-skill co-workers, or (c) firms with better financial resources and performance. The corresponding regressions predict inventors' future firm characteristics as a function of current rolling-window estimates of inventor ability. Our sample for this analysis consists of all movements by an inventor i from a firm j to a new firm n, for which we are able to obtain an estimate of the inventor effect from the rolling window ending in the year t, i.e., the last year inventor i is observed at firm j. Formally, we estimate the following regression model,

$$y_{nt} = \beta_0 + \beta_\alpha \hat{\alpha}_{it} + \beta_x x_{it} + \gamma_t + \sigma_j + \varepsilon_{it}. \qquad \text{(Equation 4: matching model)}$$

In equation (4), y_{nt} refers to a characteristic of the next firm n at time t, i.e., before inventor i has joined. These characteristics include (a) the estimated firm capability, (b) the average estimated ability of all inventors active at n prior to the move, (c) the firm's log net income and (d) Tobin's Q, calculated as described in Table 2. In all specifications, we relate these dependent variables to a constant term (β_0), the moving inventor's estimated ability ($\hat{\alpha}_{it}$), the log of inventor experience in years (x_{it}), and a set of year and industry (NAICS 2 digit level) fixed effects, γ_t and σ_j, respectively.

Table 8 reports the results obtained by estimating equation (4) using five- and ten-year rolling windows. We find that firm-specific innovation capability is negatively correlated with the ability of inventors moving into the firm, suggesting negative assortative matching based on innovation capability. Thus, firms with high estimated firm-specific innovation capabilities do not seem to, on average, attract inventors with high estimated human capital. Our results for the new firms' average inventor ability lead us to the opposite conclusion of positive assortative matching based on the moving inventors' and future coworkers' human capital. Our estimates suggest that, among moving inventors, inventors whose estimated ability is one standard deviation higher, move to firms where the average inventor's ability is 0.12-0.19 standard deviations higher ($p < 0.01$). These estimates may seem small in absolute terms, but since firms employ dozens or even hundreds of inventors, moving upward in the distribution of average inventor ability at the firm is much harder and therefore more significant in terms of influencing inventive output, than moving along the individual inventor ability distribution. Hence, firms in which the average inventor is 0.15 standard deviations "better" are indeed far more innovative ($p < 0.01$). These results suggest that more inventive individuals are more likely to move to firms where innovativeness is embedded in human capital rather than in firm-specific routines.

Insert Table 8 around here

To examine whether our findings of negative assortative matching between inventors and firms based on innovation capability, and positive assortative matching based on human capital characterize the stock of inventors at firms, not just movers, we momentarily return to the baseline AKM estimates (of Equation 2) presented in Column 1 of Table 6. We plot the firm-fixed effects and the mean estimated inventor-fixed effects at the firms in Figure 3. These estimates are derived from the AKM sample of all connected firms and incorporates information on all employees at the firms. The figure shows a large negative correlation (-0.49) between firm-fixed effects and mean inventor fixed effects. In contrast, Figure 4 shows a positive correlation (0.27) between the estimated inventor and co-worker fixed effects at the firm. Thus, even considering a snapshot of inventor-firm assignments, high-skilled inventors are more likely to be matched with firms that have other high-skilled inventors, but low firm-specific innovation capabilities.

Insert Figures 3 and 4 around here

Finally, we examine the relationship between the human capital of mobile inventors and the financial performance of the firms they move to. The last two columns of Table 8 reveal significantly positive coefficient estimates of the relationship between inventor ability on the one hand and firms' financial performance and growth, on the other (at $p<0.05$ and $p<0.01$ respectively). It appears inventors with higher human capital move to firms with superior financial performance and to firms with higher expected growth. As with all other results presented here, this estimate could not have been driven by reverse causality—that is, by higher skill inventors driving superior financial performance since inventor-specific skill is entirely calculated from the information supplied by our data prior to the inventor's move to the firm. But we cannot rule out that the estimated effects are driven by unobserved dynamic capabilities, such as improved management practices or better leadership, which may contemporaneously drive financial success and successful hiring.

VII. Concluding thoughts

Invention requires the performance of non-routine tasks and the outcomes of inventive tasks are highly uncertain. This study examined whether workers can nevertheless repeat their inventive performance. Using a sample of nearly 1.25 million patenting inventors, our empirical analysis uncovered strong evidence for persistence of inventor performance across a variety of outcomes such as patenting frequency, impact, originality, and generality. Evidence for persistence is strong even among inventors within a firm, and does not disappear after inventors change employers, suggesting something inherent in inventors drives their productivity.

We establish that these inventor-specific skills are four to five times more important than the firm-specific capabilities of their employers for explaining the observed variance in inventor performance. The relative importance of inventor human capital over firm capabilities appears greatest in skill-intensive and dynamic fields such as computers and communications. These findings may explain the intense competition among firms in information and technology related fields for human capital (Terdiman 2014). The relatively small effect of firm-specific capabilities on innovation—which include capabilities such as corporate culture and organizational routines, and take several years to build—may explain why several decades of research has not uncovered a clear advantage for established firms in innovation.

Finally, we find high human capital inventors match with firms that have (a) high skilled inventors, (b) superior financial performance and growth and (c) weak firm-specific innovation capabilities. These results are consistent with the characterization of a labor market in which financially successful firms are able to lure and retain top talent, which in turn, attracts more talent, innovation and financial success. This self-reinforcing mechanism may counter top talent from expropriating all of the profits, associated with their inventive outputs, from their employers. In contrast, firms that are unable to attract top talent may invest in firm-specific innovation capabilities, which may reduce employee turnover, but further deters highly talented inventors from moving to such firms.

Taken together, our results suggest the role of the firm is to serve as a platform, or binding glue, for highly talented workers. The findings also make the case for a more central role for human capital in theories of the firm and studies of competitive advantage.

Of course, our analysis has limitations. The rolling window technique to derive time-varying estimates of inventor and firm ability allows us to descriptively examine firm-worker matching, but it does not fix the issue of endogenous matching and mobility. Likewise, our regressions are not equipped to deal with time-varying omitted variables such as firm leadership or governance that may influence inventor productivity and firm capability. Our analyses establish the importance of inventor-specific ability for innovation performance, but we do not know what drives the fixed effects. Inventor fixed effects likely subsume the influences of a variety of intrinsic traits (e.g., innate ability and persistence) and acquired experiences (e.g., education). Unpacking and identifying these ingredients of human capital presents promising avenues for future research.

References

Abowd, J., F. Kramarz, & D. Margolis, 1999, High wage workers and high wage firms, Econometrica 67: 251–333.

Abowd, J., R. Creecy, & F. Kramarz, 2002, Computing person and firm effects using linked longitudinal employer-employee data, Technical Report 2002-06, U.S. Census Bureau.

Abowd, J., K. McKinney, & I. Schutte. 2017. Modeling Endogenous Mobility in Earnings Determination, Journal of Business and Economic Statistics, forthcoming.

