Teams in R&D: Evidence from US Inventor Data

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Abstract:

This paper exploits U.S. patent data and a panel of inventors listed on U.S. patents since 1975 to investigate the determinants of teamwork in industrial R&D. Inventor team size as well as the duration of collaboration among team members has increased over the past several decades. The focus of the paper is a test of a model of dynamic team formation where a firm must choose and then over time rebalance a team's constitution taking into account the gains to specialization, costs of coordination, technological change, and the risks that employee members of the research team will appropriate the firm's intellectual property. We use variation in policy towards noncompete agreements in employment contracts to identify the effect of researcher mobility and IP appropriation on team formation. We find that where researcher job mobility is low, teams tend to be larger and are more likely to repeat. Our evidence suggests that in assembling R&D teams, firms are sensitive to the costs of appropriation and/or coordination.

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1. Introduction

Technological innovation increasingly occurs in teams. In 1975, for example, only 42 percent of patents listed multiple inventors. Today, over two-thirds of US patents granted list multiple inventors.[2] Since 1975, average size of inventor teams increased from 1.6 to 2.6 persons. This trend in the importance of teamwork is seen in nearly all fields and regions, yet one sees striking variation across fields: for example, "Drugs and Chemical" patents averaged nearly one more inventor than “Mechanical” patents in 2003 (3.1 vs. 2.4).[3] Within fields, inventor teams vary in size across geography. Consider for example Minnesota and New Jersey, each with significant pharmaceutical and biotechnology industries, yet in New Jersey the average number of inventors on a "Drugs and Chemicals" patent is 25 percent greater (3.54 vs. 2.82). The inventor team size varies by country as well (see below). Firms that are unable to field large, diverse teams are possibly at a productivity disadvantage in R&D (see Wuchty, Jones, and Uzzi, 2007), and this disadvantage may be increasing.

Firms that are unable to keep their teams intact over a sustained research campaign may also be at a disadvantage (Akgun and Lynn, 2002). Continuity may be important if for example it takes time for members of a team to learn how to effectively work with one another, or if departing team members leave with key knowledge that is not easily transmitted to those left behind or to replacements. The patent evidence shows that teams vary in longevity and that longer-lived teams are associated with

[2] Scientists working in solitude are also less common. In 1955 only half of academic articles published in science and engineering fields listed two or more authors. In the five years leading up to 2000, however, 80 percent of articles published in science and engineering journals listed multiple authors (Wuchty, Jones, and Uzzi 2007).

[3] In science team size also varies by field. For example, authorship teams in medicine averaged over four scientists while mathematics averaged less than two for the 1996 to 2000 period (Wuchty, Jones, and Uzzi).

higher-quality innovations.[4] We also show that teams in R&D persist over longer periods of time and over more projects than in decades past, but, as in team size, team persistence varies across fields and regions.

This paper explores the determinants of team formation in industrial R&D, seeking to explain variation across time, location, and field in both team size and duration. Our point of departure is an economic model of teams (e.g., Becker and Murphy, 1992), in which the optimal size and composition of teams balance the gains to specialization against coordination or information costs. Teams are large when specialization by workers or the gains to collaboration in the technological domain is great, or when coordination costs are low. In this framework, rising team size may be due to falling coordination costs, for example, because of improved strategies that limit free-riding and agency problems, or improvements in communication technologies. Team size may also be increasing because of the rising stock of knowledge; the optimal response by researchers to rising burden of knowledge may be greater specialization which requires more collaboration (Jones 2006).

Because we are also interested in understanding team persistence and the standard model is static, we consider a dynamic variant by Kim and Marschke (2011). In their model, the firm manages its R&D workforce over multiple periods and in each period the firm and its researchers are hit with technological and human capital

[4] In regressions of forward citations on inventor team size and the number of past instances of collaboration, both team size and work history show strong and positive effects on patent quality. The effects are of comparable magnitude. The ratio of the standardized coefficients (number of past collaborations to team size) is approximately .6. These results are available from the authors upon request.

productivity shocks that change the optimal mix of skills and therefore workers, which potentially cause the researchers to depart to compete against the firm.

This model makes team formation part of the firm's IP protection strategy. With increasing inter-firm mobility of scientists and engineers in the 1990s and early 2000s came articles in the business press describing instances where high tech firms actively encouraged the defections among a competitor's technological workforce to access its technologies (Kim and Marschke, 2005). Bhide (2000) reports that 71 percent of the firms listed on the Inc 500[5] were founded by those who replicated or modified an idea developed in their previous employment.[6] R&D-performing firms face the prospect that their researchers will leave to work for competitors or start up firms of their own that directly compete against them. To the extent they face this appropriation cost they have an incentive to reduce the number of research personnel involved in a project. But these firms also have an incentive to "compartmentalize" their research projects; that is, to spread the research tasks around greater numbers of researchers so that single researchers lack sufficient information to recreate the project on their own.[7] Thus in addition to testing for gains to specialization and coordination costs as determinants of team size, team persistence and team composition, our empirical strategy will test for the threat of worker appropriation of IP.

[5] The Inc. 500 is a list of young, fast growing firms published annually by the editors of *Inc*.
[6] See also footnote 1 in Rajan and Zingales (2001).
[7] What we are calling compartmentalization is a practice that exists at least since the Industrial Revolution. According to Landes (1986) "...patents were not always the best way to protect knowledge. Instead, inventors preferred to try and keep devices and techniques secret, sometimes by so dividing the process that no one worker could penetrate the technique. This is what the great watchmaker Abraham-Louis Breguet proposed to do when he planned the mass production of watches by means of power tools and interchangeable parts: the aim was … security." (Landes, p. 615.)"

To test our model of team formation and persistence in industrial R&D, we exploit a panel data set of researchers that includes all inventors listed on U.S. patents since 1975. Because a patent lists each inventor who instrumentally contributed to the development of the underlying invention, we are able to construct measures of teams in industrial R&D. We show that teams have been increasing in size and that the number and impact of lone researchers are falling. We show teams are remaining together over longer periods of time and more projects. The results from our regression analyses of team size and team persistence suggest that scientist mobility as well as firm-level technological characteristics and coordination cost do matter. To identify the effect of mobility on team size and persistence we take advantage of a policy ‘experiment’ in the 1980s. After 1985, the state of Michigan began to enforce non-compete covenants in employer contracts (Marx, 2009). A non-compete covenant is a promise by a worker not to work with a direct competitor for a fixed period of time following the end of employment. Non-compete covenants are commonly incorporated into employment agreements of researcher employees. We reason that in states and years where non-compete agreements are enforced, the risk that the researcher will appropriate valuable intellectual property is lower.

The paper is structured as follows. Section 2 reviews recent empirical work describing teamwork in science and in industrial R&D. Section 3 gives a brief overview of the model by Kim and Marschke (2011). We describe how we will test its implications for team size and persistence and how these quantities should move with changes in the labor market and the innovative environment. In section 4 we describe our empirical approach and our data. Section 5 reports our empirical results. Section 6 discusses and concludes.

2. Literature Review

A number of studies report an increase in the size of teams in science and R&D. Adams, Black, Clemmons, and Stephan (2005) document increasing team size in science, where team size is measured by the number of authors on a scientific paper. Wuchty, Jones, and Uzzi (2007) looking at authorship counts on scientific papers and inventor counts on patents find that the size of teams has steadily increased since the 1960s. In addition, as assessed by the numbers of citations patents and papers received, the impact of works with multiple authors/inventors is greater than works with a single author/inventor.[8] These studies show that these phenomena are exhibited widely across technology and scientific fields.

A number of studies examine the determinants of teamwork and collaboration. Arora and Gambardella (1990) offer evidence that collaboration arises from complementarities in skills. Mairesse and Turner (2005) investigating a sample of French physicists find that distance matters in whether the physicists collaborate. Agrawal and Goldfarb (2008) present evidence that the rise of the internet had contributed to increased collaboration. Rosenblat and Mobius (2004) also examine the importance of communication technologies on collaboration and networking.

[8] For example the show that in the 1990s ratio of average citations for multiple inventor patents to average citations for single-inventor patents was as high as 1.25 (Supplementary Table S1, Wuchty, Jones, Uzzi, 2007s).

