The Effect of Collaboration Network on Inventors' Job Match, Productivity and Tenure.

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November 17, 2008

Abstract

It has been argued in the economic literature that job search through informal job networks improves the employer–employee match quality, especially in high wage sectors. This paper argues that inventors' research collaboration networks reduce the uncertainty of firms about the match qualities of inventors prior to hiring. We estimate the effect of inventors' collaboration networks on their productivity and mobility using the U.S. patent application database. It is found that network-recruited inventors are more productive and have longer tenure than publicly recruited inventors. The evidence from fixed-effect regressions shows that the higher productivity and longer tenure of network-recruited inventors are not solely attributable to their unobserved ability. These results are consistent with the job match hypothesis between inventors and firms through their collaboration networks.

Keywords: job networks, match quality, inventor, mobility, productivity, patent.

JEL Classification: J44, J63, O32.

1 Introduction

It is widely accepted that the mobility of inventors is an important source of knowledge transfer among research firms (e.g., Arrow, 1962; Levin, Klevorick, Nelson, Winter, Gilbert, and Griliches, 1987; Almeida and Kogut, 1999). Firms use inventors' mobility to acquire external knowledge for new innovations (Rosenkopf and Almeida, 2003; Song, Almeida, and Wu, 2003). Yet, it may not be obvious which inventors firms should hire from their large potential employee pool. The problem that they may face when hiring inventors is that the job match value is not ascertained prior to employment. Some hired inventors may be poor matches for the job they hold and thus turn out to be not as good as they initially appeared to be. Few studies have considered the job matching process between inventors and firms. Because a better job match leads to higher inventive productivity, one of the fundamental issues in the industrial organization literature is to identify a mechanism that facilitates a good match between inventors and firms. Hence, the following questions should be addressed: Which source of information do inventors and firms employ to reduce uncertainty about the match quality? How does such a matching mechanism influence inventors' mobility and productivity?

Recent developments in the networks literature may offer a clue to the above research questions. One of the most widely documented facts about job search is that networks of personal connections, often called old-boy networks or informal job networks, can be used by employers to assess their job applicants' motivation, ability, and likelihood of success. For example, Rees (1966) found that recruiting through informal job networks accounts for about 50 percent and 80 percent of all hires in white-collar and blue-collar occupations, respectively. Granovetter (1995), in his survey of residents in Newton, Massachusetts, in the late 1960s, also found that more than half of jobs were obtained through personal connections. Theoretical studies of networks analysis have studied the implications of the prevalence of informal job networks in the labor market by focusing on such functions of networks as (i) transmission of job opening information (Calvo-Armengol and Jackson, 2004; Tassier and Menczer, 2008), (ii) screening and signaling employees' unobserved abilities (Saloner, 1985; Montgomery, 1991; Casella and Hanaki, 2006), and (iii) reducing uncertainty about employee–employer match quality (Simon and Warner, 1992; Mortensen and Vishwanath, 1994).[1] This paper follows the networks literature and analyzes the effect of inventors' job networks on their mobility and productivity.

This paper develops a simple model of search for a good match value. In the theoretical model we assume that an inventor and a firm match through either net-

[1]See Ioannides and Loury (2004) for an extensive review of the literature.

work recruitment or public recruitment. We posit an inventor as network-recruited if he was employed by a firm through the reference of his collaborator (or collaborators) with whom he had worked in past research activity. Both inventors and firms are uncertain about their match value prior to hiring. However, the match value is less uncertain for network-recruited inventors than for publicly recruited inventors. A recruiting firm can infer the match value of a potential employee more precisely if references from his past collaborators is available, and, at the same time, an inventor who uses his collaborator network can estimate more precisely how well (or how bad) matched he is for the offered position by a potential employer. The main predictions of our model are (1) network-recruited inventors have higher productivity, at least initially, than publicly recruited inventors because a good match is more likely to occur, and (2) they have longer tenure because they are less likely to be disappointed with their revealed match value and thus are less likely to quit.

This paper examines the predictions of the theoretical model by making use of the U.S. patent application database provided by National Bureau of Economic Research (NBER). We recompile the patent data by each inventor. Because the name of the patent assignee, which is typically the inventor's employer, is listed in each patent application, we can track down the companies by which each inventor had been employed over time and thus can identify the inventors' employment histories. In the process of tracing down inventors' mobility, identification error, often called the "Who is Who" problem (Trajtenberg, Shiff, and Melamed, 2006), because of the possibility of multiple name spellings for the same person and the possibility of the same name for different persons, cannot be avoided . To minimize the error, we deliberately use a computer matching procedure that has been recently proposed by Trajtenberg, Shiff, and Melamed (2006).[2]

The main findings of this paper are as follows: comparing employment durations, network-recruited inventors have significantly longer tenure than publicly recruited inventors. As for inventors' productivity, which is measured by the number of successful patent applications made in a year, network-recruited inventors are more productive than publicly recruited inventors. But the productivity premium of a network-recruited inventors disappears within two or three years after job change. Finally, the evidence from the fixed-effect regression that controls for individual heterogeneity suggests that the productivity premium is not only a result of network-recruited workers having higher unobserved abilities than publicly recruited inventors. All results are consistent with the job match hypothesis that collaboration networks reduce uncertainty about the match value between inventors and firms.

[2]Recently, several papers (McHale, 2006; Schankerman, Shalem, and Trajtenberg, 2006; Marx, Strumsky, and Fleming, 2007; Hoisl, 2007) have employed a similar identification method.

This paper is related to two strands of literature. First, it is related to the empirical labor literature which estimates the effects of informal job referral on workers' tenure and wage profiles. Many studies find that workers who use references have longer employment tenure than those who do not use references (Datcher, 1983; Topel and Ward, 1992; Simon and Warner, 1992; Loury, 2006). In contrast, the results are mixed for the effect of job references on workers' wage profiles. Some studies present evidence that workers with a referral have higher wage premiums, at least initially, than workers without a referral (Simon and Warner, 1992; Marmaros and Sacerdote, 2002). In contrast, other studies conclude that higher wages are not necessarily associated with job references. Bridges and Villemez (1986); Marsden and Hurlbert (1988) find no general and initial wage premium for referred workers. Kugler (2003) finds that higher wage premiums for referred workers is only between, not within, industrial sectors. Loury (2006) shows that only young males who are referred by older-generation male relatives enjoy higher wages, but no significant job reference effect exists for other groups of workers. Finally, Pellizzari (2004) finds that, using the data of European Union countries, both wage premiums and penalties exist for referred workers across countries and industries. Most of these papers study the effect of informal job referrals for general workers, with the exception of Simon and Warner (1992) who use the 1972 Survey of Natural and Social Scientists and Engineers and study the role of informal recruitment methods through personal references in the job search of "scientific researchers". Our paper departs from these empirical studies in that we study inventors who actively engage in research activities and estimate how the existence of personal connections influences their research productivity and employment duration after moving into a new firm. Given that our focus is on inventors, we directly estimate the effect of network references on productivities rather than wages. We also refine the definition of a job reference network. In the previous studies, job references through friends, family, acquaintances and relatives are mainly considered to convey the job match information. In contrast, we use inventors' research collaboration networks as a channel for job information flows. Given that the growing importance of teams in research is one of the major trends in science nowadays, we hypothesize that past research collaboration provides rich information for both inventors and R&D-intensive firms to judge the job potential of an inventor at a research position.

The second strand of the literature to which this paper relates is the empirical industrial organization literature which studies the extent of the mobility of inventors and its implications on innovation. Kim and Marschke (2005) analyze the role of patenting for firms to protect their inventive knowledge against spillovers through labor mobility. They find that firms' patenting and inventors' mobility are positively correlated. Hoisl (2007) studies the mobility of inventors by using the German patent application data and finds that there are simultaneous relationships between inventors' mobility and productivity. It is shown that inventors with higher productivity are less likely to move, and at the same time, movers are more productive than nonmovers. Schankerman, Shalem, and Trajtenberg (2006) study inventors' mobility in the U.S. software industry and find no evidence that the quality of patents increases after their job changes. This suggests that inventor mobility does not necessarily improve the match quality between inventors and firms. While these studies focus on the relationship between inventor mobility and productivity, this paper, in contrast, studies the effects of the job search method on the mobility and productivity of inventors. According to our hypothesis, match value is improved when firms and inventors meet through a third-party reference. Therefore, inventor mobility alone may not necessarily lead to improvement of the employer–employee match value.

The rest of this paper is organized as follows. Section 2 develops a theoretical job match model of inventors and provides the hypotheses to be tested. Section 3 describes the dataset we used for estimation. Section 4 explains our empirical strategies and presents the estimation results. Section 5 concludes.

2 Matching Model

2.1 Behavioral Model

Following the study of Simon and Warner (1992), we use the simple job matching model by Jovanovic (1984). The simplicity of this model allows us to obtain a number of comparative static results, which are later used for the empirical analysis.

Consider a situation where an inventor is searching for a job. We assume that the ith inventor and the jth firm are matched randomly. The ith inventor is maximize his expected sum of discounted wages given by:

$$U = \sum_{t=0}^{\infty} \beta^t w_{ijt}. \tag{1}$$

where β is the discounting factor, and w_{ijt} is inventor i's wage at firm j in period t.

We assume that the inventor i's match productivity at firm j is given by θ_{ij}, which is unknown to both the inventor and firm in period $t = 0$. They can observe noise-ridden version of the true match value, which is given by $\theta_{ij} + \varepsilon_i$ where ε_i is a white noise. It is also assumed that they can observe the true match value θ_{ij} after the inventor work at the firm for one period. The firm chooses to pay to the inventor i to maximize the expected profit subject to a constraint of zero expected profit. It is shown by Jovanovic (1984) that one of the best strategy of the firm is to pay to the inventor the expected productivity of the match value given the firm's error-ridden prediction of it, that is, $q_{ij} = \mathrm{E}(\theta_{ij}|\theta_{ij} + \varepsilon_i)$ in the period $t = 1$, and to pay the actual productivity θ_{ij} in the period $t \geq 2$. Therefore, the wage profile paid by the firm is:

$$w_{ijt} = \begin{cases} q_{ij} & \text{if } t = 1 \\ \theta_{ij} & \text{if } t \geq 2. \end{cases} \tag{2}$$

In what follows, the subscripts i and j are suppressed for notational simplicity.

The probability structure of the job matching process is specified as follows. Let θ be a match value. The value is assumed to be firm specific. That is, whenever the inventor applies to a firm, a new productivity θ is drawn independently from an identical normal distribution with mean μ and variance σ_θ, that is, $N(\mu, \sigma_\theta^2)$. However, once it is drawn, the value does not change over time while at the firm. As noted above, θ is unobservable, and the firm estimates θ using its noisy signal $(\theta + \varepsilon)$. The estimate is paid to the inventor as an entrance wage. We assume that the noise ε is independently and identically distributed (i.i.d.) following $N(0, \sigma_\varepsilon^2)$. Because of the normality assumptions of θ and ε, the posterior distribution of the estimate on the productivity θ is also normally distributed with mean q and variance s^2. Bayes' law implies the following well-known equalities:

$$s^2 = \left(\frac{1}{\sigma_\theta^2} + \frac{1}{\sigma_\varepsilon^2}\right)^{-1}, \quad q = s^2\left(\frac{\mu}{\sigma_\theta^2} + \frac{\theta + \varepsilon}{\sigma_\varepsilon^2}\right).$$

Thus, the p.d.f. of the posterior distribution of θ is given by $f(\theta|q, s^2) = \phi\left((\theta - q)/s\right)$ and the c.d.f. is given by $F(\theta|q, s^2) = \Phi\left((\theta - q)/s\right)$. Note that the estimate q is a random variable itself, and it follows a normal distribution with mean μ and variance $\sigma_q^2 = \sigma_\theta^4/(\sigma_\varepsilon^2 + \sigma_\theta^2)$. The p.d.f. and c.d.f. of the belief q are given by $g(q|\mu, \sigma_q^2) = \phi\left((q - \mu)/\sigma_q\right)$ and $G(q|\mu, \sigma_q^2) = \Phi\left((q - \mu)/\sigma_q\right)$, respectively. The true match value θ is assumed to be perfectly revealed both to the inventor and to the firm at the beginning of period $t = 2$.

Given the wage schedule, equation (2), the inventor maximizes the expected sum of discount wages, which is given by equation (1). We assume that, since the constant match value is paid to the worker as a wage after period $t = 2$, no decision occurs after the second period. The decision problem can be solved backwardly. Suppose that the inventor is employed in period $t = 1$. At the beginning of period $t = 2$, the inventor decides to continue or quit the job when the firm offers him the match value θ. Let $J(\theta)$ be the present value of staying in the job. The present value of accepting the offer θ is given by $\theta + \beta J(\theta)$, where β is the discount factor. If he rejects it, he receives nothing, and becomes unemployed in the next period. Let W be the present value of being unemployed at the beginning of a period. Because of the assumption that the match value is invariant once it is realized, we have the following recursive equation for $J(\theta)$ such that:

$$J(\theta) = \max\{\theta + \beta J(\theta), \beta W\} \tag{3}$$

The decision of staying or leaving the job at the end of period $t = 1$ is characterized by a *reservation value*, θ^*, below which the inventor leaves the job. $J(\theta)$ is, therefore:

$$J(\theta) = \begin{cases} \frac{\theta}{1-\beta} & \text{if } \theta \geq \theta^* \\ \beta W & \text{if } \theta < \theta^* \end{cases}, \tag{4}$$

where the reservation value is given by:

$$\begin{aligned} & \theta^* + \frac{\beta\theta^*}{1-\beta} = \beta W \\ \Rightarrow \quad & \theta^* = \beta(1-\beta)W. \end{aligned} \tag{5}$$

Given the inventor's decision in period $t = 2$, we now turn to the decision problem at the beginning of $t = 1$. Suppose that the inventor is offered an entrance wage q by the firm. If he accepts the job offer, his expected present value is given by $q + \beta\,\mathrm{E}[J(\theta)]$. Because the posterior distribution of θ is $N(q, s^2)$, the expected value of the decision to stay at the job is computed by:

$$\begin{aligned} \mathrm{E}[J(\theta)] &= \int J(\theta) dF(\theta | q, s^2) \\ &= \int J(\theta) d\Phi\left((\theta - q)/s\right). \end{aligned} \tag{6}$$

Therefore, the present value of accepting the offer q is given by:

$$\begin{aligned} V(q) &= \max\{q + \beta\,\mathrm{E}[J(\theta)], \beta W\} \\ &= \max\left\{q + \beta \int J(\theta) dF(\theta | q, s^2), \beta W\right\}. \end{aligned} \tag{7}$$

The value function $V(q)$ is monotonically increasing in q, and thus the decision whether to accept the job offer is characterized by the *reservation wage* q^* that satisfies:

$$q^* + \beta \int J(\theta) dF(\theta | q^*, s^2) = \beta W. \tag{8}$$

Given that $J(\theta)$ is determined by equation (4), we have the following relationship:

$$q^* = \theta^* - \frac{\beta}{1-\beta} \int_{\theta^*} (\theta - \theta^*) dF(\theta | q^*, s^2). \tag{9}$$

Because the second term of the right-hand side of equation (9) is positive, $\theta^* > q^*$. That is the reservation value in the second period is always larger than the reservation wage in the first period.