Agarwal, R., & A. Ohyama. 2013. Industry or academia, basic or applied? Career choices and earnings trajectories of scientists. Management Science, 59(4): 950-970.

Agrawal, A., J. McHale, & A. Oettl. 2014. Why Stars Matter. NBER W. P. No. 20012.

Azoulay, P., J. Graff Zivin, J. Wang. 2010. Superstar Extinction. Quarterly Journal of Economics 125(2), 549-589.

Barney, J. 1986. Organizational Culture: Can It Be a Source of Sustained Competitive Advantage? Academy of Management Review, 11(3): 656-665.

Bartlett, C., S. Ghoshal. 2002. Building Competitive Advantage Through People. MIT Sloan Review 43(2), 34-41.

Becker, G. 1962. Investment in human capital: A theoretical analysis, Journal of Political Economy, 70(5): 9-49.

Belenzon, S. Berkovitz, T. 2010. Innovation in Business Groups, Management Science, 56, 519– 535

Bernstein, S. 2015. Does Going Public Affect Innovation? Journal of Finance. August 2015, Vol. 70, Issue 4, Pages 1365-1403.

Bertrand, M., & A. Schoar. 2003. Managing with Style: The Effect of Managers on Firm Policies, Quarterly Journal of Economics, 118(4): 1169–1208.

Bessen, J. 2009. Matching Patent Data to Compustat Firms. NBER PDP Project User Documentation

Bikard, M., F. Murray, & J. Gans. 2015. Exploring tradeoffs in the organization of scientific work: Collaboration and scientific reward. Management Science, 61(7): 1473-1495.

Bloom, N., B. Eifert, D. McKenzie, A. Mahajan and J. Roberts. 2013. Does management matter: evidence from India, Quarterly Journal of Economics, 128(1): 1-51

Campbell, Benjamin, Russell Coff, and David Kryscynski. 2012. Rethinking Sustained Competitive Advantage from Human Capital. Academy of Management Review 37(3): 376-395.

Castanias R., & C. Helfat. 2001. The managerial rents model: theory and empirical analysis. Journal of Management 27: 661–678.

Cefis, E. 2003. Is there persistence in innovative activities? International Journal of Industrial Organization 21 (2003) 489–515.

Coff, R., & D. Kryscynski, 2011. Drilling for Micro-Foundations of Human Capital-Based Competitive Advantages. Journal of Management 37(5): 1429-1443.

Coff, R. 1997. Human Assets and Management Dilemmas: Coping with Hazards on the Road to Resource-Based Theory. Academy of Management Review 22(2), 374-402.

Cohen, W. M., R. C. Levin and D. C. Mowery. 1987. Firm Size and R&D Intensity: A Re-Examination, Journal of Industrial Economics, Vol. 35, No. 4, June 1987, pp. 543-565.

Cornelissen, T. 2008. The Stata command felsdvreg to fit a linear model with two high-dimensional fixed effects, Stata Journal 8: 170–189.

Corredoira, R., L. Rosenkopf. 2010. Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. Strategic Management J. 31(2) 159–181.

Ewens, M., & M. Rhodes-Kropf. 2015. Is a VC Partnership Greater Than the Sum of Its Partners? Journal of Finance 120(3): 1081-1113.

Felin, T., Foss, N. J., Heimeriks, K. H., & Madsen, T. L. 2012. Microfoundations of routines and capabilities: Individuals, processes, and structure. Journal of Management Studies, 49(8): 1351-1374.

Geroski, P., J. Van Reenen, C.F. Walters. How persistently do firms innovate? Research Policy 26(1) 33–48.

Graham, John, Si Li and Jiaping Qiu. 2012. Managerial Attributes and Executive Compensation. Review of Financial Studies 25(1): 144–186.

Grigoriou, Konstantinos and Frank Rothaermel. 2014. Structural Microfoundations of Innovation: The Role of Relational Stars. Journal of Management 40(2), 586-615.

Groysberg Boris 2010. Chasing stars: The myth of talent and the portability of performance. New Jersey: Princeton University Press.

Groysberg, Boris, Linda-Eling Lee and Ashish Nanda. 2008. Can they take it with them? The portability of star knowledge workers' performance. Management Science, 54(7): 1213–1230.

Hall, Bronwyn H. and Rosemarie Ham Ziedonis. 2001. The patent paradox revisited: an empirical study of patenting in the U.S. semiconductor industry, 1979–1995. RAND Journal of Economics, 32(1): 101–128.

Hall, Bronwyn H, Adam B. Jaffe, and Manuel Trajtenberg, 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. NBER Working Paper No. 8498.

Hatch Nile W. and Jeffrey H. Dyer, 2004. Human capital and learning as a source of sustainable competitive advantage. Strategic Management Journal, 25: 1155–1178.

Huckman, Robert S. and Gary P. Pisano, 2006. The firm specificity of individual performance: evidence from cardiac surgery. Management Science 52(4): 473–488.

Iranzo, Susana, Fabiano Schivardi and Alisa Tosetti, 2008. Skill Dispersion and Firm Productivity: An Analysis with Employer-Employee Matched Data, Journal of Labor Economics, 26(2): 247-285.

Jones, Benjamin F., 2009. The Burden of Knowledge and the 'Death of the Renaissance Man': Is Innovation Getting Harder? Review of Economic Studies, 76(1): 283–317.

Klein, Benjamin, 1988. Vertical Integration as Organizational Ownership: The Fisher Body-General Motors Relationship Revisited, Journal of Law, Economics, & Organization, 4(1): 199-213

Lazear, Edward P., 2009. Firm-specific human capital: A skill-weights approach. Journal of Political Economy, 117: 914–940.

Levin, Richard C., Alvin K. Klevorick, Richard R. Nelson, Sidney G. Winter, Richard Gilbert and Zvi Griliches, 1987. Appropriating the Returns from Industrial Research and Development, Brookings Papers on Economic Activity, 1987(3): 783-831.

Li Guan-Cheng, Ronald Lai, Alexander D'Amour, David M. Doolin, Ye Sun, Vetle I. Torvik, Amy Z. Yu and Lee Fleming, 2014. Disambiguation and co-authorship networks of the U.S. patent inventor database (1975–2010), Research Policy, 43(6): 941-955.

Liu, Tong and Mao, Yifei and Tian, Xuan, 2017. The Role of Human Capital: Evidence from Patent Generation (May 10, 2017). Kelley School of Business Research Paper No. 16-17. Available at SSRN: https://ssrn.com/abstract=2728924

Malerba, Franco, 2005. Sectoral systems of innovation: a framework for linking innovation to the knowledge base, structure and dynamics of sectors, Economics of Innovation and New Technology, 14(1-2): 63-82.

Martinez, E., N. Beaulieu, R.Gibbons, P. Pronovost and Thomas Wang, 2015. Organizational Culture and Performance, American Economic Review, 105(5): 331-35.