A literature investigates the impact of team composition on team productivity, Hansen et al. (2006) use classroom performance on group projects to examine whether gender/racial diversity affects performance. Skilton (2009) examines whether team members' human capital affects productivity (citations) of teams.

The management literature examines persistence in collaboration (Skilton and Dooley, 2010, and Guimera, Uzzi, Spiro, and Amaral, 2005). Whether a team has worked together before may affect its productivity, for example, if repeated interaction increases trust or improves coordination or communication. Akgun and Lynn (2002) find that in product development teams in R&D-performing firms a team's longevity has a positive effect on productivity-related outcomes including team learning and cycle time, but not when there is a high degree of market and technical turbulence. Katz (1982) reports that the R&D team's longevity's effect on productivity is possibly quadratic, peaking at two to four years from the team's inception. We are unaware of any analysis of this aspect of teamwork in the economics literature.

There exists a theoretical literature in economics on teams. Marschak and Radner (1972) and Cremer (1980) discuss the coordination of tasks in teams while Holmstrom (1982) explores incentives in teams. Dessein and Santos (2003) and Corts (2007) argue that teamwork can be used to solve multitask problems and suggest that increased use of teamwork in the manufacturing and service sectors may be due to improvements in performance monitoring which reduce the inefficiency associated with joint accountability. Alchian and Demsetz (1972) argue team production is more efficient within firms because firms lower transaction (e.g., monitoring) costs. Other work explores optimal team creation as trading off gains to specialization and coordination or communication costs (Becker and Murphy, 1992; Bolton and Dewatripont 1994). In the context of science and innovation, Jones (2005) argues that accumulating knowledge increases the educational burden of scientists and inventors causing them to specialize which leaves them less able to innovate on their own.

Kim and Marschke (2011), hereafter KM, consider a dynamic model of team formation within R&D firms that incorporates the trade-off between specialization gains and coordination costs. The model emphasizes however the risk of researcher appropriation and allows team formation to be an element of an IP protection strategy. Worrying that research employees will steal intellectual property, an innovating employer may either reduce the number of researchers involved to reduce the number of potential leavers or compartmentalize research teams with more researchers.[9] The KM model adds to the standard economic model of teams the idea of compartmentalization and also allows for the team's productivity to be related to its longevity and to turbulence in the technological or market environment (Akgun and Lynn).

3. Summary of the Teamwork Model

Our empirical framework is derived from the model in KM. We outline this model briefly and describe the model's implications that we will test.

KM consider a firm with multiple R&D projects. For each project, the firm must hire a team of researchers. Each project is defined by a (non-overlapping) interval of tasks of length R. All projects are symmetric so for exposition we will focus on a

[9] A "divide and conquer" response to the threat of worker appropriation also underlies the firm's decision of hierarchical form in Rajan and Zingales (2001).

representative project.

A project cycle consists of two periods. In the first period, the researchers hired onto the project team develop a prototype. They also develop team-specific human capital and learn valuable IP that they may exploit for the firm's competitors if they separate from the firm in the second or marketing period of the two-period cycle. The external value of the IP, we denote this as ρ, is random and not revealed until the second period. Rosenberg (1996) argues that a new technology originally invented for one narrow purpose often finds high or even higher value in another purpose in an entirely different industry and these out-of-context applications are unpredictable.[10] ρ captures Rosenberg's out-of-context kind of external value as well as the in-context kind such as when the firm solves a technical problem that also vexes its competitors. The team-specific human capital benefits the firm by reducing the firm's coordination costs if the team remains together for projects in subsequent periods.

In the second period, the firm produces and markets a product based on the prototype. The product's life ends at the end of the second period. Also in the second period, the firm begins a second two-period cycle on a new round of projects, either with the researchers from the first period or if these researchers separate from the firm a new set of researchers. As in the first round, researchers develop new prototypes (and learn IP) that leads to new products which are produced and sold in the next stage of the

[10] Rosenberg (p. 104) relates this story of the dawn of the computer.

> Howard Aiken, a Harvard physics instructor who was a great pioneer in the early development of the computer, continued to think of it in the narrow context in which its early development took place--that is, purely as a device for solving esoteric scientific problems. As late as 1956 he stated: "if it should ever turn out that the basic logics of a machine designed for the numerical solution of differential equations coincide with the logics of a machine intended to make bills for a department store, I would regard this as the most amazing coincidence that I have ever encountered" (Ceruzzi 1987, p. 197).

cycle, the third period. The life-span of the firm is three periods. In the third period, because R&D ceases all researchers depart the firm, using the IP they learned in the second period to compete against their former employer.

The production technology follows Becker and Murphy (1992). For each project output (revenue), Y, is Leontief and equal to $\min_{0 \le t \le R} Y(t)$, where Y(t) is the revenue from task t. The firm hires researchers each of whom is specialized in a subset of tasks in R. The output on a task depends crucially on the number of persons in a team. Define n as the number of persons hired onto a team in the first period. The more persons on a team the greater the degree of specialization and also the more time each worker can spend on a task. Thus, Y increases with n. However, larger teams impose a greater wage bill and entail greater coordination costs for the firm.

Both the researchers and the firm are risk neutral. The firm maximizes its discounted expected profits and each researcher maximizes his discounted expected wages. In the first period, the researcher will choose to work on the firm's team if his discounted expected earnings stream is higher with the firm than in alternative employment. Bargaining is such that the researcher's wages in the first period are fully discounted by the expected external value of the IP.

In the first period, the firm chooses team size to maximize its discounted profit. Thus, the firm takes into consideration the researchers' wages, the productivity advantages of specialization, and the costs of coordination. In addition the firm's team size decision reflects future considerations. For example, by assembling a larger team the firm can ensure that each researcher operates only on a narrow set of tasks so in the second period if a researcher eventually leaves for a competitor she is less able to recreate the project on her own. This model assumes that only when researchers separate can they compete against the firm and also that separation guarantees competition. Compartmentalization reduces both the future likelihood that researchers separate and the costs their competition imposes on the firm if they do separate. But by reducing the breadth of the researchers' tasks and thus of the IP the researcher learns, the firm raises the wages it must pay its researchers in the first period. That is, ρ is a kind of general human capital as in Pakes and Nitzan (1989) with the same implications for wages.

At the beginning of the second period two types of uncertainty are resolved which determine whether the research team hired in the first period remains intact or disbands. First ρ is realized. Second the firm learns the extent that technology or the market shifts for the next round of research projects. Researchers from the first period leave if their gains from leaving and competing exceed their employer's losses. Thus for example the greater the realized ρ, the more likely the separation condition will be met. The bigger the impact of experience on coordination costs, the less willing the firm is to see its first period researchers leave. Changes to technology or the firms' market alter the optimal sorting of tasks and, because researchers are specialized to tasks, of researchers into teams. Thus if the firm wishes to keep its researchers from the first period and to maximize its revenue from second period projects, it should regroup its researchers. But regrouping researchers destroys at least some of the team-specific human capital built up in the first period, reducing the firms' desire to keep the first period researchers through the second period and increasing the likelihood that the separation condition is met.

Based on the KM model, here are the hypotheses we test.

Team Size Hypotheses

A rightward shift in the distribution of the IP's external value, ρ, can have a positive effect on team size through a couple of channels. Corresponding to the effect of general training in labor economics, improved outside opportunities lower the first period wage, making larger teams less expensive for the firm. (This effect dominates an opposing effect of rising wages in the second period to retain workers due to their improving outside opportunities). In addition, a rightward shift in the distribution of ρ increases the benefit of additional workers, as reducing the knowledge each researcher acquires (compartmentalization) becomes more valuable.

Through other channels, however, a rightward shift in the distribution of ρ may lower n. Because firms anticipate more researcher departures, an increase in the value of external opportunities raises their expected costs of R&D. This scale effect reduces team size. Additionally, suppose the optimal first period team size, n, is smaller than the team size that maximizes the profit in the second-period project so that the marginal profit of n is strictly positive in terms of the profit from the second-period project. If the probability that the researchers stay falls due a rightward shift in ρ, the expected marginal profit from the second-period project when researchers stay falls and thus the optimal n falls. The last effect, which we will call the size trend effect, would make the optimal n increased or intact if the optimal n is bigger than or equal to the optimal team size in the second period, respectively, when ρ shifts rightward.