2.2 Role of Collaboration Networks

Suppose that when a firm recruits inventors, its current employees can recommend someone with whom they have collaborated before. Of course, the firm can hire an inventor without a referral. We categorize inventors into two groups based on whether they are recruited with or without a referral from their collaborators. Let us call those inventors recruited with a referral *network-recruited* ($k = N$) and those without *publicly recruited* ($k = P$).

Let $\sigma^2_{\varepsilon k}$ be the error variance to the productivities of inventors in group k . We assume that referrals based on past collaboration are informative so that firms can predict the productivity of a network-recruited inventor *more precisely* than that of a publicly recruited inventor. That is, $\sigma^2_{\varepsilon N} < \sigma^2_{\varepsilon P}$ is assumed. For inventors in group k, let q_k be the entrance wage, and let θ_k be the match value.

We first analyze how employment duration is affected by the recruiting method. Recall that the firm and inventor can perfectly observe the true match value θ at the beginning of the second period. The inventor leaves the job if it is less than the reservation value θ^*. Therefore, the probability that an inventor leaves at the employed firm is given by

$$\int^{\theta^*} dF(\theta | q_k, s_k^2) = \Phi\left(\frac{\theta^* - \mu}{s_k}\right).$$

It can be easily shown that this probability is increasing function of $\sigma^2_{\varepsilon k}$. Because $\sigma^2_{\varepsilon N} < \sigma^2_{\varepsilon P}$, the public recruited inventors are more likely to leave the employed firm than the network recruited inventors. This observation leads to the following propositon about employment duration.

Proposition 1 *The network-recruited inventors will have longer employment duration than the publicly-recruited inventors.*

Logically, a network-recruited inventor is less likely to quit his job than a publicly-recruited inventor because he, employed through a collaboration network, is more likely to have a "good match", and is thus less likely to be disappointed with his match value with the firm. Therefore we have the following proposition.

We now turn to the effect of referrals on the average productivity in the first period. For simplicity, we assume that firms employ referred and nonreferred inventors with probability p and $1-p$, respectively. Then the value of unemployment, W, is given by:

$$\begin{aligned} W &= p\,\mathrm{E}[V(q_N)] + (1-p)\,\mathrm{E}[V(q_P)], \\ &= p\int V(q_N)dG(q_N|\mu,\sigma_{qN}^2) + (1-p)\int V(q_P)dG(q_P|\mu,\sigma_{qP}^2), \end{aligned}$$

where $\sigma_{qk}^2 = \sigma_\theta^4/(\sigma_{\varepsilon k}^2 + \sigma_\theta^2)$ for $k = N, P$. It is important to note that the reservation value θ^* does not depend on the existence of referrals because it is given by equation (5). On the other hand, the reservation wage q^* depends on whether the inventor is network recruited or publicly recruited. According to equation (9) the reservation wages are provided by:

$$q_k^* = \theta^* - \frac{\beta}{1-\beta}\int_{\theta^*}(\theta-\theta^*)dF(\theta|q_k^*, s_k^2),$$

where s_k^2 is the variance of the posterior distribution of θ for type k inventors. Note that $\int_{\theta^*}(\theta-\theta^*)dF(\theta|q^*, s^2)$ is increasing in $s^2 = (1/\sigma_\varepsilon^2 + 1/\sigma_\theta^2)^{-1}$, and thus increasing in σ_ε^2. The order of prediction precision $\sigma_{\varepsilon N}^2 < \sigma_{\varepsilon P}^2$ implies that $q_N^* > q_P^*$. It thus implies that the reservation wages of network-recruited inventors are higher than those of publicly recruited inventors.

Given the entry wage q offered by a firm, a type k inventor accepts the offer, and is employed by the firm if it is above the reservation wage $q > q_k^*$ for $k = N, P$. Therefore, the mean productivities for type k inventor are given by

$$\mathrm{E}(\theta|q > q_k^*) = \frac{\int \theta\left[\int_{q_k^*}\phi\left((\theta-q)/s_k\right)\phi\left((q-\mu)/\sigma_{q_k}\right)dq\right]d\theta}{\Phi\left((\mu-q_k^*)/\sigma_{q_k}\right)}.$$

The numerator can be computed as:

$$\int_{q_k^*}\left[\int \theta\phi\left((\theta-q)/s\right)d\theta\right]\phi\left((q-\mu)/\sigma_{q_k}\right)dq.$$

Because $q = \int\theta\phi\left((\theta-q)/s\right)d\theta$, we obtain the following result:

$$\mathrm{E}(\theta|q > q_k^*) = \frac{\int_{q_k^*} q\phi\left((q-\mu)/\sigma_{q_k}\right)dq}{\Phi\left((\mu-q_k^*)/\sigma_{q_k}\right)} = \mathrm{E}(q|q > q_k^*). \tag{10}$$

It can be easily seen that $\mathrm{E}(q|q > q_k^*)$ is an increasing function of q_k^*, and so is $E(\theta|q > q_k^*)$ given the result (10). As shown above, we have $q_N^* > q_P^*$. It is thus implied that:

$$\mathrm{E}(\theta|q > q_N^*) > \mathrm{E}(\theta|q > q_P^*).$$

This result implies the following proposition.

Proposition 2 *The network-recruited inventors exhibit a higher initial productivity than the publicly recruited inventors, on average.*

The intuitive reason for network-recruited inventors tending to show higher productivity than publicly recruited inventors is as follows: if the firm is more certain about a recruited person's match value, a mismatch is less likely to occur. Thus, the referrals allow the firm to select more inventors having a "good match", and, at the same time, allow more inventors to self-select themselves into the jobs in which they are more productive.

We turn to the mean productivity of inventors in the second period. The behavioral model implies that the inventors whose match values are less than θ^* have left the firm. Therefore, the productivity in the second period is given by $\mathrm{E}(\theta|q > q_k^*, \theta > \theta^*)$. Note that the conditional density function of θ given the event that $(q > q_k^*) \cap (\theta > \theta^*)$ occurs is provided by:

$$\begin{cases} \frac{\int_{q_k^*} f(\theta|q,s_k^2)g(q|\mu,\sigma_{qk}^2)dq}{\mathrm{Prob}\left[(q>q_k^*)\cap(\theta>\theta^*)\right]} = \frac{\int_{q_k^*} \phi((\theta-q)/s_k)\phi\left((q-\mu)/\sigma_{q_k}\right)dq}{\mathrm{Prob}\left[(q>q_k^*)\cap(\theta>\theta^*)\right]} & \text{if } \theta \geq \theta^* \\ 0 & \text{if } \theta < \theta^*. \end{cases} \quad (11)$$

We show in the appendix that the mean productivity in the *second period* is given by:

$$\mathrm{E}(\theta|q > q_k^*, \theta > \theta^*) = \frac{\int_{q_k^*} \left[q + s\lambda\left((q-\mu)/s_k\right)\right] \phi\left((q-\mu)/\sigma_{q_k}\right) dq}{\int_{q_k^*} \Phi\left((\mu-q)/s_k\right) \phi\left((q-\mu)/\sigma_{q_k}\right) dq}, \quad (12)$$

where $\lambda(t) \equiv \phi(t)/(1-\Phi(t))$ is the inverse Mill's ratio. Recall that the mean productivity in the *first period* is given by equation (10). Comparing equation (10) with equation (12), and because $s\lambda\left((q-\mu)/\sigma_{q_k}\right) \geq 0$ for any q, we can say that:

$$\mathrm{E}(\theta|q > q_k^*) \leq \mathrm{E}(\theta|q > q_k^*, \theta > \theta^*).$$

We therefore have the following proposition.

Proposition 3 *The average productivity weakly increases with tenure.*

It should be noted that, because our model assumes no human capital accumulation, the average productivity grows with tenure to the extent that inventors having lower match values leave their firm as time passes.

Following Simon and Warner (1992), we consider the use of referrals in terms of the limiting case where $\sigma^2_{\varepsilon N} \to 0$, while $\sigma^2_{\varepsilon P}$ is strictly positive for the publicly recruited inventors. Noting that $s^2_N = (1/\sigma^2_\theta + 1/\sigma^2_{\varepsilon N})^{-1}$, $\sigma^2_{\varepsilon N} \to 0$ implies $s^2_N \to 0$. Furthermore, $\sigma^2_{\varepsilon N} \to 0$ implies $\sigma^2_{qN} \to 0$, and thus $\Phi\left((q-\mu)/\sigma_{qN}\right) \to 1$. Therefore, according to equation (12), we can see that, for the network-recruited inventors,

$$\mathrm{E}(\theta | q > q^*_N) = \mathrm{E}(\theta | q > q^*_N, \theta > \theta^*).$$

This implies the following proposition.

Proposition 4 *The publicly recruited inventors have higher productivity growth than the network-recruited inventors as tenure increases.*

The intuitive reason why the average productivity growth is higher for publicly recruited inventors than network-recruited inventors is that the former are more likely to be "mismatched" , and many of them switch firms, sooner or later, once their true match value is revealed. Thus, the group average of the productivity of publicly recruited inventors increases with tenure. On the other hand, network-recruited inventors who have good match values are less likely to switch firms. Therefore their productivity is less susceptible to change.

3 Data

We base our analysis on the *NBER Patent Data File*.[3] This dataset covers all the patent applications between 1963 to 1999 and granted up to December 1999. For each patent, the list of inventors, assignee, and year of application are recorded, along with other information such as address of inventor, type of assignee, and technological category of the patent. We supplement the month of patent application with the *USPTO PatentBIB* database. The *NBER Patent Data File* contains the patent citations that were applied for after 1975. Because the citation information is required to identify unique inventors, as described below, the patents that were applied for before 1974 were excluded from our sample. It should be noted that many patents that were applied for in 1998 and 1999 are missing from the database because there is often a lag of a few years before patents are granted.[4] Therefore,

[3] For detailed information, see Hall, Jaffe, and Trajtenberg (2001)

[4] For example, Hall, Jaffe, and Trajtenberg (2001) show that the average time lag between the application and grant date in the late 1990s was 1.8 years.

we use the patents that were applied for between 1975 (the first year in which citation information is available) and 1997 (the latest year in which the effect of truncation is not substantial) in our analysis.

3.1 Employment History

In order to analyze the mobility of inventors, we are required to identify, for each inventor in the dataset, his affiliation over time from the information contained in the patents. This, however, is not a simple task because the same inventor may have his name spelled differently across his patents, or different inventors may have the same name. To overcome this difficulty, we follow the computerized matching procedure (CMP) proposed by Trajtenberg, Shiff, and Melamed (2006) in identifying inventors. In doing so, CMP utilizes not only the name of inventors recorded in the patents, but also patent citations, and inventors' addresses, while allowing for the possibility of spelling errors in names.[5] In addition, to increase the accuracy of matching individual inventors, we focus on the inventors whose addresses are in the U.S.

Once inventors are identified, the history of granted patents is generated for each inventor. Furthermore, based on the application dates and assignees of those patents, we create his employment history. Our basic strategy is to consider the longest possible employment durations by assuming that an inventor was employed by an assignee for all the period during which he applied for patents assigned to the assignee.

It should be noted, however, that if companies undergo a merger or acquisition, the acquired company appears under the name of the acquiring company after the official date of merger. To avoid identifying changes in the assignee's name because of M&A as changes in the inventor's employer, we supplement our data by *SDC Platinum, the Worldwide Mergers and Acquisitions Database*, issued by Thomson-Reuters. Among all the M&As since 1979 that are reported in *SDC Platinum*, we select the cases where the acquiring company obtains all the stock of the target company. We then consider those two companies to be in a parent–subsidiary relationship and treat them as one company after the merger. We also subsample the inventors whose lists of assignees are categorized as private companies located in the U.S.[6]

Let us now describe, in detail, how we construct the employment histories for

[5] The details of this procedure are summarized in the appendix.

[6] To identify the type of assignees listed in the patent application data we utilize the corporate and noncorporate name matching results available from Bronwyn Hall's web page of *The Patent Name-Matching Project* (`http://elsa.berkeley.edu/~bhhall/pat/namematch.html`). In this analysis, we exclude assignees categorized as government institutions, universities and hospitals.

inventors. As noted above, our basic strategy is to consider the longest possible employment durations. We list all the assignees of the patents listed in the individual history. Then, given the listed assignees, we take the earliest and the latest patent application dates, and consider the interval between the two dates as a candidate job spell (CJS).[7]

After identifying all the CJSs and sorting them based on their starting date, (1) we first eliminate all the CJSs that are contained entirely within a longer CJS. We assume that those patents that have created such shorter CJSs are the result of interassignee collaborations, and the inventor continued to be employed by the original employer during such collaborations.[8] (2) Among the remaining CJSs, we drop CJSs that overlap with each other. We do this because we are unable to determine when the inventor moved from one assignee to another. This criterion is quite stringent, and creates many empty, and often long, intervals in inventors' employment histories. Yet we have chosen to follow the rule because our aim is not to have a complete employment history of all the inventors but to analyze the job tenures and productivities of inventors for the periods of employment that are defined as clearly as possible. We consider the CJSs that have survived these two elimination processes as valid job spells (to be called job spells, below). Furthermore, during each job spell, we assume that the inventor was employed by the corresponding assignee.