Marx, M., D. Strumsky, L. Fleming. 2009. Mobility, skills, and the Michigan non-compete experiment. *Management Science*. 55(6) 875–889.

Mayer, Kyle J., Deepak Somaya and Ian O. Williamson, 2012. Firm-specific, industry-specific and occupational human capital, and the sourcing of knowledge work. Organization Science, 23: 1311–1329.

McGahan, Anita and Michael Porter. 1997. How much does industry matter, really? Strategic Management Journal 18: 15-30.

McGahan, Anita and Michael Porter. 2002. What Do We Know About Variance in Accounting Profitability? Management Science 48(7): 834-851.

Mindruta, D. 2013. Value creation in university-firm research collaborations: A matching approach. Strategic Management Journal, 34(6): 644-665.

Moen, J. 2005. Is mobility of technical personnel a source of R&D spillovers? Journal of Labor Economics. 23(1) 81–114.

Mollick, E. 2012. People and process, suits and innovators: the role of individuals in firm performance. Strategic Management Journal, 33(9): 1001-1015.

Nelson, Richard R. and Sidney G. Winter, 1984. An Evolutionary Theory of Economic Change. Belknap Press.

Oettl, A. 2012. Reconceptualizing Stars: Scientist Helpfulness and Peer Performance. Management Science 58(6), 1122-1140.

Oettl, A., A. Agrawal. 2008. International labor mobility and knowledge flow externalities. Journal of International Business Studies 39 1242–1260.

Pavitt, Keith, 1984. Sectoral patterns of technical change: Towards a taxonomy and a theory, Research Policy, 13(6): 343-373.

Peters, B., 2009. Persistence of innovation: stylised facts and panel data evidence. Journal of Technology Transfer 34, 226–243.

Quigley, Timothy J. and Donald C. Hambrick, 2015. Has the “CEO effect” increased in recent decades? A new explanation for the great rise in America's attention to corporate leaders. Strategic Management Journal 36: 821-830.

Raymond, Wladimir. Pierre Mohnen, Franz Palm, and Sybrand Schim van der Loeff. 2010. Persistence of Innovation in Dutch Manufacturing: Is it spurious? Review of Economics and Statistics 92(3): 495–504.

Rothaermel, Frank T. and Andrew M. Hess, 2007. Building dynamic capabilities: innovation driven by individual-, firm-, and network-level effects. Organization Science 18(6): 898–921.

Rumelt, Richard, 1984. Towards a Strategic Theory of the Firm. Competitive strategic management: 556-570.

Saxenian, AnnaLee, 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128, Harvard University Press.

Saxenian, AnnaLee, 2006. The New Argonauts: Regional Advantage in a Global Economy, Harvard University Press.

Singh, J., L. Fleming. 2010. Lone inventors as sources of breakthroughs: Myth or reality? Management Science 56(1) 41–56.

Singh, J. and Ajay A. 2011. Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. Management Science 57(1), 129-150.

Terdiman, D. 2014. Silicon Valley Talent Wars: https://www.cnet.com/news/silicon-valley-talent-wars-engineers-come-get-your-250k-salary/

Wernerfelt, Birger, 1984. A resource-based view of the firm. Strategic Management Journal 5(2):171-180.

Wright, Patrick, Russell Coff, and Thomas Moliterno. 2014. Strategic Human Capital: Crossing the Great Divide. Journal of Management 40(2): 353-370.

Wuchty, Stefan, Benjamin F. Jones and Brian Uzzi, 2007. The increasing dominance of teams in production of knowledge. Science 316(5827): 1036–1039.

Tables and Figures

Table 1. Sample Description

The table reports the number of inventors, number of firms, number of inventor -firm-year observations, and mean number of inventors per firm for the USPTO, Compustat, and AKM samples. From the USPTO and Compustat samples, we draw subsamples corresponding to the second, sixth, or the tenth year an inventor is observed in the dataset (represented by obs2, obs6 and obs 10 respectively). Since we draw one observation per year for each inventor, the number of inventor-firm-year observations equals the number of inventors for the USPTO and Compustat subsamples. The USPTO subsamples of U.S. patents spans grant years 1973-2010. The Compustat subsamples are obtained after matching the USPTO data with the Compustat dataset, following the procedure outlined in Bessen (2009) and spans grant years 1978-2010. The AKM estimation subsamples correspond to the "connectedness sample" or the sample of firms connected to each other by inventor mobility. The first column for the AKM subsamples describes inventors who filed for patents in at least four different years during 1978-2010, the second column describes inventors with at least four years of patenting who moved firms and the third describes the subsample with inventors with at least ten years of patenting. Since the AKM subsamples contain observations for each of the years during which the inventors patented, the number of inventor-firm-year observations are strictly greater than the number of inventor observations.

USPTO subsamples (1973-2010)	obs 2	obs 6	obs 10
Inventor-firm-year observations	1,218,959	242,735	81,395
Inventors	1,218,959	242,735	81,395
Firms	117,140	33,805	14,209
Mean number of inventors per firm	10.4	7.1	5.7
Compustat subsamples (1978-2010)	obs 2	obs 6	obs 10
Inventor-firm-year observations	336,039	58,247	15,496
Inventors	336,039	58,247	15,496
Firms	1,716	975	537
Mean number of inventors per firm	195.8	59.7	28.8
AKM estimation subsamples (1978-2010)	4+ years	Movers	10+ years
Inventor-firm-year observations	849,939	297,156	254,437
Inventors	129,576	39,378	18,928
Firms	1,760	1,760	1,149
Mean number of inventors per firm	73.6	22.3	16.4

Table 2. Variable Descriptions

Variable	Description
Innovation output measures	
Patents	Number of patents p, filed by inventor i at firm j in year t.
Cites per patent	Average number of forward citations to patents of inventor i in year t.
Citation-weighted patents	Number of patents p multiplied by the five-year forward citations (excluding self-citations) to these patents, filed by inventor i at firm j, in year t, divided by number of co-authors on patent p.
Generality	Generality of patents, filed by inventor i at firm j, in year t.
Originality	Originality of patents p, filed by inventor i at firm j, in year t.
Inventor characteristics	
Past "X"	Average value output measure "X" in previous one, five, or nine years (depending on specification) for inventor i.
Coworkers'citation-weighted patents	Average of "*Citation Weighted Patents*" by other inventors at firm j in year t excluding focal inventor i.
Years since 1st patent	Number of years between first and current patent in dataset for inventor i.
Firm characteristics	
Firm age	Firm j's age in year t in years.
Dummy R&D	Dummy whether firm j reports R&D expenditure in year t.
R&D intensity	R&D Expenditures/Sales averaged over years $t-2$ to t.
Capital intensity	PP&E/Sales averaged over years $t-2$ to t, where PP&E is Property, Plant and Equipment expenditure.
Sales	Firm j's averaged sales over years $t-2$ to t.
Operating income change	Change in operating income of firm j averaged over years $t-2$ to t.
Employees	Number of employees for firm j in year t.
Patent stock	Sum of patents at firm j in years t-2 to t.
Tobin's Q	Tobin's Q for firm j in year t computed using the formula: $\frac{AT+(CSHO*PRCC\_C)-CEQ}{AT}$, where AT is total assets, CSHO is common outstanding shares, PRCC_C is the annual closing stock price, and CEQ is common equity.
Net income	Net income for firm j in year t.