Hypothesis 1: Team Size-Mobility The effect of a shift in the distribution of ρ has an ambiguous effect on *n*. Higher anticipated mobility will increase team size if the compartmentalization plus the wage effects dominate, and will lower team size if the scale effect plus the negative size trend effect dominate.

Most other factors that we wish to test affect mobility, which has an ambiguous effect on team size. Our aim is to generate testable empirical implications, thus in our empirical examination of the determinants of team size we will control for mobility. The hypotheses below assume mobility is held constant.

Decreasing coordination costs or increasing researcher's productivity makes larger teams more attractive to the firm. This leads to the following two hypotheses.

Hypothesis 2: Team Size-Coordination Cost Higher coordination costs lower n, holding mobility constant.

Hypothesis 3: Team Size-Researcher Productivity Higher researcher productivity within the team raises n, holding mobility constant.

Because higher *general* productivity increases the researcher's reservation wage it increases the cost of larger teams.

Hypothesis 4: Team Size-General Productivity Higher researcher reservation wages lower n, holding mobility constant.

When the technologies in the second period is different from the first period technology so that the second period revenue-maximizing grouping of researchers differ from the first period one, the second period productivity of researchers falls, which decreases the team size. But also researchers are more likely to move in this case and the added mobility can then increase or decrease team size. Thus after controlling for mobility in our empirical specification, we expect to find an adverse effect of technological change on n.

Hypothesis 5: Team Size-Technological Change Higher anticipated shifts in technology lower n, holding mobility constant.

The effect of task range, R, on team size is ambiguous. On the one hand, the individual researcher's breadth of knowledge increases with R, which gives the researcher more to appropriate if she leaves the firm, lowering her first period wage. This breadth effect increases n. On the other hand, a larger R lowers the gains to specialization in the first and second periods, reducing n.

Hypothesis 6: Team Size-Task Range Higher R has an ambiguous effect on n, holding mobility constant. If the breadth effect dominates, n will increase. If instead the specialization effect dominates, n will decrease.

Team Persistence Hypotheses

A rightward shift in the distribution of ρ produces two opposing effects on the persistence of teamwork. Mobility directly reduces teamwork persistence because researchers are less likely to work together again when they depart the firm. On the other hand, if team size increases as the firm compartmentalizes its R&D, the firm will have more accumulated team-specific human capital to exploit by retaining its researchers from the first period. This will raise teamwork persistence. However, with team size held constant, we will only have the former, negative effect. Because in our empirical work we are able to control for team size, we will ignore a parameter's effects on team persistence through team size in the hypotheses concerning ρ and the other parameters.

Hypothesis 7: Team Persistence-Mobility Higher ρ decreases team persistence, holding n constant.

Coordination cost, researcher productivity, and researcher reservation wage can affect persistence only through the scientist mobility channel, and their effects depend on whether n is bigger than the optimal second period team size or not. Consistent with the observed increase in team size, the following hypotheses assume that the optimal n is smaller than the optimal second period team size. An increase in the reservation wage will make separation less likely because, with increasing team size, the total wage expense to the firm is increasing. Similarly, higher coordination costs and lower researcher productivity will lead to greater persistence.

Hypothesis 8: Team Persistence-General Productivity Higher reservation wage increases team persistence, holding n constant.

Hypothesis 9: Team Persistence-Coordination Cost Higher coordination costs increase team persistence, holding n constant.

Hypothesis 10: Team Persistence-Researcher Productivity Higher researcher productivity decreases team persistence, holding n constant.

When technology is changing rapidly, the firm's profit is reduced in the case where researchers stay. This will increase mobility and reduce the persistence of teamwork. Furthermore, the optimal sorting of tasks into projects will deviate greatly from the optimal sorting of the first period (less overlap), which will reduce the persistence of teamwork.

Hypothesis 11: Team Persistence-Technological Change Greater technological change reduces team persistence, holding n constant.

Finally, an increase in project range, R, will increase the breadth of knowledge each researcher can acquire, which increases the value of their outside opportunities and hence mobility. But the improved outside opportunities lower first period wages causing n to rise, and firms are more likely to choose projects that are similar to those in the first period to take advantage of accumulated team-specific human capital, increasing persistence. Holding n constant, we would thus predict that an increase in R would reduce persistence.

Hypothesis 12: Team Persistence-Task Range The task range R has a negative effect on team persistence, holding n constant.

4. Data description

4.1 Descriptive Statistics

We use US patent data for our empirical analysis, equating the inventor lists on patents to inventor teams. Patents legally must name as inventors all persons who conceived any portion of any claim made by the patent.[11] The standard for co-inventorship does not require that each inventor contributed to the conception of all claims, or that co-inventors physically worked together (though some demonstration of collaboration and connection among the inventors is required). Patent law narrowly circumscribes co-inventorship. For example, laboratory directorship is sufficient in many disciplines to earn a scientist co-authorship on a publication, but it is insufficient

[11] See Manual of Patent Examining Procedure (Eighth Edition, August 2001, revised July 2008), Chapter 2137.01, Inventorship [R-3] available online at http://www.uspto.gov/web/offices/pac/mpep/documents/2100_2137_01.htm (accessed June 25, 2009).

to obtain co-inventorship. Also, persons who are technicians or any others who merely took direction from an inventor do not legally qualify as co-inventor. Contributing ideas, suggestions, or materials, even if the help proved crucial in bringing about the invention, is also insufficient for co-inventorship. The litmus test is in fact whether the person contributed to the conception of a claim. While in practice the conception test may not always be followed, including persons on the patent application who do not meet this test, or excluding persons who do, risks having the patent invalidated (see Crawford and Kokjohn, 2009, and Remus and Personick, 1995).

For our analysis of team persistence, we must be able to follow inventors from patent to patent. The patent data, however, identify inventors by name only, and do not provide unique identifiers for inventors. We use the inventor "disambiguation" produced by Lai, D'Amour, Yu, Sun, Torvik and Fleming (2011) as our source of inventor-level panel data.[12]

Team Size:

Figure 1a describes the average inventor team size by year. This figure includes only patents assigned to U.S. companies and corporations that are ultimately granted, by year of application. One can see that the average team size has steadily increased from 1975 through the early 2000s—by about 1 inventor over the period or by 62 percent. We find that the number of extremely large inventor teams (upwards of 20 or more inventors) has also increased (not reported). In contrast, the fraction of patents with a single inventor declined steadily during this period from the majority of patents (58 percent) in 1975 to a minority (33 percent) in 2003 (see Figure 1b).

[12] We use the disambiguation produced by the "UPPER" parameterization of their algorithm.

The average team size by year by patent technological category is reported in Figure 2. Figure 2 shows that the increase in team size occurs across all of the categories, but that the increase is greatest in Chemicals and Drugs & Medical categories. In Figures 1a and 2, we note a distinctive blip in 1995. Prior to 1995, US patent protection ended 17 years after the patent *issuance* date. To comply with the Uruguay Round Agreements of the General Agreement on Tariffs and Trade (GATT), the US in 1995 extended patent protection to 20 years after the patent *application* date. A provision of the new law designed to ease the transition guaranteed that patent applications filed before June 7 and issued after June 8 enjoyed a monopoly period equal to 17 years post issuance or 20 years post application, whichever was longer. The blip may reflect a rush to file applications before June 7, 1995 to take advantage of the extended monopoly period. If patents with a longer shelf life are more valuable, and more valuable patents are produced by bigger inventor teams, an increase in team size in that year would seem natural. Consistent with the fact that drug patents have longer shelf life, the blip is most pronounced in the Drugs & Medical category.

Figure 3 describes the trend in team size by country or region of the patent's first inventor. Japan's inventor teams are the largest, followed by those of Europe and the UK. Between the 1970s and the early 2000s, Japanese teams have remained large and relatively constant in average size which ranged between 2.5 and 2.8 inventors per patent. By the end of this span, the European and North American mean inventor team sizes had nearly caught up to the Japanese. The fact that Japanese teams have remained constant in size indicates that rising team size in innovating US companies may not be exclusively due to changes in technology toward more specialization since Japan likely experienced similar technological changes as in the US.