The procedure is summarized in Figure 1. The inventor shown in the figure applied for 11 patents under five different assignees. Given that P_{ij} indicates the application date of the j-th patent that this inventor applied for under assignee i, the figure shows that we have five CJSs. Because CJS_3 is contained in CJS_2, it is dropped. Furthermore, because CJS_4 and CJS_5 overlap with each other, they are dropped as well. As a result, CJS_1 and CJS_2, shown in bold and with arrows, are considered as job spells, during which the inventor obtained three and four patents, respectively.

Given the data construction procedure presented above, we find 51,896 inventors who experienced at least one job change. For those inventors, 115,307 job spells are identified[9].It is found that More than 95 percent of those inventors had only either two or three spells.

[7]We allow CJSs whose spell length is zero, which happens when an inventor applied for all the patents from an assignee within a month.

[8]A similar assumption is made by previous studies (e.g., Hoisl, 2007).

[9]We find that the total number of CJSs is 118,447. This implies that the identified job spells (115,307) account for 97 percent of the total CJSs.

3.2 Recruitment Method

We can obtain information concerning the recruiting method, whether network recruited or publicly recruited, from the patent collaboration histories embodied by colisted inventors. In doing so, we define the set of collaborators of inventor i on date t by all the inventors who are colisted in the patents investor i has applied for (and later granted) before date t. For example, for the inventor shown in Figure 1, the set of collaborators on date P_{21} constitutes all of the coinventors listed in the three patents applied for during spell 1 (those applied for on P_{11}, P_{12}, and P_{13}). Given the set of his collaborators, we identify collaborator i as network recruited if at least one of his collaborators is employed by the same firm at the beginning of inventor i's job spell. If this is not the case, inventor i is considered to be recruited publicly.

It is possible that more recently established collaborations may generate more meaningful referral. Therefore, in the analyses below, we also consider more restricted sets of collaborators in defining network recruitment. Namely, in addition to the set of collaborators defined above (we call these "overall collaborations"), we also consider sets of collaborators at time t based on the successful patents that have been applied for within 12, 24, and 36 months prior to date t.

Using the definition of the overall collaboration network that encompasses all the past collaborations, we find that 10,758 jobs are originated via network recruitment, which corresponds to 9.33 percent of total jobs. If the collaboration network is restricted to 12, 24 and 36 months, the network-recruited jobs are 2,538 (2.20 percent), 5,081 (4.41 percent) and 6,794 (5.89 percent) respectively.

4 Empirical Results

In this section, we first examine the prediction presented by our theoretical model that employment durations are different between network-recruited inventors and publicly recruited inventors. We then examine the predictions of the model that productivities are also different between these two groups of inventors.

4.1 Employment Duration Results

Network-recruited inventors, with relatively better match values, should be less likely to leave firms than publicly recruited inventors, as presented by Proposition 1. We test this hypothesis using employment duration data. Because no inventors are recruited via collaboration network for the first jobs, we examine this hypothesis only for *subsequent* jobs of inventors who switched their jobs at least once. So, the first job spells are excluded from the estimation samples.

Figure 2 plots the survival curves for employment duration after job transition for network-recruited inventors and publicly recruited inventors respectively. We follow the definition of network recruitment as presented in the previous section. Because the observed job spell data are interval censored,[10] we employ a non-parametric maximum likelihood estimator for interval censored data proposed by Turnbull (1976). It is shown that the employment duration is almost uniformly longer for network-recruited inventors than for publicly recruited inventors.

Table 1 contrasts the median employment durations between publicly recruited inventors and network recruited inventors for the four collaboration networks we have considered. It shows that the median employment duration is always longer for network-recruited inventors than for publicly recruited inventors. We use the log-rank statistic (Peto and Peto, 1972) to test the equality of the survival functions between these two groups, and find that all of these tests are strongly rejected at the 1 percent significance level. We find that median employment duration is 71 months for publicly recruited inventors and 93 months for network-recruited inventors. That is, it takes about six years (eight years) for half of publicly recruited (network-recruited) inventors, respectively, to leave firms.

We also estimate hazard regression models of inventors' job turnover, controlling for their characteristics. The hazard function is given by Weibull specification with $h(t_{if}|X_{if}) = \exp(X_{if}\beta + \delta NET_{if})\alpha t_{if}^{\alpha-1}$ where t_{if} is inventor i's employment duration at firm f, and X_{if} is a vector of time-invariant individual characteristics. We explicitly control the network recruited dummy, NET_{if} which takes a value of one if inventor i is a network-recruited inventor at firm f and zero otherwise. According to Proposition 1, we expect that $\delta < 0$, that is, the network recruited inventors are less likely to leave the employed job than the publicly recruited inventors. As other explanatory variables, X_{if}, we include the years of research experience before being employed by firm f. It is given by the number of years since the inventor i applied patents for the first time until the time when he is employed by firm f. We also include research field dummies. The research field dummy is defined for the six main technological categories ($m = 6$): chemical (excluding drugs), computers and communications, drugs and medical, electrical and

[10] Our job spell data are interval censored because the value is known to lie in an interval, instead of being observed exactly. To understand this, for example, consider a researcher who changed firms twice, say, firstly from firm f_1 to firm f_2, and secondly from firm f_2 to firm f_3. Given the employment histories constructed by the patent file, we know that he entered firm f_2 sometime after the calendar month, r_1, at which time he applied for a patent at firm f_1 for the last time, and sometime before l_2 at which time he applied for a patent at firm f_2 for the first time. Similarly, we know that he stayed at firm f_2 at least until r_2 at which time he applied for a patent at firm f_2 for the last time, and not after l_3 at which time he applied for a patent at firm f_3 for the first time. In that case, the job spell at firm f_2, denoted by t_2, is interval censored data with $(l_2 - r_2) < t_2 < (l_3 - r_1)$.

electronics, mechanical, and others.[11] The mth field dummy takes a value of one if inventor i has applied for a patent in the mth field at firm f in year t. Finally, we include the total number of patents and the annual average number of patents that inventor i applied before firm f. They are used as proxies for inventor's research ability.

Table 2 presents the estimation results of the hazard regression model. As in the survival curve analysis, interval censoring is taken into account for estimation. We use the total number of previously applied patents in column (1) and use the average number of previously applied patents in column (2) to control for the inventor's ability, respectively. In both specifications, it is presented that the coefficient δ is negative and statistically significant, and thus the network recruitment method significantly decreases the hazard of leaving the employment. Therefore, it is interpreted that the network-recruited inventors are likely to stay longer than the publicly recruited inventors. In column (3)-(5), we use various network recruitment measures that limit the intervals after the collaborations were made. It is also presented that the estimates of the coefficients of network-recruited dummies are significantly negative in all specifications. These estimates imply that the network recruited inventors are about 40 percent less likely to leave the job than the publicly recruited inventors.

4.2 Productivity Results

Our theoretical model presents two main empirically testable hypotheses about inventors' productivity. The first hypothesis is given by Proposition 2 that network-recruited inventors have higher initial productivity than publicly recruited inventors. The second hypothesis is given by Proposition 4 that within-firm productivity growth rates are different between publicly recruited inventors and network-recruited inventors; in particular, the former has a steeper productivity-tenure profile than the latter.

To examine these hypotheses, we introduce a regression framework. The dependent variable of the regression is the number of successful patent applications made by an inventor in one year, which is considered to be a measure of the inventor's productivity. Because the dependent variable is an integer variable with many zeros and ones, we use *Poisson-based* specification as in Hausman, Hall, and Griliches (1984); Hall and Ziedonis (2001). Consider an inventor i who works at firm f. We assume that the expected number of patents, P_{ift}, applied for by the inventor in year t, conditional on the characteristics of the inventor and firm is given

[11] We follow the technological category definition of Hall, Jaffe, and Trajtenberg (2001)

by:

$$\mathrm{E}(P_{ift}|X_{ift}, W_{ft}, NET_{if}) = \exp(\alpha + X_{ift}\beta + W_{ft}\gamma + \rho NET_{if}), \qquad (13)$$

where X_{ift} is a vector of individual-firm time-specific variables and W_{ft} is a vector of firm time-specific variables.

A key variable in our specification above is the network-recruited dummy, NET_{if}, which takes a value of one if inventor i is a network-recruited inventor at firm f and zero otherwise. The scalar coefficient ρ of the network-recruited dummy can be interpreted as the *productivity premium* for network-recruited inventors over publicly recruited inventors. According to Proposition 2, we expect that there is a positive productivity premium.

As individual-firm-time specific variables, X_{ift}, we include the years of potential research experience since the inventor i applied patents for the first time; and the years of tenure at firm f. Both years are measured as of period t. While the years of research experience are accumulated over time, the years of tenure are resetted to be zero whenever the inventor switched his jobs. We also include research field dummies for $m = 6$ categories. The total and the annual average numbers of patents that the inventor i applied befor firm f are included in the regression. As in the hazard regression, they are used as proxies for the inventor's innate research ability. As firm-time-specific variables W_{ft}, we include the total number of patents that were applied by all inventors employed at firm f during year t. This variable is considered to be a proxy for the research capacity of the firm. It is expected that the higher the firm's research capacity, the more patents the firm produces, and vice versa.[12] Following the previous literature (e.g., Hall and Ziedonis, 2001), we also include annual dummies, which accounts for the growth of patenting propensities.

We estimate the Poisson regression model (13) presented above using the dataset described in Section 3. We again restrict samples to the inventors who experienced at least one job transition because no inventor is recruited via his collaboration network for the first job. It thus implies that we estimate the effect of referrals on inventors' productivity *after switching firms*.[13] As should be clear from the above discussion, the data have an unbalanced panel structure with individual-firm-year being the unit of analysis. The data include 286,955 units of observation for 51,896 inventors. Table 3 shows the summary statistics of the patent counts and main explanatory variables used in the regression analysis.

[12] Often research capacity of a firm is measured by its R&D expenditure. We do not use it here because in our sample there are firms that are not listed on the stock market and such data are not available.

[13] The effect of network job referrals on the first employment productivity of workers, although they are not necessarily inventors, is analyzed by Simon and Warner (1992); Loury (2006).

Table 4 presents the estimation results of the baseline model.[14] In addition to the variables that are explained above, we included the first year tenure dummy that takes a value of one for the inventor who was in the first year of employment. The variable is included to control for our job spell construction property that at least one patent is included in the first tenure year. We report the heteroskedasticity robust standard errors in parentheses. They are known to be consistent even under misspecification of the distributional assumption.[15]

Column (1) shows the estimation result using the network recruited dummy constructed from the overall collaboration network. In this specification we include the total number of patents applied in the previous job as a proxy for the inventor's research ability. It is presented that the estimated coefficient of years of potential research experience is negative and statistically significant while the estimated coefficient of years of tenure is insignificant. In column (2) we include the square terms of these variables to allow for non-linear effects of these variables on productivity. It is shown that the change in productivity is not linear with the change in potential research experience but follows convex relationship. On the other hand, the years of tenure is found to have almost no significant impact on patent productivity. We recognize that these experience and tenure years variables might be strongly correlated with *unobserved* ability of the inventor, and thus may be endogenous [16]. So, these estimates should be taken with caution. In later section we will consider more seriously the problem of the individual unobserved factors that make some explanatory variables endogenous.

As for the other control variables, the estimates are consistent with our prior expectation. The estimated coefficient of the aggregate number of patents held by a firm presents that, as expected, inventors who worked at a high-research-capacity firm are more productive than those who worked at a low-research-capacity firm. The estimated coefficients of research field dummies show that "Chemical" is the most patent active research area during the sample period, followed by "Drugs and Medical" and "Computers and Communications."

In column (3) we use the average number of previously applied patents, instead of the total number of previously applied patents, as a proxy for their research ability. The estimation result shows that the coefficient is positive and statistically significant. The estimated coefficients of all other explanatory variables are qual-

[14] In this and the following tables, the estimates of the annual dummies and research field dummies are not reported. All estimation results are reported in appendix.

[15] See Gourieroux, Monfort, and Trognon (1984) for a detailed discussion.

[16] For example, a person with higher ability will stay being an active patent inventor longer, so that his research experience will become larger. Even though we include the numbers of the previously applied patents to control for the inventors' ability, we may not be able to exclude the possibility that there is still unobserved individual ability left.

itatively identical to those in the previous specifications. So, we might be able to say that there is no significant difference in regression estimates no matter of which variable, either total or average, is used to controll for inventors' ability. Given that the average number of patents is more susceptible to interval censoring of employment duration than the total number of patents, we will use the total number of previously applied patents as a proxy for inventors' ability in what follows.

An impoprtant finding in Table 4 is that, in column (1) – (3), the estimates of productivity premium for the network recruited inventors, ρ, are all positive and statistically significant. This finding is consistently observed in columns (4) – (6) in which collaborations only from limited intervals before the job switch are considered. It should be noted that the estimated productivity premiums are positive even after controlling the proxies for the inventors' ability. All these estimation results confirm that network recruited inventors are more productive than publicly recruited inventors. More interestingly, we find that the productivity premium for network recruited inventors increases as the coverage period of collaboration networks becomes shorter. It suggests that better job matches are more likely to occur between inventors and firms if referrals are based on more recent collaborations. This result is consistent with our view that the collaboration network is a method by which agents get information about unobserved match quality, and the more recent the information is, the more certain they are about the quality of their match.