Table 3. Persistence of Inventors' Inventive Performance (USPTO Patent Sample)

The table reports Ordinary Least Squares regression estimates for persistence of inventors' inventive performance. The regressions specify as dependent variables, the following measures of inventor performance: log of number of patents (Columns 1-3), log of number of citation weighted patents (Columns 4-6), mean originality (Columns 7-9), and mean generality (Columns 10-12). For each measure, we take the inventor's patenting output per year, after dividing the measure by the number of coinventors. To address attrition bias, each regression is repeated in three subsamples, each predicting innovation performance during the inventor's second, sixth, or tenth year observation of an inventor as a function of the inventor's past performance. Each estimation sample includes one observation per inventor drawn from the inventor's Nth year of patenting (indicated by obs 'N'). Past number of patents and Past number of citation weighted patents are annual averages computed over each inventor's previous years. Robust standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Log number of patents			Log number of citation weighted patents			Mean originality			Mean generality		
Column	1	2	3	4	5	6	7	8	9	10	11	12
Sample	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10
Past log number of patents	0.43*	0.69*	0.76*									
	[0.001]	[0.004]	[0.008]									
Past log number of citation weighted patents				0.30*	0.57*	0.62*						
				[0.001]	[0.004]	[0.007]						
Past mean originality							0.33*	0.45*	0.57*			
							[0.001]	[0.004]	[0.007]			
Past mean generality										0.31*	0.56*	0.64*
										[0.002]	[0.005]	[0.011]
Years since 1st patent	-0.02*	-0.04*	-0.03*	-0.07*	-0.08*	0.08*	0.01*	0.02*	0.02*	0.00*	0.02*	0.01†
	[0.000]	[0.001]	[0.004]	[0.001]	[0.005]	[0.013]	[0.001]	[0.002]	[0.005]	[0.001]	[0.002]	[0.007]
Constant	0.33	0.29	0.25	0.46	0.53	0.45	0.35	0.23	0.18	0.39	0.23	0.19
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,218,959	242,735	81,395	1,218,959	242,735	81,395	555,156	135,828	43,070	516,643	98,535	28,807
R-squared	0.186	0.223	0.22	0.187	0.261	0.275	0.12	0.116	0.129	0.095	0.128	0.124

Table 4. Persistence of Inventors' Inventive Performance (Compustat Sample)

The table reports Ordinary Least Squares regressions in which the dependent variable is log number of citation weighted patents per inventor-year (proxy for inventive performance). Each estimation sample includes one observation per inventor drawn from the inventor's N^{th} year of patenting (indicated by obs 'N'). The estimation sample for coefficients reported in Columns 1-6 use observations on all Compustat inventors who patented in the corresponding years. Columns 7 and 8 respectively use observations from the second and third years of patenting for inventors who did not move after their first year of patenting at a firm. Columns 9 and 10 use observations from the second and third years of patenting for inventors who moved after their first and second year of patenting at a firm respectively. Column 11 uses a sample with the third observation for inventors who moved after their first observation, and then stayed with their firm between their second and third observation. All specifications control for the following firm characteristics: Age, Dummy R&D, R&D intensity, Capital intensity, Sales, Operating income change, Employees, and Patent stock (Table 2 describes each variable); year effects; and NAICS 2-digit industry effects. The specifications in Columns 4-11 include firm fixed effects. Robust standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Log number of citation weighted patents										
Column	1	2	3	4	5	6	7	8	9	10	11
Sample	All inventors						Non-movers		Moved previous obs.		Moved 2nd to last obs.
	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10	obs 2	obs 3	obs 2	obs 3	obs 3
Past log number of citation weighted patents	0.27*	0.50*	0.53*	0.25*	0.48*	0.53*	0.27*	0.39*	0.06*	0.09*	0.32*
	[0.002]	[0.007]	[0.015]	[0.002]	[0.008]	[0.016]	[0.002]	[0.004]	[0.006]	[0.013]	[0.017]
Years since 1st patent	-0.09*	-0.12*	0.02	-0.08*	-0.12*	0.02	-0.09*	-0.15*	-0.01	-0.01	-0.07*
	[0.003]	[0.011]	[0.033]	[0.003]	[0.012]	[0.035]	[0.003]	[0.005]	[0.008]	[0.018]	[0.018]
Log number of coworkers' citation weighted patents	0.07*	0.05*	0.06*	0.03*	0.03*	0.03*	0.03*	0.03*	0.03*	0.03*	0.01
	[0.001]	[0.004]	[0.008]	[0.001]	[0.004]	[0.009]	[0.002]	[0.002]	[0.005]	[0.009]	[0.008]
Constant	0.55	1.10	1.92	1.79	2.95	1.72	1.81	1.99	1.74	1.71	2.51
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes	-	-	-	-	-	-	-	-
Firm FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	336,039	58,247	15,496	336,039	58,247	15,496	303,538	163,447	32,501	11,411	12,775
R-squared	0.228	0.285	0.294	0.249	0.306	0.326	0.256	0.288	0.259	0.294	0.323

Table 5. Contributions of Inventor and Firm Fixed Effects for Inventors' Performance

The table reports AKM regression estimates obtained by using the log number of inventor weighted citations (proxy for inventive performance) as the dependent variable. Each observation in the estimation sample is at the inventor-firm-year level. Estimations in Columns 1-2 use the full AKM sample of inventors with at least four years of patenting, Column 3 uses the subsample of AKM sample inventors who moved at least once, Column 4 uses a subsample of AKM inventors with ten or more patenting-year observations, Column 5 uses the full AKM sample after filling in zeros for intermediate years that do not have records of patents and Column 6 uses only those AKM inventor observations drawn from firms that did not experience mergers or acquisitions during the study period. Cov(y, inventor FE)/Var(y), Cov(y, firm FE)/Var(y), and Cov(y, year FE)/Var(y) report the estimated contribution of inventor fixed effects, firm fixed effects and year fixed effects towards explaining the observed variance in y (inventor's annual output of citation weighted patents). All estimations include firm characteristics reported in Table 2 and are implemented using the Stata command "FELSDVREG" as described in Cornelissen (2008). Standard errors, clustered at the inventor level, are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Log number of citation weighted patents					
Column	1	2	3	4	5	6
Sample	AKM (4+)	AKM (4+)	AKM Movers	AKM (10+)	AKM Filled	AKM No Merger
Estimation	AKM					
Cov(y, inventor FE)/Var(y)	0.266	0.272	0.232	0.239	0.288	0.266
Cov(y, firm FE)/Var(y)	0.040	0.039	0.052	0.030	0.045	0.040
Cov(y, year FE)/Var(y)	0.116	0.116	0.110	0.109	0.119	0.116
F-test on Inventor and Firm FE (*p*-value)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Years since 1st patent	0.08*	--	0.07*	0.17*	0.07*	0.08*
	[0.003]		[0.005]	[0.007]	[0.002]	[0.003]
Firm characteristics	Yes	No	Yes	Yes	Yes	Yes
#Firms	1,760	1,760	1,760	1,149	1,809	1,739
#Movers	37,703	37,703	37,703	8,865	37,703	36,706
#Inventors	129,576	129,576	37,703	18,928	129,576	127,775
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	849,939	849,939	297,156	254,437	1,103,343	838,343
R-squared	0.429	0.428	0.400	0.380	0.460	0.430