Team Persistence:

We use the occurrence of multiple patents featuring the same inventors in a given window of time as an indicator of persistence. Teams make themselves visible when they patent and these patents reveal teams' size and composition–the number and identity of scientists working together. If the same subsets of inventors appear on multiple patents over time we know the teams persist. If patenting rates remain constant, then a rise in "repeats" means that persistence is increasing. If persistence is increasing it means either that the projects in which teams are working are lasting longer, or that the teams are serially working on more projects.

We first examine the repetition of the same pairs of inventors. To measure persistence in year T, we ask what fraction of inventor pairs formed in year T, form again within three years. A possible repeating pair is identified in the following way: inventors A and B are on a patent applied for in year T.[13] If inventors A and B are found on a patent application dated within three years of their year T appearance, A and B are considered a repeating pair. (Note that the date of *first appearance* may not be the first patent that A and B are on together.) Table 1 shows the fraction of pairs that repeat by year. Table 1 shows persistence rising: 28% of pairs that appear in 1975 repeat sometime in the subsequent three years. By 1995, the fraction reaches 40%.

Some of what we call persistence in the team may be due to the following: a research team works on a project and the project produces multiple patentable outputs

[13] The patent may have more than two inventors. The possible pairs from a patent containing inventors A, B, and C, say, are A-B, A-C, and B-C.

simultaneously. These patentable outputs result in a cluster of patents which cause pairs to be recorded as persisting. Because of the difficulty linking patents to R&D projects, our measure of persistence captures both the notion of the inventor pair staying together from project to project but also the inventor pair coming together for only one project that produces multiple patents. Because patents that are filed three or more months apart are more likely to be from different projects we can formulate a measure of project-to-project persistence by counting only those patents that are filed at least three months after the original pairing. Indeed the persistence measure falls by about one fifth when we omit the first three months of the span (far right column); however the rise in persistence over time remains. This makes us more confident that teams indeed are increasingly staying together for multiple projects.[14]

Table 2 shows the result from an analysis of inventor trios. Though trios repeat slightly less often than pairs, they too show an upward trend in persistence.

Table 3 conveys a sense of the duration of teams. It shows for pairs that are observed on the same patent in a year, the fraction that are observed on patents at various intervals subsequently. For example, of the inventor pairs observed in 1975, 10% pair again on patents applied within 3 months of their 1975 pairing, 12% on patents that are applied for between 3 months and 12 months following their 1975 pairing, etc. In the third year following their 1975 pairing, a pair's likelihood of appearing on a patent together is 6%. Table 3 shows that the incidence of re-pairing of

[14] Until the late 1980's the number of patents granted had remained fairly steady, but since then the number has soared. Increasing patent rates may bias team persistence upward in recent years because we can identify repetitions of pairs only when patents are issued. However, because rising persistence has started well before 1990 the upward trend in team persistence we argue is not due to the rising number of patents.

any of the pair samples falls the further one gets from the date the pairs were identified. So, for example, for the 1995 pairs, the fraction that are again observed on a patent falls from 18% in the second year following their 1995 patent, to 14% in the third year and 8% in the fourth year following their 1995 patent. This pattern is observed for all five inventor samples. Note that almost half of the re-pairing that occurs in the first year following the base year pairing occurs in the first 3 months. For the 1995 pairs, most of what re-pairing occurs in the first year occurs in the first 3 months.

Table 3 shows that the duration of collaboration between inventors is increasing. If we observe a pairing of inventors in 1975, their probability of pairing again sometime between two and three years later is about .09. For pairs observed in 1995, that likelihood is greater—about .14. For pairs observed in 1975, their likelihood of pairing sometime between three and four years later is .06. For pairs observed in 1995, that likelihood is .08.

4.2 Model Specification of the Regression Analyses

This section describes our specifications of the regression-based tests of the hypotheses enumerated in Section 3. In our analysis of team size, the unit of observation is a patent and the dependent variable is the number of inventors appearing on a patent. The analysis includes all patents applied for between 1975 and 1999. In the team persistence analysis, in the first set of regressions each observation is a pair of inventors that worked together on a patent that has two or more inventors. For patents that had more than two inventors, we randomly chose one pair (e.g., four inventors on a patent imply six pairs of which we randomly choose one to include in the analysis). The dependent variable is the number of additional times between three months and three years of first appearing that the pair reappears on a patent, and the analysis includes all inventor pairs that occur on patents applied for between 1975 and 1995.

The basic specification for our regression analysis of team size and persistence is a Poisson model with firm-level fixed effects. We employ the Poisson regression method because in both sets of analyses our dependent variable is a count variable with nonnegative values. Our models also include dummy variables for six patent technological categories (Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, Mechanical, and Others) and year dummies.

The basic set of explanatory variables includes a dummy variable for states' enforcement of non-compete covenants, the number of inventors within 50 miles of the first inventor on the patent, firm-level R&D expenditures, industry-level R&D expenditures, and the median wage for scientists by industry. In the team persistence analysis, these variables are measured in the first year the pair appears in our data. We also use as additional regressors the average number of patents per inventor in the previous three year period, average distance between inventors, a measure of generality of a patent, the number of citations received in the first five years following the granting of the patent, and the number of claims. These additional regressors are not included in our basic set because they may be endogenous. All regressors except those which can take a zero value are in logarithmic form.

We do not directly observe ρ, the instigator of mobility in our model. Instead we use variation in enforcement of non-compete clauses to investigate the relationship between scientist mobility and team size or persistence. A non-compete covenant is a promise by a worker to an employer not to work for a direct competitor for a fixed period of time following the end of employment. Non-compete covenants are commonly incorporated into employment agreements of senior research employees. Many states enforce non-compete covenants, but some are reluctant to enforce non-compete covenants because of the restrictions they place on the worker's ability to secure employment (see Dworkin and Callahan, 1998; Gilson, 1999; Koh,1998). Previous research appears to show that states' enforcement policies are of economic consequence. Fallick, Fleischman and Rebitzer (2006) find evidence that non-compete enforcement reduces firm-to-firm mobility of computer workers. Using Michigan's 1985 reversal on its long-held refusal to enforce non-compete covenants, Marx, Strumsky, and Fleming (2009) show enforcement of non-compete covenants reduces the mobility of certain kinds of inventors. Stuart and Sorenson (2003) find that start-ups are more frequent in regions where non-compete clauses are not enforced. We use variations in enforcement of non-compete covenants across states over time to evaluate the importance of worker mobility in limiting teamwork. Following Marx et al. (2009) and Marx (2009), we use Malsberger (1996) to identify the states that restrict non-compete enforcement. According to Malsberger, the following states had specific legislation restricting enforcement of non-competes: Alaska, California, Connecticut, Minnesota, Montana, North Dakota, Nevada, Oklahoma, Washington, and West Virginia. In addition, prior to March 1985, Michigan restricted enforcement of such contracts.

We use the number of inventors within 50 miles of the address of the first inventor as a proxy for the outside opportunities available to the inventors on the patent. Isolated inventors will have higher costs of moving and will show lower mobility rates.

The lower mobility may lead to smaller or larger teams depending on whether the scale or compartmentalization effect dominates. On the other hand, denser labor markets permit greater specialization and therefore larger teams (Smith, 1976; Becker and Murphy, 1992). In sum, teams may be larger or smaller in areas with fewer inventors depending on whether the scale effect dominates the specialization and compartmentalization effects.

We obtain firm-level and industry-level R&D expenditures from the Compustat database, using the link between the patent assignees and the Compustat firms created by the NBER Patent Data Project (PDP) (Iain Cockburn, PI). Our analyses are based on patents applied for between 1975 and 1999. We use the firm's R&D expenditures as a measure of the size of its research enterprise. For firm-years where R&D is reported as zero we substitute in the minimum non-zero R&D expenditure in the data and include an indicator that is equal to one for such firm-years (and equal to zero otherwise). This allows us to take the natural log of R&D without dropping firm-years from the analysis. Besides the scale effect in research, this variable may reflect the maturity of the firm's technology. We use as a measure of the amount of technological change in the firm's environment, the log of industry productivity, defined as sales net of (non-labor) costs per worker. We report in the Appendix the industry classification for the measure of industry-level R&D expenditures, which is roughly the same as the two-digit code for classifying industries used by Bound et al. (1984).