We now turn to the second hypothesis that within-firm productivity growth is different between network-recruited and publicly recruited inventors. In order to examine this hypothesis, we add the *interaction terms* of the network-recruited dummy and tenure dummies to the baseline regression model (13). The regression model is then given by:

$$\begin{aligned} &\mathrm{E}(P_{ift}|X_{ift}, W_{ft}, NET_{if}) = \\ &\exp(\alpha + X_{ift}\beta + W_{ft}\gamma + \sum_{k=1}^{K} \rho_k (NET_{if} \cdot Tenure_{iftk}), \end{aligned} \tag{14}$$

where $Tenure_{iftk}$ is the kth tenure year dummy for inventor i at firm f, and takes one if inventor i is employed in kth year by firm f. In this within-firm productivity growth regression, the coefficient ρ_k of the interaction term captures the productivity premium for network-recruited inventors over publicly recruited inventors observed in the kth tenure year. A higher value of ρ_k means that the network-recruited inventors have a higher productivity than publicly recruited inventors in tenure year k. As can be shown easily, $\sum_k \rho_k = \rho$. Although the model assumes that agents learn about the true value of productivity after one period, such learning may take place over several years in reality. Therefore, given the hypothesis that within-firm productivity growth is faster for the publicly recruited inventors than for the network-recruited inventors, it is predicted that the coefficient ρ_k is weakly *decreasing* with tenure year k, i.e., $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_K$.

Table 5 presents the estimation results for the within-firm productivity growth regression model (14). The set of controls other than the network-recruited dummy are the same as before. Because of the space limitation, only the estimates of the coefficient ρ_ks up to 10 years are presented. The full estimation results are found in appendix.

The estimation results show that the estimates of the coefficients ρ_k of the interaction terms are only significant for the initial tenure years for all specifications. In the best specifications, given by Column (2), (4), (5) and (6), these coefficients for the first four to six tenure years are positive and statistically significant, while they become negative but insignificant for later tenure years. These estimation results imply that the initial positive productivity premium for network-recruited over publicly recruited inventors diminishes with tenure years, and the productivity difference between the two groups disappears in the end. This result is consistent with the hypothesis that publicly recruited inventors have a steeper tenure-productivity profile than network-recruited inventors, and thus supports the hypothesis presented by our theoretical model.

4.3 Controlling for Unobserved Heterogeneity

The estimation results presented above indicate that the positive productivity premium for the network recruited inventors are consistent with our theory that the past research collaborations may create better matches between inventors and firms. However, it is possible to deliver an alternative explanation to such a story. As often argued in the previous literature (e.g., Montgomery, 1991; Saloner, 1985), more productive workers may receive more referral offers, and thus referrals may be strongly correlated with the unobserved ability of an inventor. If this is the case, the observed productivity difference between the network recruited and publicly recruited inventors can be explained by the difference in the unobserved ability between these groups. As discussed in Simon and Warner, however, the observed *difference* in the average productivity growth between the two groups cannot explained by the alternative theory presented above. It can be consistently explained by the exit of mismatched inventors as our matched-base theory predicts. Thus, the previous estimation results on different within-firm productivity growth pattern may support for our theory that firms and inventors might rely on research collaboration networks to collect information about their match quality.

In what follows, furthermore, we will present more direct support for our productivity match hypothesis. Given a panel structure of our data set, we may be able to control for the time-invariant unobserved individual factors, including inventor's innate research abilities, by incorporating fixed effects in the productivity regression model. For that purpose we augmented the baseline regression model (13) by adding an individual time-invariant fixed effect:

$$\mathrm{E}(P_{ift}|X_{ift}, W_{ft}, NET_{if}) = \exp(\alpha_i + X_{ift}\beta + W_{ft}\gamma + \rho NET_{if}). \quad (15)$$

The fixed-effect, α_i, captures inventor i's unobserved heterogeneity that affects his overall research productivity. By the same token, we incorporate the fixed-effect term α_i into the within-firm productivity growth regression model (14) .

Table 6 and 7 presents the estimation results from the fixed-effect specifications.[17] Table 6 presents the estimation results for the baseline model while Table 7 presents the estimation results for the within-firm productivity growth model.

Table 6 shows that, for all definitions of network recruitment reported in columns (1)–(4), the productivity premium ρ is again positive and statistically significant, at least, at the 1 percent level. Furthermore, the effect increases among the more recent collaborations, as was found in Table 4. Thus, our hypothesis that the collaboration networks bring about better matches between inventors and firms is supported even after controlling for unobserved heterogeneity among inventors.

Table 7 shows the estimated coefficients of the interaction term, ρ_k. The interaction terms up to of the nineth tenure year are positive and statistically significant at less than the 10 percent level for all the specifications for the overall collaboration network, and they are significant up to the eight tenure year if the collaboration with limited intervals are used. Furthermore, it can be seen that the estimated productivity premiums are not significant after those years. In particular, the estimation results show that the productivity premium for the network-recruited inventors are persistent only in the early phase of tenure, and disappears quickly after these periods. These results confirm our hypothesis that network-recruited inventors are initially more productive than publicly recruited inventors, but the productivity advantage disappears with tenure, and as the fixed effect estimation results show, the convergence of productivity between the two groups occurs within from eight to nine years. It suggests that inventors learn their match productivity rather quickly after moving into a new firm.

Looking at the estimated coefficients of explanatory variables other than network recruitment dummies, it can be also noticed that the coefficient of the total number of patents in the previous employment are negative and statistically significant for all specifications under the fixed effect specification [18]. This is contrast

[17]The full estimation results are presented in the appendix.

[18]The same estimation results are also found in the fixed-effects regression where we use the average number of the patents that were applied in the previous jobs, instead. The estimated coefficient is found to be negative and statistically significant.

with the estimates in Table 4 and Table 5 when we ignore the unobserved individual factors, and found that the estimated coefficients were positive and statistically significant. One explanation for these findings is that the total number of previously applied patents may capture some part of individual ability, so that it is positively associated with inventors' productivity. Yet, once time-invariant individual ability is controlled by fixed effect, the variable may represent a genuine match value in the previous employment. Thus the estimation results indicate that, after inventors' ability is taken into account, the match values between the past and present employment may be negatively correlated. Our simple search model does not predict this empirical regularity, so that the further extension of the theoretical model is needed in the future research.

Finally it is apparent from Table 6 and Table 7 that there is a significant positive relationship between research experience and patent productivity. Furthermore, although the relationship is less clear in Table 6, it is presented in Table 7 that within-firm tenure is significantly associated with productivity though the association is nonlinear with *concave* relationship. This finding is partly compatible with Proposition 3 stating that the average productivity increases with tenure, although the existence of the peak in the average productivity over tenure cannot be fully explained by our model. Perhaps, other factors, such as job adjustment or job training, may affect the tenure-productivity profile. The development of a model that fully accounts for those factors is left for future research, once such data is available.

5 Conclusion

This paper develops a simple model of job match between inventors and firms through research collaboration networks. The model's prediction is tested using panel data of affiliations and productivities of inventors constructed from the NBER patent database. The empirical analysis supports the prediction of the theoretical model. It was found that inventors who moved to companies where their collaborators were employed had about two years longer tenure in median employment duration than those who moved to companies with which they had no personal connections. Moreover, on average the former group produced more patents by about 20 percent than the latter group. Finally, the fixed-effect estimates of the productivity premium show that unobserved individual characteristics cannot explain all of the productivity difference between network-recruited inventors and publicly recruited inventors. Thus some of the productivity premium can be attributed to improved match quality by the reference through the collaboration network.

Our findings suggest that firms use interfirm research collaboration networks not only as a way of exploiting external knowledge, as previously reported (Singh, 2005), but also as a way of recruiting inventors with good match values. This unique role of collaboration networks as a recruiting method has been played down by previous studies. The empirical analysis of this paper thus offers a speculation that firms with higher connectivity in R&D networks can recruit better matched inventors than those with lower connectivity. This may explain the observed relationship between firms' inventive productivity and their network connectivity in R&D networks (Ahuja, 2000; Schilling and Phelps, 2007). Thus a future extension of this paper will analyze the relationship between firms' R&D network position and employer–employee match value in patent production. This will be a step forward in understanding the mechanism of how the global R&D network structure influences firm-level innovation.

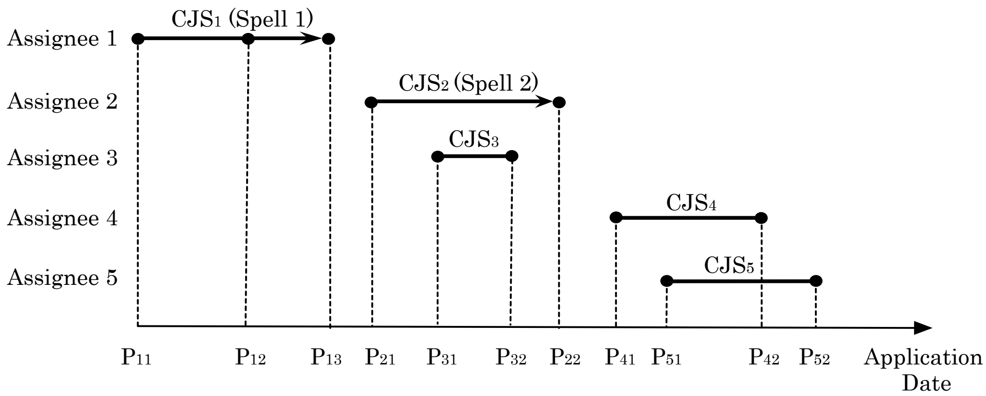

Figure 1: The Construction of Job Spells

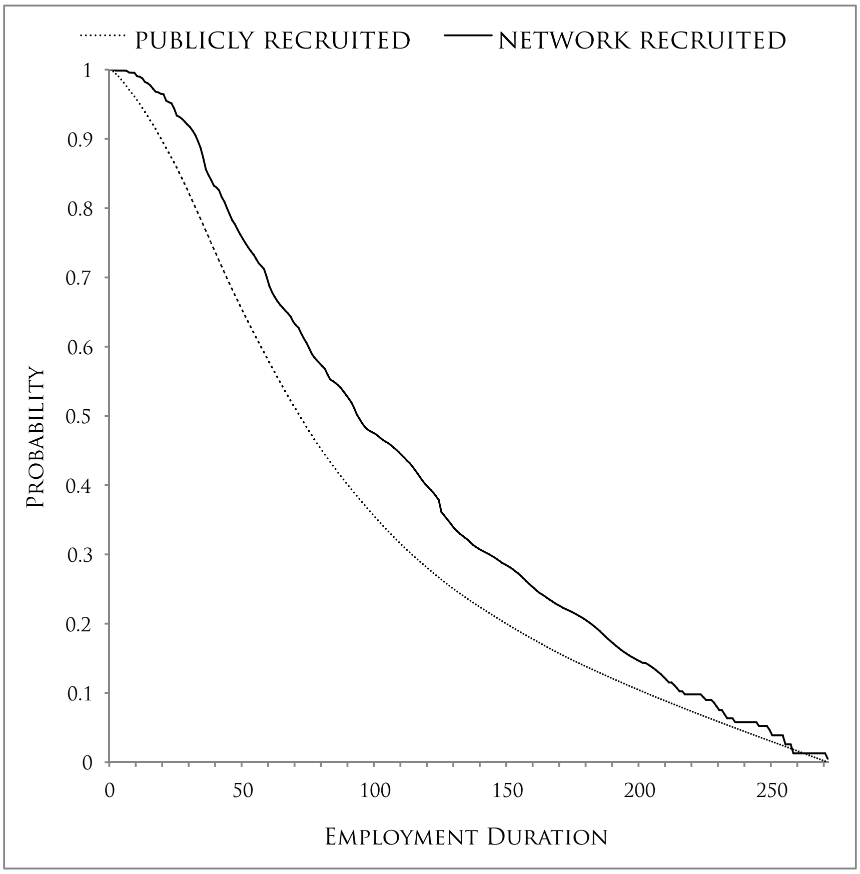

Figure 2: Survival Curves for Employment Duration after Job Transition

Table 1: Median Employment Durations

	OVERALL COLLBORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
Publicly Recruited	71	75	78	82
Network Recruited	93	110	117	124
Log-Rank	-10.33	-8.16	-7.99	-5.32
	(3.56)	(2.84)	(2.56)	(1.73)

NOTE.– Standard errors are in parentheses. All test results are statistically significant for χ^2 test at less than one percent level ($p < .01$). † Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch.

Table 2: Weibull Hazard Regression Results

	OVERALL COLLBORATION		LIMITED INTERVAL COLLABORATION†		
			WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)
Network referral dummy: δ	$-.5058$	$-.4675$	$-.4325$	$-.4269$	$-.4395$
	$(.031)$	$(.030)$	$(.039)$	$(.044)$	$(.060)$
Field dummies:					
Chemical	-1.2045	-1.1882	-1.2110	-1.2136	-1.2171
	$(.031)$	$(.031)$	$(.031)$	$(.031)$	$(.031)$
Comp.& Comm.	-1.0751	-1.0771	-1.0783	-1.0782	-1.0783
	$(.035)$	$(.035)$	$(.035)$	$(.035)$	$(.035)$
Drugs & Medical	-1.0293	-1.0223	-1.0362	-1.0367	-1.0387
	$(.039)$	$(.039)$	$(.038)$	$(.038)$	$(.038)$
Elec. & Electronics	-1.1066	-1.1008	-1.1000	-1.1003	-1.0996
	$(.031)$	$(.031)$	$(.031)$	$(.031)$	$(.031)$
Mechanical	-1.1505	-1.1476	-1.1476	-1.1490	-1.1489
	$(.030)$	$(.030)$	$(.030)$	$(.030)$	$(.030)$
Others	-1.0775	-1.0782	-1.0763	-1.0769	-1.0748
	$(.031)$	$(.030)$	$(.030)$	$(.030)$	$(.030)$
Previously applied patents:					
Total number	$.0287$		$.0273$	$.0269$	$.0259$
	$(.002)$		$(.002)$	$(.002)$	$(.002)$
Annual average		$.0326$			
		$(.004)$			
Potential research years	$-.0893$	$-.0819$	$-.0965$	$-.0958$	$-.0900$
	$(.009)$	$(.009)$	$(.009)$	$(.009)$	$(.009)$
Potential research years squared	$.0036$	$.0035$	$.0039$	$.0039$	$.0037$
	$(.000)$	$(.000)$	$(.000)$	$(.000)$	$(.000)$
$\log \alpha$ [a]	$.4142$	$.4125$	$.4183$	$.4200$	$.4231$
	$(.010)$	$(.010)$	$(.010)$	$(.010)$	$(.010)$
Constant	-5.0659	-5.0755	-5.1001	-5.1243	-5.1809
	$(.074)$	$(.074)$	$(.075)$	$(.074)$	$(.074)$
Log-likelihood	-16489	-16510	-16573	-16592	-16619
Observations	33178	33178	33178	33178	33178

NOTE.– Robust standard errors are in parentheses. All variables are statistically significant at less than one percent level ($p < .01$).