Table 6. Contributions of Inventor and Firm Fixed Effects for Inventors' Performance, by Technology Field

The table reports AKM regression estimates (as in Column 1 of Table 5) estimated separately for each of the six NBER technology fields See Table 5 Notes for additional information. Standard errors, clustered at the inventor level, are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Log number of citation weighted patents					
Column	1	2	3	4	5	6
Sample	Chemicals	Comp. & Comm.	Drug & Med	Elec & Elec	Mechanical	Other
Estimation	AKM					
Cov(y, inventor FE)/Var(y)	0.261	0.243	0.306	0.293	0.305	0.263
Cov(y, firm FE)/Var(y)	0.031	0.014	0.049	0.015	0.038	0.056
Cov(y, year FE)/Var(y)	0.089	0.183	0.132	0.104	0.071	0.093
Years since 1st patent	0.07*	0.07*	0.06*	0.07*	0.06*	0.04*
	[0.007]	[0.006]	[0.011]	[0.007]	[0.010]	[0.013]
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
#Firms	581	614	444	584	422	439
#Inventors	20,384	39,776	9,710	27,924	11,180	8,527
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	No	Yes	Yes	Yes	Yes
Observations	126,466	241,753	56,452	172,008	63,244	47,707
R-squared	0.376	0.460	0.488	0.443	0.429	0.426

Table 7. Effects of Inventor and Firm Fixed Effects on Inventor Mobility

The table reports Linear Probability Model regression estimates obtained by using a binary dependent variable which equals one if the inventor moved to another firm in the next observation (conditional on staying in the data). Inventor effects, firm effects and mean coworker effects are calculated from rolling window AKM estimations and represent effects at the firm in the year prior to the inventor's move/non-move. Standard errors are bootstrapped to correct for the use of estimated explanatory variables. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Inventor moved to a new firm?	
Column	1	2
Rolling Window	5 years	10 years
Inventor effect	-0.03*	-0.02*
	[0.001]	[0.000]
Current firm effect	-0.01*	-0.00*
	[0.001]	[0.001]
Mean coworker effect at current firm	-0.03*	-0.03*
	[0.002]	[0.001]
Log years since 1st patent at firm	-0.05*	-0.05*
	[0.001]	[0.001]
Constant	0.09	0.11
NAICS FE	Yes	Yes
Year FE	Yes	Yes
Observations	188,289	264,231
R-squared	0.031	0.026

Table 8. Inventor-Firm Matching

The table reports Ordinary Least Squares regression results obtained by using different characteristics of the firms that AKM inventors move to as dependent variable. The dependent variable in Column 1 is the fixed effect of this "next" firm obtained through rolling window AKM estimations (constructed by drawing information from windows prior to the move); in Column 2, it is the mean of the fixed effects of inventors at the next firm (constructed by drawing information from windows prior to the move), in Column 3, it is the next firm's log net income (in the year of the inventors move), and in Column 4 it is the next firm's Tobin's Q (in the year of the move). The main independent variable is the moving inventors' fixed effect, estimated by AKM rolling windows from years prior to the move. All inventor and firm effects are used after standardization by subtracting the population mean and dividing by the standard deviation. Bootstrapped standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Next firm's firm effect	Next firm's mean inventor effect	Next firm's log net income	Next firm's Tobin's Q
Column	1	2	3	4
Rolling Window	5 years			
Estimated inventor fixed effect	-0.09*	0.17*	0.03†	0.25*
	[0.012]	[0.005]	[0.015]	[0.024]
Log years since 1st patent	0.02	-0.07*	-0.04‡	-0.35*
	[0.014]	[0.005]	[0.024]	[0.023]
Constant	-0.35	0.46	6.14	5.56
NAICS FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,541	14,541	13,120	14,283
R-squared	0.039	0.181	0.161	0.142
Rolling Window	10 years			
Estimated inventor fixed effect	-0.04*	0.13*	0.04*	0.21*
	[0.011]	[0.004]	[0.016]	[0.020]
Log years since 1st patent	0.05*	-0.08*	-0.06*	-0.36*
	[0.013]	[0.005]	[0.019]	[0.033]
Constant	-0.44	0.32	6.17	4.79
NAICS FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	18,058	18,058	16,253	17,611
R-squared	0.057	0.161	0.149	0.124

Figure 1. Distribution of Inventor Fixed Effects Drawn from AKM Estimation

The figure plots the distribution of the 129,576 inventor fixed effects estimated through the AKM specification and sample corresponding to Column (1) of Table 5. The estimated inventor fixed effects have been standardized by subtracting the population mean from the estimates. The vertical lines indicate the top quartile, median, and bottom quartile of the estimated inventor fixed effects.