Our proxy for the productivity of scientists employed by the firm, or reservation wage, is the median wage and salary for scientists in the firm's industry.[15] The data for scientist wage are taken from the Annual Demographic Files (March Supplements) of the Current Population Survey (CPS), conducted by the U.S. Census Bureau. The median wage is calculated from annual wage and salary of all scientists and engineers. The March CPS yields records on 2,600 scientists and engineers on average annually between 1975 and 1999. This variable as well as the firm-level and industry-level R&D expenditures is in constant 1982-84 dollars.

We also include a measure of generality of a patent, the number of citations received in the next 5 years, and the number of claims. The measure of generality is an index which ranges between zero and one, and is higher for patents that are cited by subsequent patents from a wide range of fields. If we consider forward citations as a measure of the impact of a patent, a high generality value suggests that the patent has a widespread impact (Hall et al., 2001). We thus regard the generality measure as a proxy for the project rage (R) in our model. The number of claims can be used as a measure of the scope or the width of the invention (Lanjouw and Schankerman, 2004) and may also proxy the project range (R) in our model. We include the number of citations received as a regressor to account for the success of the team in its first observed encounter. Alternatively, this variable can be considered as a proxy for the researcher's productivity in the firm.

[15] We include the following occupation categories for scientists and engineers (the three-digit 1980 standard occupational classifications are in parentheses): Engineers (044-059), Mathematical and computer scientists (064-068), Natural scientists (069-083), Clinical laboratory technologists and technicians (203), Engineering and related technologists and technicians (213-216), Science technicians (223-225), and Computer programmers (229).

The data for both the average number of patents by an inventor in the last three years and the average distance between inventors are taken from the inventor-level patent data constructed by Lai et al. The former variable is used as a measure of an inventor's research productivity, or as a control for patenting rate in the team persistence analysis. The latter variable reflects variations in coordination cost across firms: a firm with lower coordination cost likely tends to have longer distance between its inventors.

Table 4 displays the definitions and some simple statistics of the variables used in the regression analysis.

5. Results

5.1 Results from the Team Size Analysis

Table 5 shows the results from the analysis of team size. In the first column we report the results with only our basic set of variables as regressors. Note that in the Poisson specification the estimated coefficients for the log-transformed regressors have an elasticity interpretation.

In Model 1, the dummy variable for whether the first inventor on a patent is located in a state that enforces non-compete covenants is statistically significant and positive. This implies that all else equal, research teams that are in a state where non-compete clauses are enforced are larger by about 1 percent. If enforceable, non-compete covenants reduce the external value of knowledge transfer, and therefore inventor-employees in states where non-compete clauses are enforced are less likely to move. An interpretation of our finding is that a higher risk of worker appropriation results in net reduction in team size—that is, the scale effect dominates.

While the use of non-compete covenants in the employment contracts of key research personnel is now commonplace, we know of no evidence about how their use has changed over time. We therefore do not know how much of the increase in team size they might account for. In model 2 we interact the non-compete dummy with a time trend. The coefficient on the interaction term is insignificant suggesting that non-compete use has not increased over time.

The number of inventors within 50 miles of the first inventor on a patent has a positive, though small and statistically insignificant effect on team size. This effect is, according to our interpretation, a product of three effects: a greater supply of specialized workers and the KM model's scale and compartmentalization effects. We interact the non-compete dummy with the number of inventors and add this term to the specification of which the results are reported in the third column. We reason that in states where non-competes are enforced the effect of the size of the local population of inventors should be dominated by the labor market scale (specialization) effect, i.e. non-enforcement should lead to a negative effect of inventor population size on team size. This prompts us to predict a positive coefficient on the interaction term. For states where non-competes are not enforced the influence of the local inventor population should be a mix of the two opposing effects. Model 3 shows that the effect of the local population of inventors in states where non-competes are enforced is positive (-.005 + .009 = .004). In states where non-competes are not enforced, the effect of the number of inventors on team size is negative (elasticity is -.005). The effect of being in a non-compete state on team size is positive for most patents (log value of the number of local inventors (NI) for about 88 percent of observations is big enough that -.053 + .009·log(NI) is greater than zero).

We find consistently in Table 5 a positive (and statistically significant) relationship between the size of the firm's R&D enterprise and the size of its teams. We show that the median wage for researchers is positively correlated with team size, though the implied elasticity is small (about .06). This finding is consistent with the KM model where median wage is interpreted as reflecting researcher quality..

The Team Size-Technological Change hypothesis predicts a negative relationship between industry productivity and team size. That is, interpreting industry productivity as a measure of technological change, we expect smaller team sizes. Our prediction is the same if instead industry productivity reflects external employment opportunities. In Models 1 through 3, however the estimated effect of industry productivity on team size is insignificant. We have also proxied technological change by industry-level R&D expenditures. The coefficient on industry R&D expenditures (not reported) is negative and significant.

Model 4 adds to the base specification the average number of patents produced by the inventors on the patent in the previous three years, the average distance between inventors' home residences, a citation-based measure of the generality of the patent, the number of citations received by the patent in its first five years, and the number of claims. As a measure of an inventor's research productivity, we expect the average number of patents produced by an inventor in the last three years to have a positive effect on team size. However, our regression result shows the opposite effect. One possible reason for this is that persons who have had more patents in the past are older, and older inventors, either because they were more likely to have been trained as generalists (Jones, 2005) or because of habit, are less inclined to team with others.

Firms may take advantage of lower coordination costs—due to, say, improvements in communication technologies, cheaper air travel, and managerial innovations—by bringing in talent from farther away. We take average distance as an indirect measure of coordination costs and predict a positive association between distance and team size. This is confirmed in our regression result: the average distance between inventors is significantly and positively correlated with team size.

Table 5 shows that the generality measure, a proxy for the project range, is positively correlated with team size (and statistically significant). The number of claims as a measure of the scope or the width of an invention—and possibly also capturing the project range—is shown to have a significantly positive association with team size, suggesting the breadth effect dominates the specialization effect.

As a measure of how successful a team is or its research productivity, we expect that the number of forward citations has a positive association with team size, which is confirmed in Table 5.

Table 5A reports the results of a difference-in-difference analysis that exploits the policy change in Michigan. All models use California-based patents as the comparison. We restrict the comparison to California, because, as in Michigan before 1986, both the courts and the legislature took the same approach in proscribing noncompetes virtually without exception. The coefficient of interest is the coefficient on the interaction of Michigan and "After_1986", indicators that the patent's first inventor resides in Michigan and that the application was filed after the beginning of 1986, when Michigan first began enforcing noncompetes. We interpret that coefficient as identifying the effect of enforcing noncompetes on team size.

Model 5 includes all patents of all technology classes from the two states. Models 6 and 7 show the results when we compare similar patents in Michigan and California. Model 6 compares patents within the automobile and auto parts industry. Model 7 first performs the Coarsened Exact Matching (CEM) procedure (Iacus et al 2011a and 2011b) on the sample before employing difference-in-differences. CEM matches to each Michigan patent a California patent that is identical by industry (according to the 23 ARDSIC industry categories; see Hall and Vopel, 1997) and by groups of assignee size in sales, employment and R&D expenditures (where no matches can be found, the observation is omitted). The difference-in-difference analysis generates larger estimated effects of allowing noncompetes on team size. After CEM, the effect of noncompete enforcement increases team size by 6 percent; comparing only within the automobile/parts industries, allowing noncompetes raises team size by over 10 percent.

5.2 Results from the Team Persistence Analysis

The results of our team persistence analysis are shown in Tables 6. Table 6 features the same right-hand side specifications as in Table 5, with team size as an additional regressor. In Table 6 we investigate the persistence of inventor pairs.

As predicted by our model, holding team size constant, the dummy variable for non-compete covenant enforcement shows a positive effect on team persistence. An inventor pair in a state that enforces noncompetes has a 16 percent greater chance of repeating in three years than an inventor pair in a non-enforcing state. Inventors in states that enforce non-compete covenants face lowered external value of knowledge transfer and are therefore less likely to move. This increases team persistence. Across specifications, firms with larger R&D enterprises show more persistence in their teams. We find that the coefficient on log industry productivity is negative. Because we control for team size, this results is consistent with our assumption that industry productivity reflects the amount of technological change in the industry, or the opportunities for inventors to move. Under both interpretations, we would expect a negative relationship between industry R&D and persistence.