[a] The duration dependence is represented by parameter α.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch.

Table 3: Summary Statistics

VARIABLE	TOTAL	NETWORK RECRUITED	PUBLICLY RECRUITED
Number of patents made by an individual in a year	1.003	1.126	.989
	(1.083)	(1.206)	(1.067)
Network referral dummies:			
overall	.102	–	–
	(.303)		
within 36 months	.064	–	–
	(.245)		
within 24 months	.050	–	–
	(.217)		
within 12 months	.026	–	–
	(.159)		
Previously applied patents:			
Total number	1.716	4.769	1.368
	(3.706)	(6.338)	(3.087)
Annual average	.906	2.139	.765
	(2.153)	(3.438)	(1.900)
Potential research years	5.713	8.109	5.439
	(5.353)	(5.269)	(5.294)
Tenure years	3.344	3.045	3.378
	(3.176)	(2.653)	(3.229)
Number of patents made by a firm in a year (in thousand)	.088	.078	.090
	(.185)	(.183)	(.186)
Research field dummies:			
Chemical	.316	.349	.312
	(.465)	(.477)	(.463)
Comp.& Comm.	.194	.182	.195
	(.395)	(.386)	(.396)
Drugs & Medical	.131	.178	.125
	(.337)	(.383)	(.331)
Elec. & Electronics	.288	.248	.293
	(.453)	(.432)	(.455)
Mechanical	.307	.273	.311
	(.461)	(.446)	(.463)
Others	.295	.265	.298
	(.456)	(.441)	(.458)
N	286954	29393	257561

Table 4: Baseline Productivity Regression Estimates

	Overall Collaboration			Limited Interval † Collaboration		
				Within 36	Within 24	Within 12
	(1)	(2)	(3)	(4)	(5)	(6)
Network referral dummy: ρ	$.0782^{***}$	$.0809^{***}$	$.1009^{***}$	$.0934^{***}$	$.0991^{***}$	$.1016^{***}$
	$(.0065)$	$(.0065)$	$(.0065)$	$(.0080)$	$(.0091)$	$(.0121)$
Previously applied patents:						
Total number	$.0113^{***}$	$.0111^{***}$		$.0113^{***}$	$.0114^{***}$	$.0117^{***}$
	$(.0006)$	$(.0006)$		$(.0007)$	$(.0007)$	$(.0007)$
Annual average			$.0078^{***}$			
			$(.0009)$			
Potential research years	$-.0065^{***}$	$-.0111^{***}$	$-.0088^{***}$	$-.0100^{***}$	$-.0097^{***}$	$-.0094^{***}$
	$(.0005)$	$(.0011)$	$(.0011)$	$(.0011)$	$(.0011)$	$(.0011)$
Potential research years squared		$.0003^{***}$	$.0003^{***}$	$.0002^{***}$	$.0002^{***}$	$.0002^{***}$
		$(.0001)$	$(.0001)$	$(.0001)$	$(.0001)$	$(.0001)$
Tenure years	$.0017$	$-.0038$	$-.0064$	$-.0046$	$-.0049$	$-.0053$
	$(.0011)$	$(.0033)$	$(.0033)$	$(.0033)$	$(.0033)$	$(.0033)$
Tenure years squared		$.0003^{*}$	$.0003$	$.0004^{*}$	$.0004^{*}$	$.0004^{*}$
		$(.0002)$	$(.0002)$	$(.0002)$	$(.0002)$	$(.0002)$
The first tenure year dummy	$.4737^{***}$	$.4600^{***}$	$.4594^{***}$	$.4592^{***}$	$.4590^{***}$	$.4577^{***}$
	$(.0056)$	$(.0075)$	$(.0075)$	$(.0075)$	$(.0075)$	$(.0075)$
Number of patents made by firm	$.1726^{***}$	$.1716^{***}$	$.1720^{***}$	$.1728^{***}$	$.1727^{***}$	$.1718^{***}$
	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$
Constant	$-.3525^{***}$	$-.3311^{***}$	$-.3289^{***}$	$-.3307^{***}$	$-.3294^{***}$	$-.3254^{***}$
	$(.0095)$	$(.0124)$	$(.0124)$	$(.0124)$	$(.0124)$	$(.0124)$
Log-likelihood	-355449	-355435	-355628	-355441	-355449	-355478
Observations	286954	286954	286954	286954	286954	286954

NOTE.– All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C1. Robust standard errors are in parentheses.
† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $*\, p < .1$. $**\ p < .05$. $***\, p < .01$.

Table 5: Within-firm Productivity Growth Regression Estimates

	Overall Collaboration			Limited Interval† Collaboration		
				Within 36	Within 24	Within 12
	(1)	(2)	(3)	(4)	(5)	(6)
Interaction terms of network and tenure dummies: ρ_k						
year 1	$.0571^{***}$	$.0623^{***}$	$.0819^{***}$	$.0630^{***}$	$.0693^{***}$	$.0726^{***}$
	$(.0070)$	$(.0071)$	$(.0071)$	$(.0090)$	$(.0105)$	$(.0147)$
year 2	$.0797^{***}$	$.0756^{***}$	$.0974^{***}$	$.1248^{***}$	$.1303^{***}$	$.1527^{***}$
	$(.0177)$	$(.0179)$	$(.0180)$	$(.0219)$	$(.0248)$	$(.0352)$
year 3	$.1708^{***}$	$.1713^{***}$	$.1920^{***}$	$.2138^{***}$	$.2174^{***}$	$.2219^{***}$
	$(.0195)$	$(.0195)$	$(.0196)$	$(.0245)$	$(.0265)$	$(.0331)$
year 4	$.1294^{***}$	$.1334^{***}$	$.1545^{***}$	$.1512^{***}$	$.1492^{***}$	$.1469^{***}$
	$(.0243)$	$(.0244)$	$(.0244)$	$(.0295)$	$(.0330)$	$(.0430)$
year 5	$.0901^{***}$	$.0966^{***}$	$.1182^{***}$	$.0961^{**}$	$.0957$	$.0105$
	$(.0320)$	$(.0321)$	$(.0321)$	$(.0421)$	$(.0497)$	$(.0470)$
year 6	$.0858^{**}$	$.0934^{**}$	$.1144^{***}$	$.0869^{*}$	$.0673$	$.0797$
	$(.0369)$	$(.0370)$	$(.0371)$		$(.0561)$	$(.0777)$
year 7	$.0823$	$.0900^{*}$	$.1053^{**}$	$.0471$	$.0073$	$-.0518$
	$(.0502)$	$(.0504)$	$(.0504)$	$(.0663)$	$(.0816)$	$(.0855)$
year 8	$.0856$	$.0920$	$.1079^{**}$	$.1028$	$.1123$	$.1248$
	$(.0519)$	$(.0521)$	$(.0522)$	$(.0680)$	$(.0690)$	$(.0902)$
year 9	$-.0581$	$-.0538$	$-.0385$	$-.0470$	$.0410$	$.0335$
	$(.0648)$	$(.0649)$	$(.0650)$	$(.0787)$	$(.0883)$	$(.1259)$
year 10	$-.0624$	$-.0602$	$-.0464$	$-.0168$	$-.0035$	$-.1208$
	$(.0720)$	$(.0721)$	$(.0722)$	$(.0913)$	$(.1102)$	$(.1505)$
Previously applied patents:						
Total number	$.0112^{***}$	$.0111^{***}$		$.0112^{***}$	$.0114^{***}$	$.0117^{***}$
	$(.0006)$	$(.0006)$		$(.0006)$	$(.0007)$	$(.0007)$
Annual average			$.0078^{***}$			
			$(.0009)$			
Potential research years	$-.0065^{***}$	$-.0113^{***}$	$-.0090^{***}$	$-.0102^{***}$	$-.0098^{***}$	$-.0095^{***}$
	$(.0005)$	$(.0011)$	$(.0011)$	$(.0011)$	$(.0011)$	$(.0011)$
Potential research years squared		$.0003^{***}$	$.0004^{***}$	$.0003^{***}$	$.0002^{***}$	$.0002^{***}$
		$(.0001)$	$(.0001)$	$(.0001)$	$(.0001)$	$(.0001)$
Tenure years	$.0030^{***}$	$-.0030$	$-.0055$	$-.0029$	$-.0037$	$-.0042$
	$(.0011)$	$(.0035)$	$(.0035)$	$(.0035)$	$(.0034)$	$(.0034)$
Tenure years squared		$.0004^{*}$	$.0003$	$.0003$	$.0004^{*}$	$.0004^{*}$
		$(.0002)$	$(.0002)$	$(.0002)$	$(.0002)$	$(.0002)$
The first tenure year dummy	$.4841^{***}$	$.4686^{***}$	$.4685^{***}$	$.4701^{***}$	$.4671^{***}$	$.4628^{***}$
	$(.0059)$	$(.0080)$	$(.0080)$	$(.0078)$	$(.0077)$	$(.0076)$
Number of patents made by firm	$.1720^{***}$	$.1708^{***}$	$.1711^{***}$	$.1713^{***}$	$.1714^{***}$	$.1706^{***}$
	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$	$(.0109)$
Constant	$-.3642^{***}$	$-.3403^{***}$	$-.3387^{***}$	$-.3433^{***}$	$-.3391^{***}$	$-.3319^{***}$
	$(.0098)$	$(.0130)$	$(.0130)$	$(.0128)$	$(.0127)$	$(.0126)$
Log-likelihood	-355405	-355390	-355581	-355393	-355410	-35546
Observations	286954	286954	286954	286954	286954	286954

NOTE.– All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C2. Robust standard errors are in parentheses.
† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $*\,p < .1$. $**\ p < .05$. $***\,p < .01$.

Table 6: Fixed-effect Productivity Regression Estimates

	OVERALL COLLABORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
Network referral dummy: ρ	.1259***	.1519***	.1801***	.2094***
	(.0093)	(.0111)	(.0124)	(.0166)
Previously applied patents [a]	−.0385***	−.0382***	−.0381***	−.0374***
	(.0008)	(.0008)	(.0008)	(.0008)
Potential research years	.0155***	.0165***	.0169***	.0178***
	(.0015)	(.0015)	(.0015)	(.0015)
Potential research years squared	.0011***	.0010***	.0010***	.0010***
	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	.0064**	.0053*	.0051*	.0046
	(.0031)	(.0031)	(.0031)	(.0031)
Tenure years squared	−.0007***	−.0007***	−.0006***	−.0006***
	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	.5395***	.5390***	.5392***	.5382***
	(.0071)	(.0071)	(.0071)	(.0071)
Number of patents made by firm	.3058***	.3083***	.3096***	.3104***
	(.0172)	(.0172)	(.0172)	(.0172)
Log-likelihood	-236446	-236444	-236432	-236458
Observations	286954	286954	286954	286954

NOTE.– All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C3. Standard errors are in parentheses.

[a] Total numbers of previously applied patents is used.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $*\, p < .1$. $**\, p < .05$. $***\, p < .01$.

Table 7: Fixed-effect Productivity Growth Regression

	OVERALL COLLABORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
Interaction terms of network and tenure dummies: ρ_k				
year 1	.1033***	.1185***	.1448***	.1659***
	(.0111)	(.0133)	(.0149)	(.0205)
year 2	.1558***	.2096***	.2389***	.2890***
	(.0165)	(.0195)	(.0217)	(.0285)
year 3	.2398***	.2886***	.3112***	.3393***
	(.0181)	(.0218)	(.0242)	(.0320)
year 4	.1807***	.2022***	.2208***	.2518***
	(.0222)	(.0277)	(.0310)	(.0416)
year 5	.1237***	.1350***	.1560***	.1067**
	(.0268)	(.0336)	(.0382)	(.0524)
year 6	.1111***	.1329***	.1457***	.2008***
	(.0317)	(.0404)	(.0467)	(.0612)
year 7	.0824**	.0613	.0658	.0496
	(.0375)	(.0487)	(.0568)	(.0783)
year 8	.0775*	.1096**	.1570**	.2066**
	(.0434)	(.0539)	(.0616)	(.0815)
year 9	−.0954*	−.0602	.0415	.0688
	(.0548)	(.0677)	(.0750)	(.1014)
year 10	−.0969	−.0443	−.0179	−.1013
	(.0630)	(.0759)	(.0864)	(.1261)
Previously applied patents [a]	−.0386***	−.0383***	−.0382***	−.0374***
	(.0008)	(.0008)	(.0008)	(.0008)
Potential research years	.0148***	.0160***	.0167***	.0176***
	(.0015)	(.0015)	(.0015)	(.0015)
Potential research years squared	.0011***	.0011***	.0010***	.0010***
	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	.0105***	.0087***	.0076**	.0064**
	(.0033)	(.0032)	(.0032)	(.0031)
Tenure years squared	−.0008***	−.0007***	−.0007***	−.0007***
	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	.5570***	.5544***	.5511***	.5458***
	(.0076)	(.0074)	(.0073)	(.0072)
Number of patents made by firm	.3036***	.3057***	.3079***	.3084***
	(.0172)	(.0172)	(.0172)	(.0172)
Log-likelihood	-236375	-236377	-236380	-236426
Observations	286954	286954	286954	286954

NOTE.– All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C4. Standard errors are in parentheses.

[a] Total numbers of previously applied patents is used.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $*\, p < .1$. $**\ p < .05$. $***\, p < .01$.