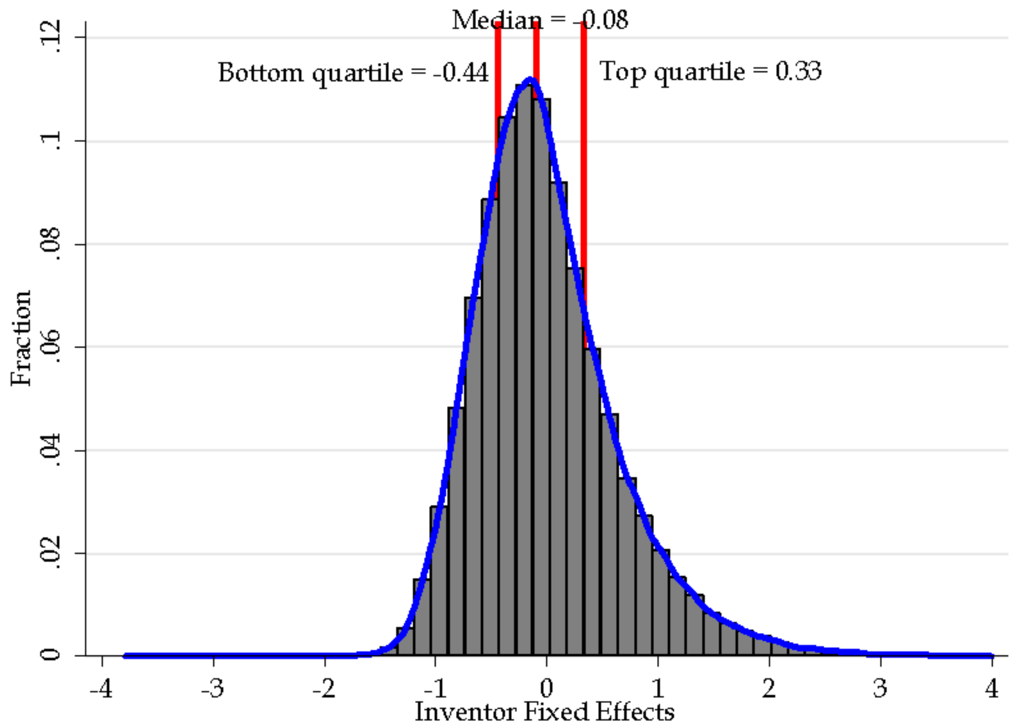


Figure 2. Distribution of Firm Fixed Effects Drawn from AKM Estimation

The figure plots the distribution of the 1,760 firm fixed effects estimated through the AKM specification and sample corresponding to Column (1) of Table 5. The estimated firm fixed effects have been standardized by subtracting the population mean from the estimates. The vertical lines indicate the top quartile, median and bottom quartile of the estimated firm fixed effects.

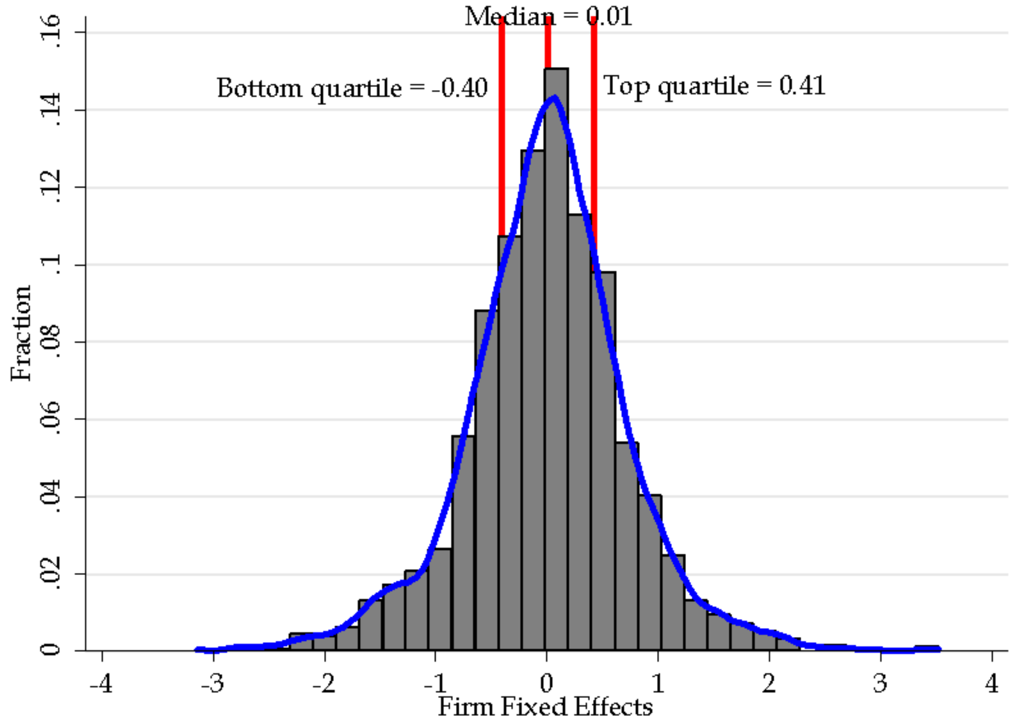


Figure 3. **Inventor Fixed Effects v/s Firm Fixed Effects**

The figure plots estimated firm fixed effects against the mean estimated inventor fixed effect at the firms. The figure is based on 1,760 estimated firm fixed effects and the same number of inventor fixed effects obtained by averaging estimated inventor fixed effects of all inventors at each firm. Fixed effects are obtained through the AKM specification and sample corresponding to Column (1) of Table 5. The estimated fixed effects have been standardized by subtracting the population mean from the estimates.

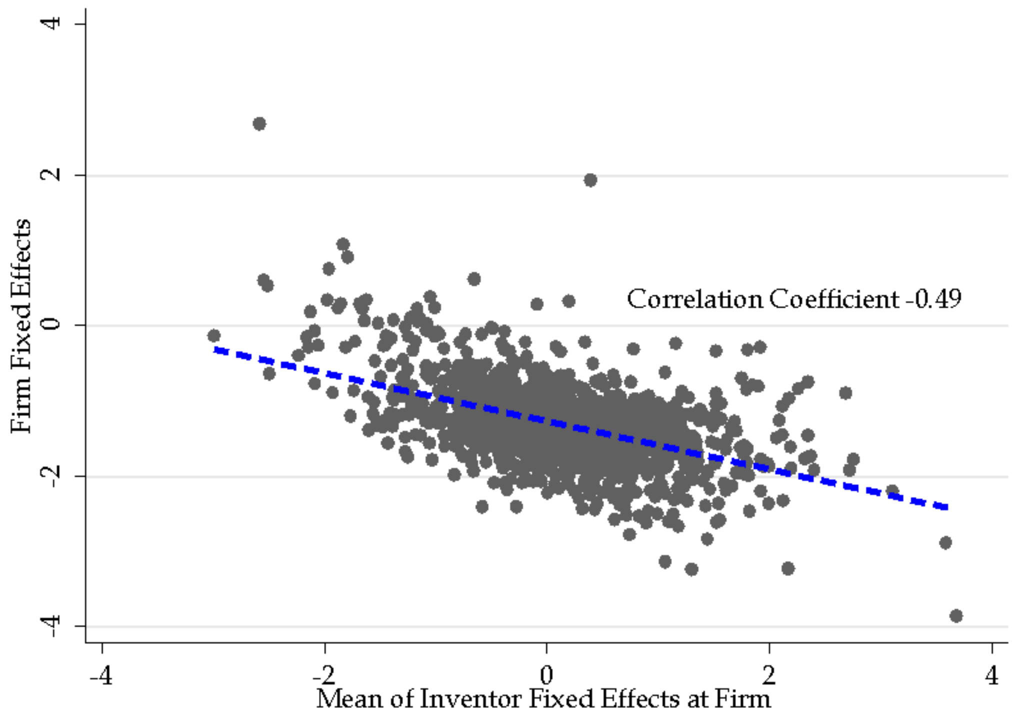
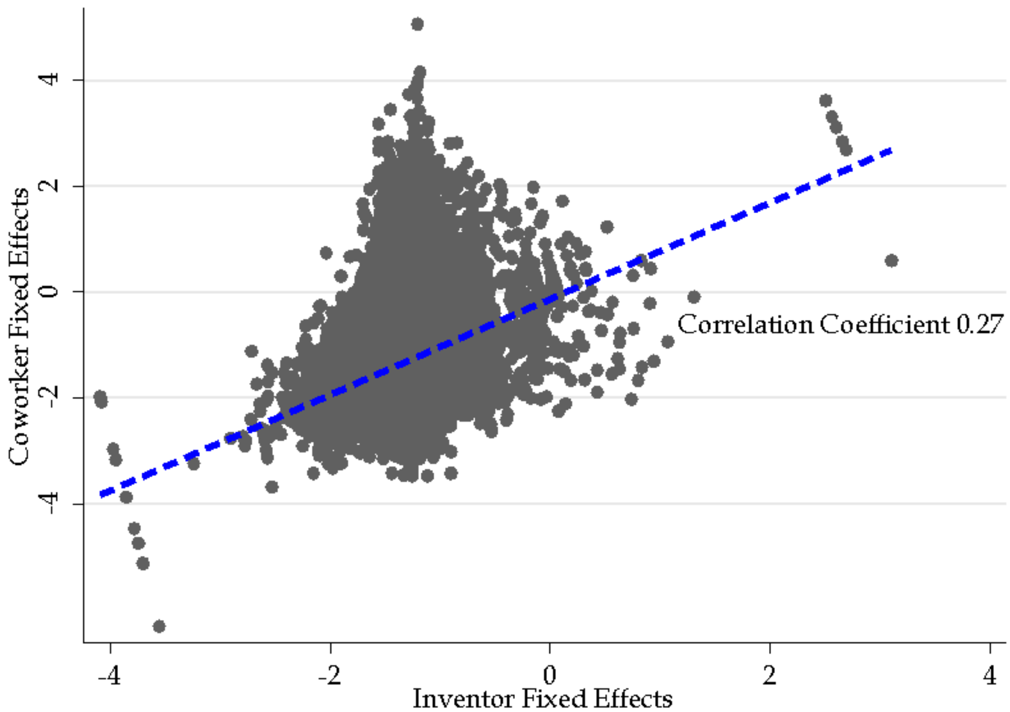