The median wage of scientists is shown in Table 6 to have a negative and significant effect on team persistence which contradicts hypothesis Team Persistence-General Productivity. One possible explanation for this finding is that the median wage reflects the productivity of researchers, and more productive workers tend to be older workers, and age reduces mobility (e.g., Hall, 1982).

Interestingly, the number of inventors in the area has a positive influence on persistence. We have controlled for team size, so the greater opportunities for moving represented by the larger local inventor populations should reduce persistence and yet it does not. Perhaps we are omitting a variable that is correlated with the density of inventiveness and team persistence. The effect of the number of inventors on persistence as a proxy for mobility opportunities should be less in states that do not enforce non-compete covenants. In Model 3 we add an interaction term. Our findings for pairs suggest that in states where non-competes are not enforced, the effect of inventor population size is positive but less than its effect for states that enforce non-competes (.078 vs. .078+.014=.092). The difference in effects can be interpreted as removing the omitted variable.

Why might labor market size increase team persistence? The number of inventors on a patent (which is our team size variable in the regressions) will imperfectly reflect the size of research teams because for example a three-person team may have various pair combinations in different patents that they produce and our team size variable will be two although the real research team size is three. If larger labor markets induce larger research teams, and larger teams accumulate more team specific human capital, the market size variable will be positively correlated with persistence.

The results from model 4 show that the average number of patents of an inventor in the last three years has a significant and positive effect on team persistence. We think that this is mainly due to the fact that by construction teams with more patents are more likely to show up again in later patents just because they produce more patents, thereby showing higher persistence. As this variable is included as a regressor, we can control for a team's patent productivity and estimate the effects of other regressors without this concern.

A firm with lower coordination cost should have longer distance between its inventors. If the optimal team size is expected to grow over time, lower coordination cost reduces the incentive for firms to retain scientists and hence lowers persistence. This story is consistent with the finding in the tables: the average distance between inventors is negatively and significantly correlated with team persistence.

Table 6 shows that the generality and claims measures—both are proxies for the project range—are positively correlated with team persistence. As a measure of how successful a team is, we expect forward citations to have a positive association with team persistence. We find this expectation confirmed in the results reported in Table 6.

Table 6A reports the difference-in-difference results based on the Michigan policy change. We find, except for the automobile-only specification, a stronger (positive) effect of allowing noncompetes on persistence.

6. Discussion and Conclusion

In this paper we show that earlier reported trends in team size extend to the mid-2000s. Between 1975 and 2003 mean inventor team size increased by 62 percent and the fraction of single inventor patents fell from 58 to 33 percent. We show that this trend extends across technological classes but the increase in team size has been greatest in Chemicals and Drugs & Medical categories. We also show that the trends in inventor team size by country of patent origin. Over the 1975-2003 period, the size of Japanese inventor teams on patents filed in the US have remained relatively steady and high by world standards, at about 2.5 inventors per patent. But by 2003 European and North American inventor teams had largely caught up with the Japanese. We also show evidence that inventor team size has responded to changes in laws governing patent protection during the mid-1990s.

We also show the first econometric evidence, we believe, that inventor teams are remaining intact for longer periods and over more projects. We find, for example, that two-person inventor teams formed in the mid 1970s had a 24 percent chance of appearing again on a patent within three years (omitting the first three months following their formation). By the mid 1990s that likelihood had increased to 33 percent. The analogous numbers for three-person inventor teams are 16 percent and 28 percent, respectively.

We then analyze the determinants of inventor team size. We use states' policies toward employment non-compete covenants to proxy for appropriation risk. We find that in states where non-competes are enforced, inventor teams tend to be larger. This finding is inconsistent with a compartmentalization story, but is consistent with firms scaling back teams to minimize appropriation cost. It is also consistent with a coordination cost story. In our model, coordination costs fall within a team as team members gain experience working with one another. If a firm anticipates its researchers will be retained, it will create larger teams to exploit the returns to specialization, because in an environment where researchers do not turn over, the firm is able to offset high initial coordination costs with lower coordination costs later on.

We also find some indirect evidence that coordination costs matter in the determination of team size. In firms and years where teams comprise inventors who reside greater distances from one another, team size tends to be larger. This is consistent with the following story: with the lowering of some kinds of coordination costs (such as communication-related costs), firms will respond by searching farther afield geographically to obtain the right kinds of inventor expertise. Firms will also take advantage of the fall in coordination costs to increase the size of the team. For this reason we argue that team size co-varying with average distance among the team's inventors is indirect evidence of a coordination cost effect on team size.

We analyze our model's implications for team persistence. We find that in states where non-competes are enforced, inventor teams are more likely to repeat. This is consistent with the appropriation part of our model: where non-competes are enforced, inventors will not leave an employer to appropriate the employer's IP elsewhere. Of course one does not need the appropriation story to explain an increase in persistence from non-competes. Enforcing non-competes make it harder for inventors to seek employment elsewhere for non-IP reasons as well. Other findings include: teams are more likely to persist when they are (1) located in larger R&D shops; (2) on patents that describe more broad-based technological advances or on patents that assert more claims; and (3) on patents that generate more citations. (2) is consistent with our story that controlling for an inventor's outside options with the employer's IP, inventor teams are more likely to persist on research programs that require more and varied skill sets. (3) Is consistent with the story that teams that prove successful on one project are more likely to re-assemble for additional ones.