A Appendix: Computation of the Mean Productivity

The denominator of the conditional density (11) is computed by:

$$\text{Prob}\left[(q > q^*) \cap (\theta > \theta^*)\right] = \int_{\theta^*} \int_{q^*} \phi\left((\theta - q)/s\right) \phi\left((q - \mu)/\sigma_{q_k}\right) dq d\theta.$$

Therefore, the mean productivity in the second period is given by:

$$\begin{aligned}
\text{E}(\theta | q > q^*, \theta > \theta^*) &= \frac{\int_{\theta^*} \theta \int_{q^*} \phi\left((\theta - q)/s\right) \phi\left((q - \mu)/\sigma_{q_k}\right) dq d\theta}{\text{Prob}\left[(q > q^*) \cap (\theta > \theta^*)\right]} \\
&= \frac{\int_{\theta^*} \theta \int_{q^*} \phi\left((\theta - q)/s\right) \phi\left((q - \mu)/\sigma_{q_k}\right) dq d\theta}{\int_{\theta^*} \int_{q^*} \phi\left((\theta - q)/s\right) \phi\left((q - \mu)/\sigma_{q_k}\right) dq d\theta} \\
&= \frac{\int_{q^*} \left[\int_{\theta^*} \theta \phi\left((\theta - q)/s\right) d\theta\right] \phi\left((q - \mu)/\sigma_{q_k}\right) dq}{\int_{q^*} \left[\int_{\theta^*} \phi\left((\theta - q)/s\right) d\theta\right] \phi\left((q - \mu)/\sigma_{q_k}\right) dq} \qquad (16)
\end{aligned}$$

We can use the following equalities:

$$\begin{aligned}
\int_{\theta^*} \phi\left((\theta - q)/s\right) d\theta &= \Phi\left((\mu - q)/\sigma_{q_k}\right), \\
\int_{\theta^*} \theta \phi\left((\theta - q)/s\right) d\theta &= q + s\lambda\left((q - \mu)/\sigma_{q_k}\right).
\end{aligned}$$

We obtain equation (12) by substituting these equations into equation (16)

B Computerized Matching Process

The essence of the computerized matching process (CMP) proposed by Trajtenberg, Shiff, and Melamed (2006) is to adjust for possible spelling errors in inventors' names listed in patents in order to avoid identifying an inventor as two different inventors while minimizing the possibilities of identifying two different inventors as the same person by utilizing other information such as addresses, assignees, and patent classes.

The former is done by converting the last name and first name of the listed inventors into "soundex" codes following the rule described in Trajtenberg, Shiff, and Melamed (2006, p. 17, Table 3.1). This conversion allows us to group inventors whose names are spelled in a similar manner into one depending on the numbers assigned to them. We then utilize other information to distinguish inventors with the same "soundex" code. The information we employ in matching inventors are (1) full address, (2) self-citations, (3) shared collaborators, (4) middle names, (5) surname modifier, (6) assignee, (7) city, and (8) patent class. Each information gives a score to a pair of names (soundex code), and depending on the‘ total score obtained, we decide whether two inventors are the same person or not. The name-matching criteria we have employed are summarized in Table B. 1. While criterion A follows Trajtenberg, Shiff, and Melamed (2006), criterion B is more stringent. Let us describe the scoring procedure in more detail below.

When full street addresses are identical between the inventors listed in two different patents, the pair obtains a score of 120.[19] When a patent is citing an older patent applied for by the inventor with a similar soundex code, then we consider that these two patents are applied for by the same person (self-citation) and the pair of names obtains a score of 120.[20] In addition, if two patents are each applied for by two or more inventors and one of them is identified individually, then the remaining inventors are considered to have collaborated with the identified inventor. If there is a pair of inventors (listed in both patents) who have similar soundex codes, then we consider them to be one person who has collaborated repeatedly with an already identified inventor (shared collaborators) and this inventor obtains a score of 120.

If the pair of records share more than two letters from the middle name (full middle name), a score of 100 is given, and if they share the same surname modifier, they get a score of 50. In the case where two records share only the middle name initials, assignee, city, or patent classes, the score depends on whether such records are "rare" or not. Namely, we assume, for example, that a city is "rare," if the number of records that share the same city is smaller than the cutoff value. The cutoff value is set to the median of the frequency distribution of the city name. Otherwise, it is considered to be "common." If a pair of records shares either the middle name initials, assignee, or city, it obtains a score of 100 if it is considered to be "rare" and 80 if it is "common". In the case of patent class, the pair obtains a score of 80 or 50, respectively. These scores are summarized in Table B. 2

We also consider the cases in which we categorize the names to be "rare" or "common" as in Trajtenberg, Shiff, and Melamed (2006). Similarly to the cases of cities and assignees, a name is considered to be "rare," if it appears less frequently in the data than the median of the frequency distribution. Furthermore, when a name is considered to be "rare", the likelihood that two records correspond to one inventor is higher. Therefore, less strict criteria are set for other information. Namely, the middle name initials, assignee, city, and patent class obtain a higher score (the one corresponding to "rare" cases) if they are below the 75 percentile of the frequency distribution, instead of the median.

In total, we consider four cases, depending on which matching criterion is uti-

[19]It should be noted that the value of the score itself has no significant meaning.

[20]There are only 121 pairs of patents that satisfy this criterion.

lized and whether rareness of names is considered or not. The results of the four cases are summarized in Table B. 3. As the table shows, the four cases we have considered do not differ substantially in terms of number of unique inventors identified. The procedure that uses criteria A and treats "rare" names differently (second row in the table) identifies the least number of inventors; however the difference between the one that identifies the highest number of inventors (the one using criteria B and does not treat "rare" names differently, reported in the third row in the table) is less than one percent of the total number of inventors identified. Our analysis is based on the procedure that uses criteria A and does not treat "rare" names differently (the base line case reported in the first row).

Table B. 1: Matching Criteria in CMP

Criteria A (Trajtenberg, Shiff, and Melamed, 2006)	Cutoff value
(1) Identical Last name and First name, and non zero part of soundex code is more than 5 digits	100
(2) Identical Last name, and non zero part of soundex code is more than 2 digits	120
(3)Others	180
Criteria B (this paper)	**Cutoff value**
(1) Identical Last, First, and middle name, and non zero part of soundex code is more than 5 digits	100
(2) Identical Last name, and non zero part of soundex code is more than 2 digits	120
(3) Others	180

Table B. 2: List of Scores in CMP

	score	
Full Address	120	
Self Citation	120	
Shared Partners	120	
Full middle name	100	
Surname Modifier	50	
	rare	common
Middle name initial	100	80
Assignee	100	80
City	100	80
Patent Class	80	50

Table B. 3: CMP Results

	cutoff values		Number of
	for rare names	for common names	unique inventors
Criteria A	50	50	746,991
Criteria A	75	50	744,381
Criteria B	50	50	748,646
Criteria B	75	50	746,368

Table C. 1: Productivity Regression: All Estimation Results

	OVERALL COLLABORATION			LIMITED INTERVAL† COLLABORATION		
				WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)
Network referral dummy: ρ	$.0782^{***}$	$.0809^{***}$	$.1009^{***}$	$.0934^{***}$	$.0991^{***}$	$.1016^{***}$
	(.0065)	(.0065)	(.0065)	(.0080)	(.0091)	(.0121)
Previously applied patents:						
Total number	$.0113^{***}$	$.0111^{***}$		$.0113^{***}$	$.0114^{***}$	$.0117^{***}$
	(.0006)	(.0006)		(.0007)	(.0007)	(.0007)
Annual average			$.0078^{***}$			
			(.0009)			
Potential research years	$-.0065^{***}$	$-.0111^{***}$	$-.0088^{***}$	$-.0100^{***}$	$-.0097^{***}$	$-.0094^{***}$
	(.0005)	(.0011)	(.0011)	(.0011)	(.0011)	(.0011)
Potential research years squared		$.0003^{***}$	$.0003^{***}$	$.0002^{***}$	$.0002^{***}$	$.0002^{**}$
		(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	.0017	$-.0038$	$-.0064$	$-.0046$	$-.0049$	$-.0053$
	(.0011)	(.0033)	(.0033)	(.0033)	(.0033)	(.0033)
Tenure years squared		.0003	.0003	.0004	.0004	.0004
		(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	$.4737^{***}$	$.4600^{***}$	$.4594^{***}$	$.4592^{***}$	$.4590^{***}$	$.4577^{***}$
	(.0056)	(.0075)	(.0075)	(.0075)	(.0075)	(.0075)
Number of patents made by firm	$.1726^{***}$	$.1716^{***}$	$.1720^{***}$	$.1728^{***}$	$.1727^{***}$	$.1718^{***}$
	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)
Field dummies:						
Chemical	$.2914^{***}$	$.2916^{***}$	$.2952^{***}$	$.2919^{***}$	$.2920^{***}$	$.2923^{***}$
	(.0049)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)
Comp.& Comm.	$.2294^{***}$	$.2300^{***}$	$.2308^{***}$	$.2300^{***}$	$.2299^{***}$	$.2298^{***}$
	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)
Drugs & Medical	$.2886^{***}$	$.2890^{***}$	$.2925^{***}$	$.2888^{***}$	$.2886^{***}$	$.2891^{***}$
	(.0075)	(.0075)	(.0075)	(.0075)	(.0075)	(.0075)
Elec. & Electronics	$.1899^{***}$	$.1902^{***}$	$.1916^{***}$	$.1901^{***}$	$.1900^{***}$	$.1900^{***}$
	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)
Mechanical	$.1882^{***}$	$.1884^{***}$	$.1886^{***}$	$.1884^{***}$	$.1884^{***}$	$.1884^{***}$
	(.0047)	(.0047)	(.0047)	(.0047)	(.0047)	(.0047)
Others	$.1779^{***}$	$.1783^{***}$	$.1778^{***}$	$.1783^{***}$	$.1783^{***}$	$.1779^{***}$
	(.0051)	(.0051)	(.0051)	(.0051)	(.0051)	(.0051)
Annual dummies						
year 2	$-.1388^{***}$	$-.1434^{***}$	$-.1445^{***}$	$-.1428^{***}$	$-.1439^{***}$	$-.1463^{***}$
	(.0133)	(.0133)	(.0133)	(.0133)	(.0133)	(.0133)
year 3	$-.1907^{***}$	$-.1935^{***}$	$-.1945^{***}$	$-.1933^{***}$	$-.1943^{***}$	$-.1964^{***}$
	(.0145)	(.0145)	(.0145)	(.0145)	(.0145)	(.0145)
year 4	$-.2379^{***}$	$-.2382^{***}$	$-.2390^{***}$	$-.2384^{***}$	$-.2393^{***}$	$-.2413^{***}$
	(.0152)	(.0152)	(.0152)	(.0152)	(.0152)	(.0152)
year 5	$-.2460^{***}$	$-.2441^{***}$	$-.2446^{***}$	$-.2443^{***}$	$-.2452^{***}$	$-.2473^{***}$
	(.0147)	(.0146)	(.0146)	(.0146)	(.0146)	(.0146)
year 6	$-.2709^{***}$	$-.2672^{***}$	$-.2675^{***}$	$-.2674^{***}$	$-.2683^{***}$	$-.2703^{***}$
	(.0135)	(.0135)	(.0135)	(.0135)	(.0135)	(.0135)
year 7	$-.2962^{***}$	$-.2913^{***}$	$-.2911^{***}$	$-.2916^{***}$	$-.2926^{***}$	$-.2945^{***}$
	(.0130)	(.0130)	(.0130)	(.0130)	(.0130)	(.0130)

(Continued from previous page)

	Overall Collaboration			Limited Interval† Collaboration		
				Within 36	Within 24	Within 12
	(1)	(2)	(3)	(4)	(5)	(6)
year 8	$-.3329^{***}$	$-.3269^{***}$	$-.3268^{***}$	$-.3271^{***}$	$-.3280^{***}$	$-.3301^{***}$
	(.0122)	(.0122)	(.0122)	(.0122)	(.0122)	(.0122)
year 9	$-.3510^{***}$	$-.3447^{***}$	$-.3448^{***}$	$-.3452^{***}$	$-.3460^{***}$	$-.3479^{***}$
	(.0118)	(.0119)	(.0119)	(.0119)	(.0119)	(.0119)
year 10	$-.3552^{***}$	$-.3484^{***}$	$-.3483^{***}$	$-.3488^{***}$	$-.3496^{***}$	$-.3517^{***}$
	(.0114)	(.0115)	(.0115)	(.0115)	(.0115)	(.0115)
year 11	$-.3261^{***}$	$-.3192^{***}$	$-.3189^{***}$	$-.3195^{***}$	$-.3203^{***}$	$-.3220^{***}$
	(.0110)	(.0111)	(.0111)	(.0111)	(.0111)	(.0111)
year 12	$-.3414^{***}$	$-.3346^{***}$	$-.3343^{***}$	$-.3346^{***}$	$-.3354^{***}$	$-.3370^{***}$
	(.0108)	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)
year 13	$-.3220^{***}$	$-.3156^{***}$	$-.3157^{***}$	$-.3154^{***}$	$-.3160^{***}$	$-.3173^{***}$
	(.0107)	(.0107)	(.0107)	(.0107)	(.0107)	(.0107)
year 14	$-.2896^{***}$	$-.2837^{***}$	$-.2848^{***}$	$-.2834^{***}$	$-.2842^{***}$	$-.2852^{***}$
	(.0103)	(.0104)	(.0104)	(.0104)	(.0104)	(.0104)
year 15	$-.2687^{***}$	$-.2633^{***}$	$-.2647^{***}$	$-.2627^{***}$	$-.2633^{***}$	$-.2644^{***}$
	(.0102)	(.0102)	(.0102)	(.0102)	(.0102)	(.0102)
year 16	$-.2599^{***}$	$-.2548^{***}$	$-.2572^{***}$	$-.2544^{***}$	$-.2549^{***}$	$-.2557^{***}$
	(.0101)	(.0101)	(.0101)	(.0101)	(.0101)	(.0101)
year 17	$-.2554^{***}$	$-.2510^{***}$	$-.2542^{***}$	$-.2506^{***}$	$-.2510^{***}$	$-.2516^{***}$
	(.0098)	(.0098)	(.0098)	(.0098)	(.0098)	(.0098)
year 18	$-.2405^{***}$	$-.2368^{***}$	$-.2394^{***}$	$-.2366^{***}$	$-.2368^{***}$	$-.2371^{***}$
	(.0097)	(.0097)	(.0097)	(.0097)	(.0097)	(.0097)
year 19	$-.2108^{***}$	$-.2077^{***}$	$-.2103^{***}$	$-.2074^{***}$	$-.2076^{***}$	$-.2070^{***}$
	(.0093)	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)
year 20	$-.1605^{***}$	$-.1579^{***}$	$-.1613^{***}$	$-.1575^{***}$	$-.1574^{***}$	$-.1561^{***}$
	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)
year 21	$-.0054$	$-.0030$	$-.0054$	$-.0029$	$-.0025$	$-.0004$
	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)
year 22	$-.0482^{***}$	$-.0462^{***}$	$-.0483^{***}$	$-.0464^{***}$	$-.0459^{***}$	$-.0438^{***}$
	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)
Constant	$-.3525^{***}$	$-.3311^{***}$	$-.3289^{***}$	$-.3307^{***}$	$-.3294^{***}$	$-.3254^{***}$
	(.0095)	(.0124)	(.0124)	(.0124)	(.0124)	(.0124)
Log-likelihood	-355449	-355435	-355628	-355440.73	-355449	-355478
Observations	286954	286954	286954	286954	286954	286954

NOTE.– Robust standard errors are in parentheses.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $* p < .1$. $** \ p < .05$. $*** p < .01$.