Figure 4. **Inventor and Average Co-worker Fixed Effects Drawn from AKM Estimation**

The figure plots estimated inventor fixed effects against estimated coworkers' fixed effects. The figure is based on 188,109 estimated inventor and coworker fixed effects (greater than the number of inventor effects—129, 576—since some inventors change employers and thus coworkers). All fixed effects are obtained through the AKM specification and sample corresponding to Column (1) of Table 5. The estimated fixed effects have been standardized by subtracting the population mean from the estimates.



Supplementary Internet Appendix (For Online Publication Only)

Table A1: Movers per firm and moves per inventor

The table describes inventor movements in the USPTO and AKM estimation samples. In the top panel we describe the number of movers per firm, i.e. the number of inventors associated with the firm who are also employed by another firm at another point in the sample. As identification in AKM rests on the existence of at least one mover per firm, this sample contains only firms that had at least one mover. The AKM sample has relatively larger firms with more moving inventors (since it is restricted to firms with inventors that has at least four distinct years of patenting during the study period). In the bottom panel, we show the mobility patterns of inventors in the two estimation samples.

Panel A: Number of movers per firm						
Sample	USPTO sample			AKM sample		
# Movers	# firms	% firms	Cum. % firms	# firms	% firms	Cum. % firms
0	35,094	29.96%	29.96%	0	0	0
1	23,051	19.68%	49.64%	202	11.48%	11.48%
2-10	42,565	36.33%	85.97%	614	34.88%	46.36%
11-50	12,200	10.42%	96.39%	490	39.32%	74.20%
51-200	2,965	2.53%	98.92%	109	14.21%	88.41%
201-1000	1,000	0.86%	99.78%	135	8.52%	96.93%
1000+	265	0.23%	100%	54	3.07%	100%
Total	117,140	100%	100%	1,760	100%	100%

Panel B: Number of moving inventors and moves					
Sample		USPTO sample		AKM sample	
Mover	# firms	# inventors	% inventors	# inventors	% inventors
No	1	846,884	69.48%	91,873	70.90%
Yes	2	191,063	15.67%	18,369	14.18%
	3	82,201	6.74%	8,035	6.20%
	4	39,476	3.24%	4,264	3.29%
	5	21,491	1.76%	2,279	1.76%
	6	12,444	1.02%	1,302	1.00%
	6+	25,400	2.08%	3,460	2.67%
Total		1,218,959	100%	129,576	100%

Table A2. Summary statistics for USPTO and Compustat samples

The table shows summary statistics for each of the USPTO and Compustat samples comprising inventors with two, six, and ten observations. In each case, the subsample contains only the second, sixth, or the tenth observation Each subsample includes one observation per inventor drawn from the inventor's Nth year of patenting (indicated by obs 'N').

Sample	USPTO Sample			Compustat Sample		
Subsample	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10
Observations	1,218,959	242,735	81,395	336,039	58,247	15,496
Log Citation-Weighted Patents	0.43	0.51	0.57	0.82	0.98	1.03
	[0.27]	[0.35]	[0.40]	[1.07]	[1.26]	[1.34]
Log Past Citation-Weighted Patents	0.43	0.51	0.57	0.89	1.25	1.47
	[0.26]	[0.23]	[0.24]	[1.05]	[0.89]	[0.88]
Log Citation-Weighted Patents by coworkers	--	--	--	7.76	7.95	8.06
				[2.51]	[2.50]	[2.46]
Years since 1st patent	0.87	2.29	2.72	1.28	2.34	2.75
	[0.85]	[0.47]	[0.34]	[0.61]	[0.40]	[0.30]
Firm Age	--	--	--	2.79	3.03	3.16
				[0.56]	[0.43]	[0.36]
Dummy R&D	--	--	--	0.99	0.99	0.99
				[0.12]	[0.10]	[0.10]
R&D Intensity	--	--	--	0.09	0.08	0.08
				[0.18]	[0.19]	[0.21]
Capital Intensity	--	--	--	0.27	0.26	0.26
				[0.18]	[0.19]	[0.18]
Firm Sales	--	--	--	9.71	9.98	10.15
				[1.76]	[1.61]	[1.50]
Operating Income Change	--	--	--	0.11	0.09	0.07
				[0.58]	[0.54]	[0.47]
Employees	--	--	--	3.93	4.14	4.30
				[1.60]	[1.49]	[1.40]
Patent Stock	--	--	--	7.62	8.18	8.48
				[1.74]	[1.62]	[1.56]