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Figure 1a

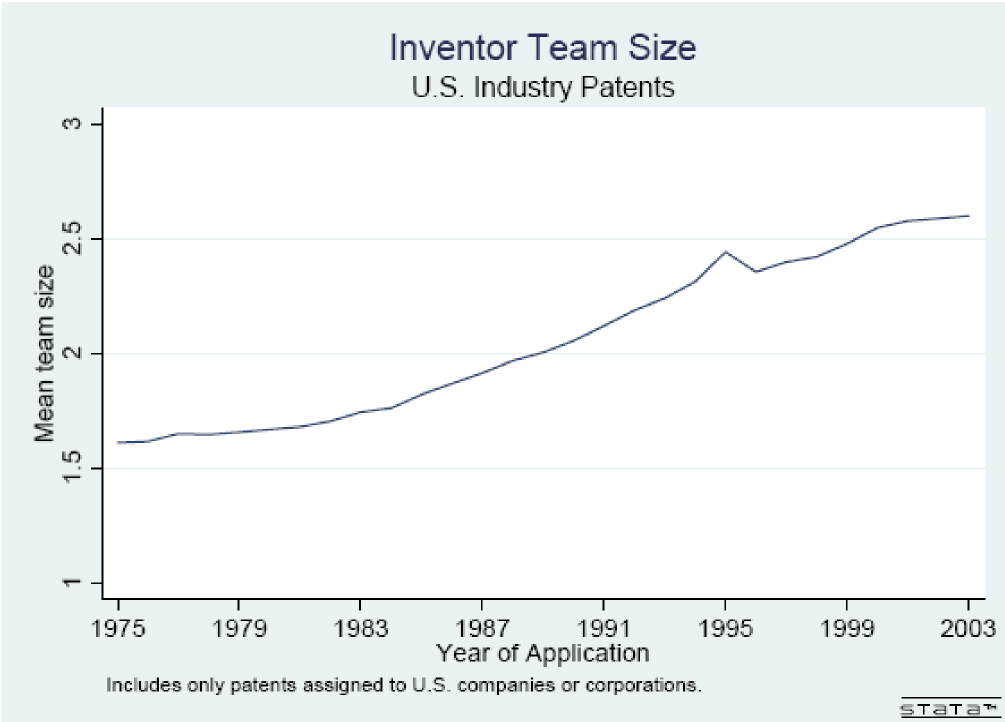

Figure 1b

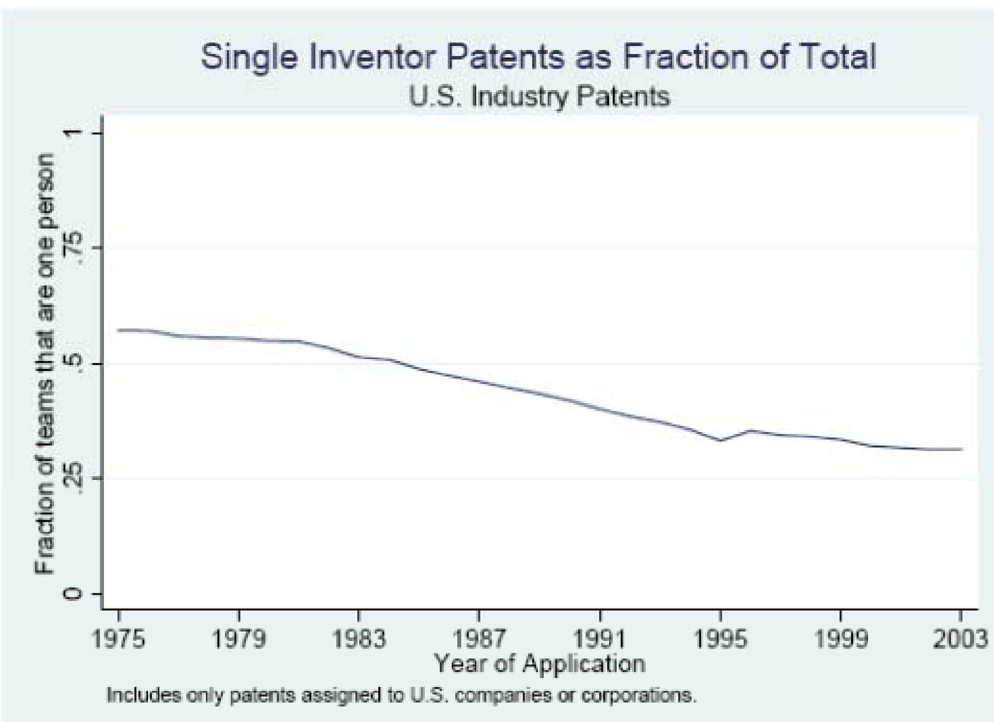

Figure 2

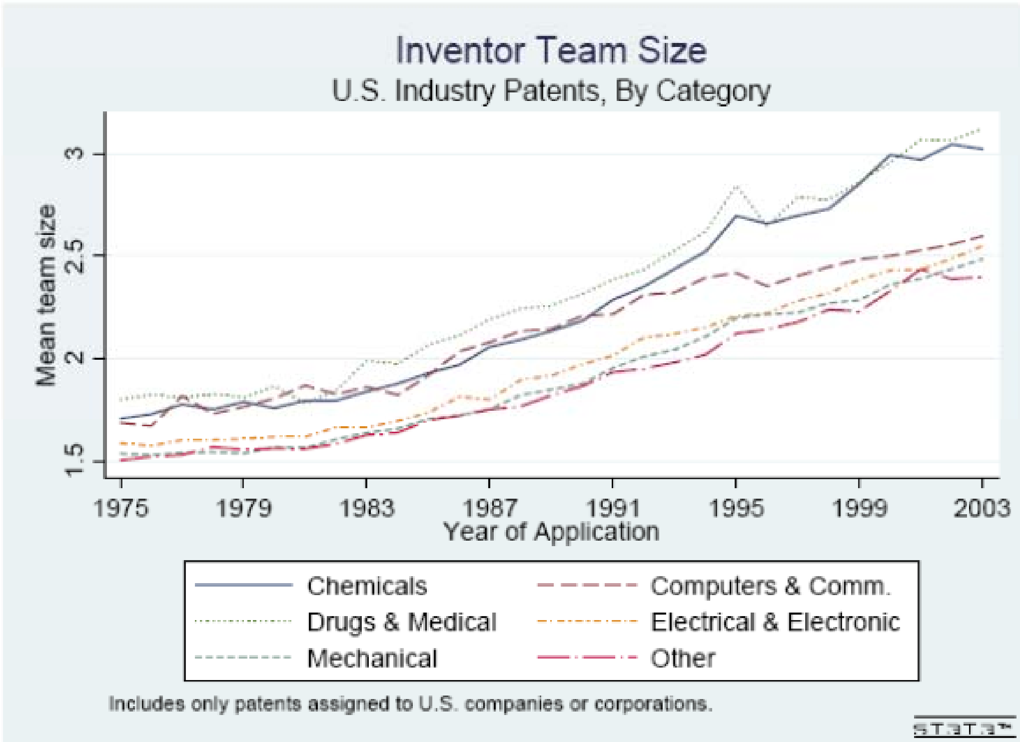

Figure 3

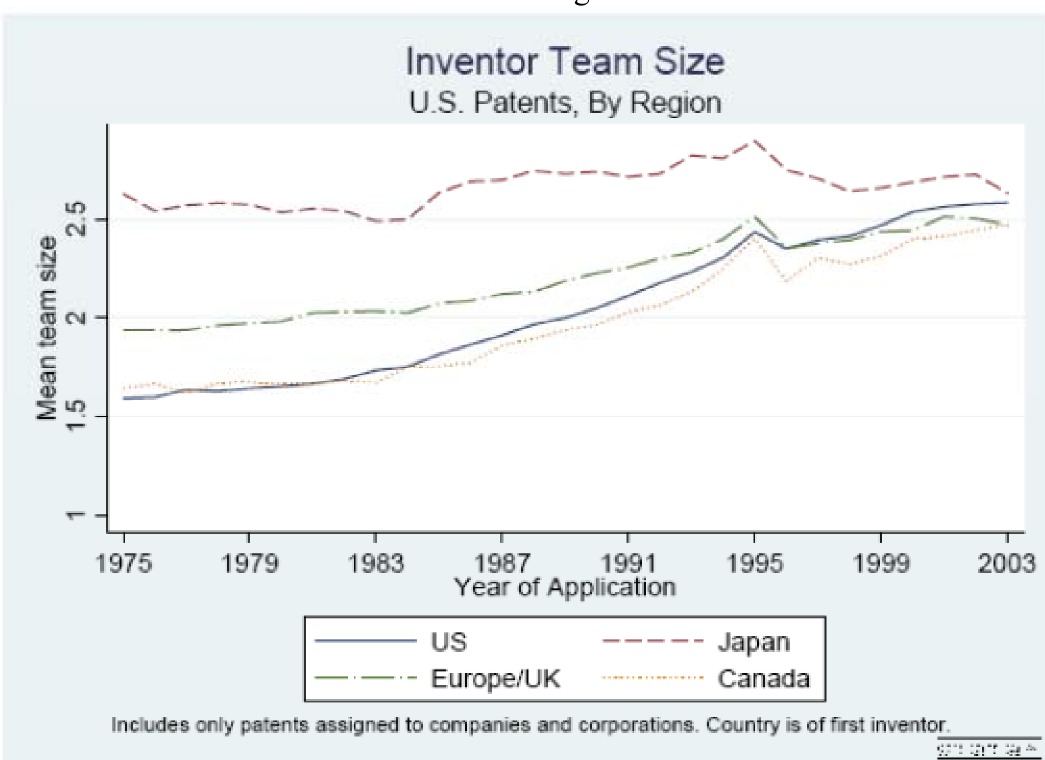

Table 1 Persistence of Inventor Pairs By Year		
	Fraction of inventor pairs that appear again sometime…	
Year of patent application date	0 to 3 years after patent application date	3 months to 3 years after patent application date
1975	.28	.24
1980	.29	.25
1985	.30	.26
1990	.33	.29
1995	.40	.33

Table 2 Persistence of Inventor Trios By Year		
	Fraction of inventor trios that appear again sometime…	
Year of patent application date	0 to 3 years after patent application date	3 months to 3 years after patent application date
1975	.19	.16
1980	.24	.19
1985	.22	.18
1990	.29	.25
1995	.37	.28

Table 3 Duration of Teamwork					
	Fraction of inventor pairs that appear again in the span				
	0 to 3 months after patent application date	3 months to 1 year after patent application date	1 to 2 years after patent application date	2 to 3 years after patent application date	3 to 4 years after patent application date
1975	.10	.12	.14	.09	.06
1980	.10	.12	.14	.09	.06
1985	.09	.12	.14	.11	.08
1990	.10	.12	.16	.12	.08
1995	.15	.13	.18	.14	.08