Table C. 2: Within-firm Productivity Growth Regression Estimates: All Estimation Results

	Overall Collaboration			Limited Interval† Collaboration		
				Within 36	Within 24	Within 12
	(1)	(2)	(3)	(4)	(5)	(6)
Interaction terms of network and tenure dummies: ρ_k						
year 1	$.0571^{***}$	$.0623^{***}$	$.0819^{***}$	$.0630^{***}$	$.0693^{***}$	$.0726^{***}$
	(.0070)	(.0071)	(.0071)	(.0090)	(.0105)	(.0147)
year 2	$.0797^{***}$	$.0756^{***}$	$.0974^{***}$	$.1248^{***}$	$.1303^{***}$	$.1527^{***}$
	(.0177)	(.0179)	(.0180)	(.0219)	(.0248)	(.0352)
year 3	$.1708^{***}$	$.1713^{***}$	$.1920^{***}$	$.2138^{***}$	$.2174^{***}$	$.2219^{***}$
	(.0195)	(.0195)	(.0196)	(.0245)	(.0265)	(.0331)
year 4	$.1294^{***}$	$.1334^{***}$	$.1545^{***}$	$.1512^{***}$	$.1492^{***}$	$.1469^{***}$
	(.0243)	(.0244)	(.0244)	(.0295)	(.0330)	(.0430)
year 5	$.0901^{**}$	$.0966^{**}$	$.1182^{***}$	$.0961^{*}$	.0957	.0105
	(.0320)	(.0321)	(.0321)	(.0421)	(.0497)	(.0470)
year 6	$.0858^{*}$	$.0934^{*}$	$.1144^{**}$	.0869	.0673	.0797
	(.0369)	(.0370)	(.0371)	(.0469)	(.0561)	(.0777)
year 7	.0823	.0900	$.1053^{*}$	.0471	.0073	−.0518
	(.0502)	(.0504)	(.0504)	(.0663)	(.0816)	(.0855)
year 8	.0856	.0920	$.1079^{*}$	.1028	.1123	.1248
	(.0519)	(.0521)	(.0522)	(.0680)	(.0690)	(.0902)
year 9	−.0581	−.0538	−.0385	−.0470	.0410	.0335
	(.0648)	(.0649)	(.0650)	(.0787)	(.0883)	(.1259)
year 10	−.0624	−.0602	−.0464	−.0168	−.0035	−.1208
	(.0720)	(.0721)	(.0722)	(.0913)	(.1102)	(.1505)
year 11	−.0078	−.0093	.0053	−.0456	.0206	.1084
	(.0961)	(.0960)	(.0970)	(.1289)	(.1173)	(.1589)
year 12	−.0935	−.1004	−.0827	−.1334	−.1395	−.0902
	(.1010)	(.1009)	(.1010)	(.1283)	(.1508)	(.1858)
year 13	−.1300	−.1424	−.1233	−.1812	−.0859	−.1777
	(.1087)	(.1086)	(.1085)	(.1335)	(.1560)	(.2091)
year 14	−.1082	−.1261	−.1106	−.1747	−.2083	−.2084
	(.1478)	(.1480)	(.1483)	(.1487)	(.1855)	(.2636)
year 15	−.1240	−.1503	−.1354	−.2201	−.1780	−.0326
	(.1760)	(.1761)	(.1764)	(.1874)	(.2131)	(.2708)
year 16	.3835	.3471	.3625	−.1771	−.3193	−.1398
	(.3914)	(.3910)	(.3916)	(.2933)	(.3317)	(.4866)
year 17	$-.4398^{*}$	$-.4857^{*}$	$-.4685^{*}$	−.4422	$-.6250^{*}$	−.5043
	(.2073)	(.2078)	(.2072)	(.2404)	(.2666)	(.3600)
year 18	−.0599	−.1153	−.1030	−.1283	.0225	−.4438
	(.2006)	(.2009)	(.2000)	(.2253)	(.2185)	(.4110)
year 19	−.6005	−.6671	−.6476	−.6646	−.8942	−.6866
	(.3806)	(.3810)	(.3763)	(.3811)	(.6014)	(.5612)
year 20	−.0136	−.0937	−.0709	−.0897	−.0860	−.0408
	(.0952)	(.0992)	(.0907)	(.0993)	(.0995)	(.1082)
year 21	−.9343	−1.0303	−1.0279	−1.0241	−1.0197	−1.0128
	(.5539)	(.5547)	(.5574)	(.5546)	(.5546)	(.5544)

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	OVERALL COLLABORATION			LIMITED INTERVAL† COLLABORATION		
				WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)
year 22	$-.2844$	$-.3964^{*}$	$-.3965^{*}$	$-.3891^{*}$	$-.3840^{*}$	$-.3742^{*}$
	(.1549)	(.1598)	(.1571)	(.1600)	(.1599)	(.1600)
Previously applied patents:						
Total number	$.0112^{***}$	$.0111^{***}$		$.0112^{***}$	$.0114^{***}$	$.0117^{***}$
	(.0006)	(.0006)		(.0006)	(.0007)	(.0007)
Annual average			$.0078^{***}$			
			(.0009)			
Potential research years	$-.0065^{***}$	$-.0113^{***}$	$-.0090^{***}$	$-.0102^{***}$	$-.0098^{***}$	$-.0095^{***}$
	(.0005)	(.0011)	(.0011)	(.0011)	(.0011)	(.0011)
Potential research years squared		$.0003^{***}$	$.0004^{***}$	$.0003^{***}$	$.0002^{***}$	$.0002^{**}$
		(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	$.0030^{**}$	$-.0030$	$-.0055$	$-.0029$	$-.0037$	$-.0042$
	(.0011)	(.0035)	(.0035)	(.0035)	(.0034)	(.0034)
Tenure years squared		.0004	.0003	.0003	.0004	.0004
		(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	$.4841^{***}$	$.4686^{***}$	$.4685^{***}$	$.4701^{***}$	$.4671^{***}$	$.4628^{***}$
	(.0059)	(.0080)	(.0080)	(.0078)	(.0077)	(.0076)
Number of patents made by firm	$.1720^{***}$	$.1708^{***}$	$.1711^{***}$	$.1713^{***}$	$.1714^{***}$	$.1706^{***}$
	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)
Field dummies:						
Chemical	$.2919^{***}$	$.2921^{***}$	$.2957^{***}$	$.2924^{***}$	$.2925^{***}$	$.2927^{***}$
	(.0049)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)
Comp.& Comm.	$.2296^{***}$	$.2301^{***}$	$.2310^{***}$	$.2301^{***}$	$.2301^{***}$	$.2298^{***}$
	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)	(.0057)
Drugs & Medical	$.2889^{***}$	$.2892^{***}$	$.2928^{***}$	$.2890^{***}$	$.2887^{***}$	$.2891^{***}$
	(.0075)	(.0075)	(.0075)	(.0075)	(.0075)	(.0075)
Elec. & Electronics	$.1901^{***}$	$.1904^{***}$	$.1918^{***}$	$.1903^{***}$	$.1902^{***}$	$.1901^{***}$
	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)	(.0048)
Mechanical	$.1885^{***}$	$.1886^{***}$	$.1888^{***}$	$.1887^{***}$	$.1887^{***}$	$.1885^{***}$
	(.0047)	(.0047)	(.0047)	(.0047)	(.0047)	(.0047)
Others	$.1782^{***}$	$.1786^{***}$	$.1781^{***}$	$.1784^{***}$	$.1784^{***}$	$.1778^{***}$
	(.0051)	(.0051)	(.0051)	(.0051)	(.0051)	(.0051)
Annual dummies						
year 2	$-.1359^{***}$	$-.1409^{***}$	$-.1419^{***}$	$-.1395^{***}$	$-.1411^{***}$	$-.1446^{***}$
	(.0133)	(.0133)	(.0133)	(.0133)	(.0133)	(.0133)
year 3	$-.1870^{***}$	$-.1902^{***}$	$-.1911^{***}$	$-.1894^{***}$	$-.1912^{***}$	$-.1947^{***}$
	(.0145)	(.0145)	(.0145)	(.0145)	(.0145)	(.0145)
year 4	$-.2344^{***}$	$-.2350^{***}$	$-.2357^{***}$	$-.2347^{***}$	$-.2364^{***}$	$-.2397^{***}$
	(.0152)	(.0152)	(.0152)	(.0152)	(.0152)	(.0152)
year 5	$-.2429^{***}$	$-.2412^{***}$	$-.2417^{***}$	$-.2412^{***}$	$-.2427^{***}$	$-.2457^{***}$
	(.0146)	(.0146)	(.0146)	(.0146)	(.0146)	(.0146)
year 6	$-.2681^{***}$	$-.2645^{***}$	$-.2647^{***}$	$-.2646^{***}$	$-.2660^{***}$	$-.2689^{***}$
	(.0135)	(.0135)	(.0135)	(.0135)	(.0135)	(.0135)
year 7	$-.2936^{***}$	$-.2887^{***}$	$-.2885^{***}$	$-.2888^{***}$	$-.2902^{***}$	$-.2930^{***}$
	(.0130)	(.0130)	(.0130)	(.0130)	(.0130)	(.0130)
year 8	$-.3306^{***}$	$-.3246^{***}$	$-.3245^{***}$	$-.3247^{***}$	$-.3259^{***}$	$-.3288^{***}$
	(.0123)	(.0123)	(.0123)	(.0123)	(.0123)	(.0122)
year 9	$-.3492^{***}$	$-.3427^{***}$	$-.3428^{***}$	$-.3430^{***}$	$-.3441^{***}$	$-.3469^{***}$
	(.0118)	(.0119)	(.0119)	(.0119)	(.0119)	(.0119)
year 10	$-.3534^{***}$	$-.3465^{***}$	$-.3463^{***}$	$-.3466^{***}$	$-.3477^{***}$	$-.3505^{***}$

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	Overall Collaboration			Limited Interval† Collaboration		
				Within 36	Within 24	Within 12
	(1)	(2)	(3)	(4)	(5)	(6)
	(.0114)	(.0115)	(.0115)	(.0115)	(.0115)	(.0115)
year 11	−.3241***	−.3172***	−.3168***	−.3173***	−.3183***	−.3208***
	(.0110)	(.0110)	(.0111)	(.0111)	(.0111)	(.0111)
year 12	−.3392***	−.3324***	−.3320***	−.3322***	−.3334***	−.3359***
	(.0108)	(.0109)	(.0109)	(.0109)	(.0109)	(.0109)
year 13	−.3204***	−.3139***	−.3139***	−.3135***	−.3144***	−.3162***
	(.0107)	(.0107)	(.0108)	(.0107)	(.0108)	(.0107)
year 14	−.2881***	−.2821***	−.2832***	−.2813***	−.2824***	−.2841***
	(.0103)	(.0104)	(.0104)	(.0104)	(.0104)	(.0104)
year 15	−.2669***	−.2615***	−.2628***	−.2605***	−.2614***	−.2631***
	(.0102)	(.0102)	(.0102)	(.0102)	(.0102)	(.0102)
year 16	−.2582***	−.2531***	−.2554***	−.2523***	−.2530***	−.2546***
	(.0101)	(.0101)	(.0101)	(.0101)	(.0101)	(.0101)
year 17	−.2539***	−.2496***	−.2527***	−.2485***	−.2491***	−.2506***
	(.0098)	(.0098)	(.0098)	(.0098)	(.0098)	(.0098)
year 18	−.2391***	−.2355***	−.2381***	−.2346***	−.2349***	−.2358***
	(.0097)	(.0097)	(.0097)	(.0097)	(.0097)	(.0097)
year 19	−.2088***	−.2057***	−.2084***	−.2051***	−.2056***	−.2060***
	(.0093)	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)
year 20	−.1581***	−.1557***	−.1590***	−.1553***	−.1554***	−.1549***
	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)
year 21	−.0028	−.0004	−.0028	−.0001	−.0002	.0013
	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)	(.0094)
year 22	−.0465***	−.0444***	−.0465***	−.0449***	−.0447***	−.0431***
	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)	(.0091)
Constant	−.3642***	−.3403***	−.3387***	−.3433***	−.3391***	−.3319***
	(.0098)	(.0130)	(.0130)	(.0128)	(.0127)	(.0126)
Log-likelihood	-355405	-355390	-355581	-355393	-355410	-355451
Observations	286954	286954	286954	286954	286954	286954

NOTE.– Robust standard errors are in parentheses.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $* p < .1$. $** \ p < .05$. $*** p < .01$.