Table A3. Persistence regressions for corporate and individual inventors

The table reports Ordinary Least Squares regression results for inventors' persistence, with the log number of citation weighted patents per year as the dependent variable. Column 1 reports estimates obtained from the full USPTO inventor sample of repeat inventors, Column 2 estimates are from the subsample of inventors who are employed at firms during both years of invention, Column 3 estimates are from the subsample of inventors who moved from being independent to a firm between the two years of invention, Column 4 estimates are from the subsample of inventors who moved from a firm to being independent, and Column 5 estimates are from the subsample of inventors who stayed independent between the two years of invention. The top panel draws measures of performance from the inventor's second year of patenting and the bottom panel draws measures of performance from the inventor's sixth year of patenting. Robust standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Log number of citation weighted patents				
Column	1	2	3	4	5
Sample	All inventors	Firm to firm	Ind. to firm	Firm to ind.	Ind. to ind.
Subsample	obs 2	obs 2	obs 2	obs 2	obs 2
Past log number of citation weighted patents	0.30*	0.30*	0.22*	0.32*	0.34*
	[0.001]	[0.001]	[0.006]	[0.008]	[0.005]
Years since 1st patent	-0.07*	-0.08*	-0.00	-0.13*	-0.02*
	[0.001]	[0.001]	[0.004]	[0.005]	[0.004]
Constant	0.46*	0.47*	0.46*	0.51*	0.32*
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,218,959	1,057,951	48,848	39,789	72,371
R-squared	0.187	0.192	0.150	0.165	0.173
Subsample	obs 6	obs 6	obs 6	obs 6	obs 6
Past log number of citation weighted patents	0.57*	0.55*	0.61*	0.73*	0.76*
	[0.004]	[0.004]	[0.023]	[0.024]	[0.025]
Years since 1st patent	-0.08*	-0.08*	-0.03	-0.23*	-0.13*
	[0.005]	[0.005]	[0.029]	[0.034]	[0.033]
Constant	0.53*	0.55*	0.00	0.91*	0.40b
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	242,735	220,861	7,543	7,112	7,219
R-squared	0.261	0.259	0.271	0.281	0.303

Table A4: Persistence of inventor performance (Compustat sample)

The table reports Ordinary Least Squares regression results for inventors' persistence, with the log number of citation weighted patents per year as the dependent variable. The regressions are estimated on our Compustat sample, after omitting the additional controls reported in Table 4. The number of observations differs slightly from Table 4, as fewer firms have missing values for this smaller set of controls. Robust standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Citation-weighted patents		
Column	1	2	3
Sample	obs 2	obs 6	obs 10
Past citation-weighted patents	0.28*	0.51*	0.54*
	[0.002]	[0.007]	[0.015]
Years since 1st patent	-0.09*	-0.11*	0.02
	[0.003]	[0.011]	[0.032]
Constant	0.62*	0.90*	1.44*
Year FE	Yes	Yes	Yes
NAICS FE	Yes	Yes	Yes
Observations	350,690	60,171	15,912
R-squared	0.220	0.280	0.289

Table A5. Correlations among fixed effects obtained from alternative specifications AKM model

The table shows pairwise correlations among inventor and firm fixed effects in different specifications of the AKM model. Correlations are taken at the level of the individual inventor or firm. Individual effects were demeaned before calculating correlations. All coefficients are significantly different from zero at 0.01 level.

Pairwise Correlation	Inventor Fixed Effects					
Model	Baseline	No controls	Movers	10+ obs.	Filled out	No merger
Baseline	1					
No controls	0.9928	1				
Movers	0.9985	0.9966	1			
10+ obs	0.983	0.9651	0.9772	1		
Filled out	0.9992	0.9945	0.9986	0.9792	1	
No merger	0.9962	0.9888	0.9946	0.9796	0.9953	1
Pairwise Correlation	Firm Fixed Effects					
Model	Baseline	No controls	Movers	10+ obs.	Filled out	No merger
Baseline	1					
No controls	0.7988	1				
Movers	0.9855	0.8185	1			
10+ obs	0.8844	0.6775	0.8908	1		
Filled out	0.9954	0.8102	0.9795	0.8722	1	
No merger	0.9959	0.7912	0.9804	0.8825	0.9913	1

Table A6: Persistence of inventor performance by technology field (Compustat sample)
The table reports Ordinary Least Squares regression results for inventors' persistence for each of the six technology fields defined by the NBER patent technology classification. Robust standard errors are reported in parentheses. Significance: * p<0.01, † p<0.05, ‡ p<0.1

Dependent Variable	Citation-Weighted Patents					
Column	1	2	3	4	5	6
Sample	obs 2	obs 6	obs 10	obs 2	obs 6	obs 10
Industry Subsample	Chemicals			Comp. & Comm.		
Past citation-weighted patents	0.28*	0.50*	0.45*	0.23*	0.44*	0.51*
	[0.006]	[0.019]	[0.035]	[0.004]	[0.013]	[0.026]
Years since 1st patent	-0.06*	-0.14*	-0.16†	-0.13*	-0.16*	0.14†
	[0.006]	[0.026]	[0.068]	[0.005]	[0.021]	[0.060]
Log number citation-weighted patents by coworkers	0.03*	0.03*	0.05*	0.06*	0.06*	0.05*
	[0.003]	[0.008]	[0.016]	[0.003]	[0.008]	[0.016]
Constant	0.60	0.77	0.40	1.14	0.49	3.19
Observations	54,736	10,201	2,935	106,209	18,164	4,740
R-squared	0.154	0.226	0.222	0.280	0.312	0.336
Industry Subsample	Drug & Med			Elec & Elec		
Past citation-weighted patents	0.32*	0.47*	0.44*	0.27*	0.55*	0.59*
	[0.008]	[0.027]	[0.057]	[0.005]	[0.016]	[0.030]
Years since 1st patent	-0.04*	-0.06	-0.26†	-0.09*	-0.07*	0.09
	[0.009]	[0.038]	[0.102]	[0.006]	[0.024]	[0.069]
Log number citation-weighted patents by coworkers	0.04*	0.05*	0.04	0.06*	0.05*	0.03
	[0.004]	[0.011]	[0.026]	[0.003]	[0.008]	[0.019]
Constant	0.92	1.33	-0.17	0.88	1.39	2.99
Observations	27,121	4,513	1,011	72,979	14,156	3,967
R-squared	0.245	0.308	0.354	0.208	0.299	0.328
Industry Subsample	Mechanical			Other		
Past citation-weighted patents	0.26*	0.53*	0.64*	0.24*	0.49*	0.50*
	[0.006]	[0.024]	[0.050]	[0.007]	[0.024]	[0.056]
Years since 1st patent	-0.05*	-0.11*	0.06	-0.06*	-0.14*	-0.14
	[0.007]	[0.034]	[0.112]	[0.007]	[0.035]	[0.106]
Log number citation-weighted patents by coworkers	0.05*	0.05*	0.09*	0.06*	0.06*	0.10*
	[0.004]	[0.012]	[0.026]	[0.004]	[0.012]	[0.029]
Constant	0.53*	1.43*	0.20	0.74*	1.57*	4.37*
Observations	40,066	6,031	1,525	34,862	5,169	1,316
R-squared	0.163	0.248	0.311	0.185	0.273	0.298