Table 4 Variable Description and Summary Statistics					
Variable	Description	Mean	St. Dev	Min	Max
Team size	Number of inventors appearing on a patent	2.094	1.373	1	30
Number of repeats for pairs	Number of later patents for a pair of inventors to reappear together within 3 years of first appearance	0.325	1.069	0	97
Noncompete	=1 if the first inventor is located in a state that enforces non-compete covenants	0.742	0.437	0	1
Log number of inventors w/i 50 miles	Logarithm of the number of unique inventors residing within 50 miles from the first inventor's residence	7.258	1.158	0	9.724
Log R&D	Logarithm of R&D expenditures of a firm (constant 1982-84 price)	4.986	2.660	-9.210	8.643
Log industry productivity	Logarithm of (sales-cost of goods sold + labor cost)/employment of a firm's industry (constant 1982-84 price)				
Log median wage for scientists	Logarithm of median wage and salary of scientists by industry (constant 1982-84 price)	10.29	0.168	9.733	11.20
Average patents per inventor	Average number of patents per inventor over all inventors on a patent in the last 3 years	3.373	7.818	0	344
Average distance between inventors	Average distance between inventors on a patent (in miles)	116.9	329.4	0	5015
Generality	Index of how widely a patent is cited by subsequent patents in various technology fields	0.363	0.285	0	0.929
Citation received	Number of citations a patent received in 5 years following its granting	3.898	5.297	0	241
Log number of claims	Logarithm of the number of claims on a patent	2.302	0.809	0	5.746

Table 5
Determinants of Team Size

Dependent Var.: team size Poisson model

Variable	Model 1	Model 2	Model 3	Model 4
Noncompete	0.01299 (3.50)	0.01164 (1.76)	-0.05323 (-2.45)	0.01040 (1.82)
T*Noncompete		0.00011 (0.25)		
Log number of inventors within 50 miles	0.00119 (0.85)	0.00123 (0.87)	-0.00542 (-2.12)	0.00284 (1.32)
Noncompete*Log number of inventors			0.00891 (3.09)	
Log R&D ($1982-84)	0.00659 (2.05)	0.00663 (2.06)	0.00709 (2.20)	0.01028 (1.69)
Zero R&D dummy	0.39083 (2.14)	0.39120 (2.14)	0.39516 (2.16)	0.29430 (0.90)
Log industry productivity ($1982-84)	0.00577 (0.51)	0.00574 (0.50)	0.00599 (0.52)	0.04310 (2.12)
Log median wage for scientists ($1982-1984)	0.06301 (3.61)	0.06294 (3.61)	0.06293 (3.61)	-0.00156 (-0.06)
Average patents per inventor in last 3 years				-0.00199 (-4.55)
Average distance between inventors				0.00006 (10.73)
Generality				0.02984 (4.37)
Citation received in next 5 years after granted				0.00352 (10.72)
Log number of claims				0.02864 (12.12)
Log likelihood	-548,397	-548,398	-548,393	-182,258
Observations	356,524	356,524	356,524	115,813

Notes:

1. T-statistics in parentheses.
2. All models include fixed effects at the firm level.
3. All models include as regressors dummies for patent technology categories and for calendar years.
4. We include inventors whose address is in the US.
5. Inventors from patents applied for between 1975 and 1999, inclusive, only.

Table 5A
Determinants of Team Size

Dependent Var.: team size — Difference-in-Differences model

Variable	Model 5	Model 6	Model 7
Michigan*After_1986	0.04903 (3.37)	0.10471 (3.46)	0.05743 (3.81)
Michigan	-0.03787 (-2.55)	-0.04474 (-1.66)	-0.03719 (-2.45)
After_1986	0.37199 (10.95)	0.04195 (0.42)	0.36454 (10.26)
Log number of inventors within 50 miles	0.00479 (0.98)	0.02418 (1.68)	0.00990 (1.81)
Log R&D ($1982-84)	-0.02145 (-2.64)	0.19108 (2.21)	-0.02367 (-2.78)
Zero R&D dummy	0.14161 (0.61)		0.12110 (0.51)
Log industry productivity ($1982-84)	0.06641 (2.18)	0.07939 (0.55)	0.05315 (1.68)
Log median wage for scientists ($1982-1984)	0.01598 (0.36)	0.26829 (1.05)	0.03116 (0.67)
Log likelihood	-100,450	-18,373	-90,919
Observations	66,516	12,426	60,267

Notes:

1. The specification of all models is Poisson model.
2. All models include fixed effects at the firm level.
3. All models include as regressors dummies for patent technology categories and for calendar years.
4. In model 6, we only include patents in Motor Vehicles industry.
5. In model 7, we employ the CEM method.
6. We include inventors whose address is in the US.
7. Inventors from patents applied for between 1975 and 2001, inclusive, only.
8. Control group includes only patents by firms in California.

Table 6
Determinants of Persistence of Pairs
Dep. Var.: number of repeats within 3 years of first appearance[1] Poisson model

Variable	Model 1	Model 2	Model 3	Model 4
Log team size	-0.09542 (-11.97)	-0.09552 (-11.98)	-0.09548 (-11.97)	-0.22462 (-21.65)
Noncompete	0.15562 (16.29)	0.18769 (11.29)	0.05199 (0.88)	0.07263 (6.12)
T*Noncompete		-0.00284 (-2.36)		
Log number of inventors within 50 miles	0.08873 (25.94)	0.08792 (25.60)	0.07750 (10.81)	0.04686 (10.93)
Noncompete*Log number of inventors			0.01398 (1.78)	
Log R&D ($1982-84)	0.14213 (17.14)	0.14163 (17.07)	0.14254 (17.18)	0.13734 (11.84)
Zero R&D dummy	19.61291 (0.01)	19.60747 (0.01)	19.61620 (0.01)	
Log industry productivity ($1982-84)	-0.55928 (-19.47)	-0.55558 (-19.31)	-0.55913 (-19.46)	-0.16203 (-4.48)
Log median wage for scientists ($1982-1984)	-0.20224 (-5.16)	-0.20231 (-5.16)	-0.20187 (-5.15)	0.08197 (1.65)
Average patents per inventor in last 3 years				0.04610 (125.20)
Average distance between inventors				-0.00032 (-23.93)
Generality				0.07933 (6.39)
Citation received in next 5 years after granted				0.02201 (52.84)
Log number of claims				0.12525 (28.93)
Log likelihood	-254,190	-254,187	-254,188	-158,819
Observations	148,766	148,766	148,766	102,759

Notes:
1. First appearance during the period 1975 – 1995
2. T-statistics in parentheses.
3. All models include fixed effects at the firm level.
4. All models include as regressors dummies for patent technology categories and for calendar years.
5. We include inventors whose address is in the US.
6. Inventors from patents applied for between 1975 and 2001, inclusive, only.

Table 6A
Determinants of Persistence of Pairs
Dep. Var.: number of repeats within 3 years of first appearance[1] Diff-in-Diff model

Variable	Model 5	Model 6	Model 7
Log team size	-0.18261 (-8.92)	-0.35345 (-6.06)	-0.20849 (-7.65)
Michigan*After_1986	0.18830 (5.52)	-0.10695 (-1.24)	0.31523 (7.75)
Michigan	0.06119 (1.62)	-0.01648 (-0.20)	0.01481 (0.36)
After_1986	0.17191 (2.47)	-1.20694 (-4.41)	-0.03653 (-0.40)
Log number of inventors within 50 miles	0.05954 (4.34)	0.17608 (3.88)	0.09030 (5.60)
Log R&D ($1982-84)	0.19707 (9.44)	1.68889 (6.89)	0.27469 (7.24)
Zero R&D dummy	16.16746 (0.03)		
Log industry productivity ($1982-84)	-0.68498 (-9.82)	-0.76331 (-2.08)	-0.56067 (-5.81)
Log median wage for scientists ($1982-1984)	0.07835 (0.69)	0.73208 (1.14)	-0.76795 (-4.89)
Log likelihood	-39,849	-7,580	-26,508
Observations	27,068	6,622	19,364

Notes:

1. First appearance during the period 1975 – 1995
2. The specification of all models is Poisson model.
3. All models include fixed effects at the firm level.
4. Models 6 and 7 include as regressors dummies for patent technology categories and for calendar years.
5. In model 6, we only include patents in Motor Vehicles industry.
6. In model 7, we employ the CEM method.
7. We include inventors whose address is in the US.
8. Inventors from patents applied for between 1975 and 1999, inclusive, only.