Table C. 3: Productivity Regression Estimates from Fixed-effects Model: All Estimation Results

	OVERALL COLLBORATION	LIMITED INTERVAL[†] COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
Network referral dummy: ρ	.1259***	.1519***	.1801***	.2094***
	(.0093)	(.0111)	(.0124)	(.0166)
Previously applied patents [a]	−.0385***	−.0382***	−.0381***	−.0374***
	(.0008)	(.0008)	(.0008)	(.0008)
Potential research years	.0155***	.0165***	.0169***	.0178***
	(.0015)	(.0015)	(.0015)	(.0015)
Potential research years squared	.0011***	.0010***	.0010***	.0010***
	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	.0064*	.0053	.0051	.0046
	(.0031)	(.0031)	(.0031)	(.0031)
Tenure years squared	−.0007***	−.0007***	−.0006***	−.0006**
	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	.5395***	.5390***	.5392***	.5382***
	(.0071)	(.0071)	(.0071)	(.0071)
Number of patents made by firm	.3058***	.3083***	.3096***	.3104***
	(.0172)	(.0172)	(.0172)	(.0172)
Field dummies:				
Chemical	.1970***	.1973***	.1977***	.1979***
	(.0101)	(.0101)	(.0101)	(.0101)
Comp.& Comm.	.1632***	.1642***	.1642***	.1651***
	(.0122)	(.0122)	(.0122)	(.0122)
Drugs & Medical	.1701***	.1708***	.1709***	.1710***
	(.0155)	(.0155)	(.0155)	(.0155)
Elec. & Electronics	.1815***	.1820***	.1819***	.1830***
	(.0099)	(.0099)	(.0099)	(.0099)
Mechanical	.1685***	.1698***	.1713***	.1714***
	(.0089)	(.0089)	(.0089)	(.0089)
Others	.1808***	.1814***	.1825***	.1823***
	(.0092)	(.0092)	(.0092)	(.0092)
Annual dummies				
year 2	.0104	.0099	.0098	.0093
	(.0163)	(.0163)	(.0163)	(.0163)
year 3	−.0412**	−.0424**	−.0427**	−.0429**
	(.0160)	(.0160)	(.0160)	(.0160)
year 4	−.1031***	−.1048***	−.1053***	−.1056***
	(.0157)	(.0157)	(.0157)	(.0157)
year 5	−.1328***	−.1347***	−.1351***	−.1358***
	(.0153)	(.0153)	(.0153)	(.0153)
year 6	−.1734***	−.1754***	−.1757***	−.1766***
	(.0149)	(.0149)	(.0149)	(.0149)
year 7	−.2158***	−.2179***	−.2183***	−.2198***
	(.0147)	(.0147)	(.0147)	(.0147)
year 8	−.2738***	−.2759***	−.2761***	−.2782***
	(.0144)	(.0144)	(.0144)	(.0144)

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	OVERALL COLLBORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
year 9	$-.3143^{***}$	$-.3166^{***}$	$-.3172^{***}$	$-.3193^{***}$
	(.0142)	(.0142)	(.0142)	(.0142)
year 10	$-.3373^{***}$	$-.3396^{***}$	$-.3401^{***}$	$-.3428^{***}$
	(.0139)	(.0139)	(.0139)	(.0139)
year 11	$-.3137^{***}$	$-.3158^{***}$	$-.3168^{***}$	$-.3193^{***}$
	(.0134)	(.0134)	(.0134)	(.0134)
year 12	$-.3359^{***}$	$-.3377^{***}$	$-.3386^{***}$	$-.3414^{***}$
	(.0132)	(.0132)	(.0132)	(.0132)
year 13	$-.3386^{***}$	$-.3403^{***}$	$-.3411^{***}$	$-.3439^{***}$
	(.0127)	(.0127)	(.0127)	(.0127)
year 14	$-.3170^{***}$	$-.3178^{***}$	$-.3187^{***}$	$-.3217^{***}$
	(.0123)	(.0123)	(.0123)	(.0123)
year 15	$-.3086^{***}$	$-.3089^{***}$	$-.3100^{***}$	$-.3135^{***}$
	(.0121)	(.0121)	(.0121)	(.0121)
year 16	$-.3233^{***}$	$-.3234^{***}$	$-.3242^{***}$	$-.3277^{***}$
	(.0120)	(.0120)	(.0120)	(.0120)
year 17	$-.3366^{***}$	$-.3359^{***}$	$-.3371^{***}$	$-.3407^{***}$
	(.0120)	(.0120)	(.0120)	(.0120)
year 18	$-.3361^{***}$	$-.3350^{***}$	$-.3361^{***}$	$-.3403^{***}$
	(.0119)	(.0119)	(.0119)	(.0119)
year 19	$-.3143^{***}$	$-.3125^{***}$	$-.3136^{***}$	$-.3167^{***}$
	(.0118)	(.0118)	(.0118)	(.0118)
year 20	$-.2718^{***}$	$-.2696^{***}$	$-.2701^{***}$	$-.2723^{***}$
	(.0117)	(.0117)	(.0117)	(.0117)
year 21	$-.1026^{***}$	$-.1011^{***}$	$-.1017^{***}$	$-.1028^{***}$
	(.0115)	(.0115)	(.0115)	(.0115)
year 22	$-.1516^{***}$	$-.1508^{***}$	$-.1514^{***}$	$-.1514^{***}$
	(.0122)	(.0122)	(.0122)	(.0122)
Log-likelihood	-236446	-236444	-236432	-236458
Observations	286954	286954	286954	286954

NOTE.– Standard errors are in parentheses.

[a] Total numbers of previously applied patents is used.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $*\ p < .1$. $**\ p < .05$. $***\ p < .01$.

Table C. 4: Within-Firm Productivity Growth Estimates from Fixed-effects Regression: All Estimation Results

	OVERALL COLLBORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
Interaction terms of network and tenure dummies: ρ_k				
year 1	$.1033^{***}$	$.1185^{***}$	$.1448^{***}$	$.1659^{***}$
	$(.0111)$	$(.0133)$	$(.0149)$	$(.0205)$
year 2	$.1558^{***}$	$.2096^{***}$	$.2389^{***}$	$.2890^{***}$
	$(.0165)$	$(.0195)$	$(.0217)$	$(.0285)$
year 3	$.2398^{***}$	$.2886^{***}$	$.3112^{***}$	$.3393^{***}$
	$(.0181)$	$(.0218)$	$(.0242)$	$(.0320)$
year 4	$.1807^{***}$	$.2022^{***}$	$.2208^{***}$	$.2518^{***}$
	$(.0222)$	$(.0277)$	$(.0310)$	$(.0416)$
year 5	$.1237^{***}$	$.1350^{***}$	$.1560^{***}$	$.1067^{*}$
	$(.0268)$	$(.0336)$	$(.0382)$	$(.0524)$
year 6	$.1111^{***}$	$.1329^{**}$	$.1457^{**}$	$.2008^{**}$
	$(.0317)$	$(.0404)$	$(.0467)$	$(.0612)$
year 7	$.0824^{*}$	$.0613$	$.0658$	$.0496$
	$(.0375)$	$(.0487)$	$(.0568)$	$(.0783)$
year 8	$.0775$	$.1096^{*}$	$.1570^{*}$	$.2066^{*}$
	$(.0434)$	$(.0539)$	$(.0616)$	$(.0815)$
year 9	$-.0954$	$-.0602$	$.0415$	$.0688$
	$(.0548)$	$(.0677)$	$(.0750)$	$(.1014)$
year 10	$-.0969$	$-.0443$	$-.0179$	$-.1013$
	$(.0630)$	$(.0759)$	$(.0864)$	$(.1261)$
year 11	$-.0674$	$-.1006$	$-.0081$	$.1658$
	$(.0716)$	$(.0875)$	$(.0976)$	$(.1320)$
year 12	$-.2238^{*}$	$-.2372^{*}$	$-.2082$	$-.0725$
	$(.0905)$	$(.1082)$	$(.1281)$	$(.1785)$
year 13	$-.2787^{**}$	$-.2644^{*}$	$-.1160$	$-.1244$
	$(.1061)$	$(.1253)$	$(.1407)$	$(.2074)$
year 14	$-.2223$	$-.2666$	$-.2795$	$-.1592$
	$(.1322)$	$(.1498)$	$(.1726)$	$(.2508)$
year 15	$-.2852$	$-.3410$	$-.2380$	$-.0681$
	$(.1516)$	$(.1750)$	$(.1893)$	$(.2526)$
year 16	$.1524$	$-.3540$	$-.4745^{*}$	$-.2576$
	$(.1418)$	$(.2029)$	$(.2362)$	$(.3114)$
year 17	$-.6984^{**}$	$-.6615^{*}$	$-.8180^{*}$	$-.6305$
	$(.2489)$	$(.2740)$	$(.3228)$	$(.4176)$
year 18	$-.1382$	$-.1487$	$.1025$	$-.2694$
	$(.2461)$	$(.2608)$	$(.2713)$	$(.4605)$
year 19	$-.5802$	$-.5945$	$-.6748$	$-.4903$
	$(.4584)$	$(.4585)$	$(.5896)$	$(.5918)$
year 20	$.2957$	$.2832$	$.3231$	$.3800$
	$(.4309)$	$(.4310)$	$(.4314)$	$(.4730)$
year 21	$-.5475$	$-.5591$	$-.5176$	$-.4729$

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	OVERALL COLLBORATION	LIMITED INTERVAL[†] COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
	(1.0226)	(1.0226)	(1.0228)	(1.0235)
year 22	−.0460	−.0555	−.0139	.0317
	(.7390)	(.7390)	(.7393)	(.7402)
Previously applied patents [a]	−.0386***	−.0383***	−.0382***	−.0374***
	(.0008)	(.0008)	(.0008)	(.0008)
Potential research years	.0148***	.0160***	.0167***	.0176***
	(.0015)	(.0015)	(.0015)	(.0015)
Potential research years squared	.0011***	.0011***	.0010***	.0010***
	(.0001)	(.0001)	(.0001)	(.0001)
Tenure years	.0105**	.0087**	.0076*	.0064*
	(.0033)	(.0032)	(.0032)	(.0031)
Tenure years squared	−.0008***	−.0007***	−.0007***	−.0007***
	(.0002)	(.0002)	(.0002)	(.0002)
The first tenure year dummy	.5570***	.5544***	.5511***	.5458***
	(.0076)	(.0074)	(.0073)	(.0072)
Number of patents made by firm	.3036***	.3057***	.3079***	.3084***
	(.0172)	(.0172)	(.0172)	(.0172)
Field dummies:				
Chemical	.1983***	.1982***	.1985***	.1985***
	(.0101)	(.0101)	(.0101)	(.0101)
Comp.& Comm.	.1638***	.1646***	.1643***	.1651***
	(.0122)	(.0122)	(.0122)	(.0122)
Drugs & Medical	.1714***	.1719***	.1715***	.1715***
	(.0155)	(.0155)	(.0155)	(.0155)
Elec. & Electronics	.1822***	.1825***	.1821***	.1833***
	(.0099)	(.0099)	(.0099)	(.0099)
Mechanical	.1700***	.1714***	.1725***	.1721***
	(.0089)	(.0089)	(.0089)	(.0089)
Others	.1818***	.1820***	.1830***	.1825***
	(.0092)	(.0092)	(.0092)	(.0092)
Annual dummies				
year 2	.0165	.0152	.0139	.0118
	(.0163)	(.0163)	(.0163)	(.0163)
year 3	−.0346*	−.0367*	−.0383*	−.0406*
	(.0160)	(.0160)	(.0160)	(.0160)
year 4	−.0972***	−.0999***	−.1015***	−.1035***
	(.0158)	(.0157)	(.0157)	(.0157)
year 5	−.1279***	−.1308***	−.1320***	−.1339***
	(.0153)	(.0153)	(.0153)	(.0153)
year 6	−.1694***	−.1723***	−.1731***	−.1749***
	(.0150)	(.0150)	(.0149)	(.0149)
year 7	−.2125***	−.2151***	−.2160***	−.2183***
	(.0147)	(.0147)	(.0147)	(.0147)
year 8	−.2713***	−.2738***	−.2741***	−.2770***
	(.0145)	(.0144)	(.0144)	(.0144)
year 9	−.3124***	−.3148***	−.3154***	−.3183***
	(.0142)	(.0142)	(.0142)	(.0142)
year 10	−.3353***	−.3376***	−.3381***	−.3412***
	(.0140)	(.0139)	(.0139)	(.0139)
year 11	−.3120***	−.3139***	−.3147***	−.3177***

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	OVERALL COLLBORATION	LIMITED INTERVAL† COLLABORATION		
		WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)
	(.0135)	(.0134)	(.0134)	(.0134)
year 12	−.3341***	−.3358***	−.3368***	−.3403***
	(.0132)	(.0132)	(.0132)	(.0132)
year 13	−.3377***	−.3389***	−.3397***	−.3427***
	(.0127)	(.0127)	(.0127)	(.0127)
year 14	−.3160***	−.3159***	−.3168***	−.3203***
	(.0124)	(.0124)	(.0124)	(.0123)
year 15	−.3073***	−.3067***	−.3079***	−.3119***
	(.0121)	(.0121)	(.0121)	(.0121)
year 16	−.3220***	−.3210***	−.3220***	−.3262***
	(.0120)	(.0120)	(.0120)	(.0120)
year 17	−.3354***	−.3336***	−.3346***	−.3392***
	(.0120)	(.0120)	(.0120)	(.0120)
year 18	−.3348***	−.3324***	−.3334***	−.3381***
	(.0119)	(.0119)	(.0119)	(.0119)
year 19	−.3124***	−.3097***	−.3109***	−.3152***
	(.0118)	(.0118)	(.0118)	(.0118)
year 20	−.2695***	−.2670***	−.2675***	−.2704***
	(.0117)	(.0117)	(.0117)	(.0117)
year 21	−.1001***	−.0980***	−.0987***	−.1001***
	(.0115)	(.0115)	(.0115)	(.0115)
year 22	−.1505***	−.1491***	−.1497***	−.1502***
	(.0122)	(.0122)	(.0122)	(.0122)
Log-likelihood	-236375	-236377	-236380	-236426
Observations	286954	286954	286954	286954

NOTE.– Standard errors are in parentheses.

[a] Total numbers of previously applied patents is used.

† Collaborations from limited intervals before the job switch are considered. The Intervals are within 36 months, 24 months, and 12 months before the job switch. $* \, p < .1$. $* * \, p < .05$. $* * * \, p < .01$.

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