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

by

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

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Abstract

It has been argued in the economic literature that job search through informal job networks improves the employer–employee match quality. 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.

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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, because firms may face difficulty in ascertaining how well an inventor is matched with them 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. 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 improve the match quality? How does such a mechanism influence inventors' mobility and productivity?

Recent developments in the literature on social and economic networks 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) finds 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 finds that more than half of the respondent's jobs were obtained through personal connections.

Theoretical studies of informal networks in labor markets[1] investigate 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' abilities (Saloner, 1985; Montgomery, 1991; Casella and Hanaki, 2006, 2008) (that is, referrals through job networks may provide firms with information about unobserved workers' abilities, allowing firms to use the information to select high-ability workers); and (iii) reducing uncertainty about employee–employer match quality (Simon and Warner, 1992; Mortensen and Vishwanath, 1994) (that is, referral through job networks may provide workers with information about unobserved match quality, allowing workers to self-select themselves to

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

firms representing a good match). This paper follows this literature and analyzes the effect of inventors' job networks on their mobility and productivity.

We develop 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 network 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 are available, and, at the same time, an inventor who uses his collaborator network can estimate more precisely how well (or how badly) 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 US patent application database provided by the 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 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 substantially more productive than publicly recruited inventors. It is also found that after-job-switch productivity is substantially higher for the network-recruited inventors who are referred by high-productive referees than for those who are re-

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

ferred by low-productive referees, suggesting that the collaboration network acts as a screening mechanism to identify inventors' research ability. Nonetheless, even after controlling for positive association between the recruited inventor's productivity and their referee's productivity, a substantial productivity advantage of network-recruited inventors over publicly recruited inventors remains. Furthermore, the initial productivity advantage of network-recruited over publicly recruited inventors declines as tenure progresses. All these findings are consistent with the job match hypothesis that the job network reduces ex ante uncertainty about match value between inventors and firms. Finally, the evidence from the fixed-effect regression that controls for individual heterogeneity suggests that the observed productivity difference between network-recruited and publicly recruited inventors is not only a result of network-recruited workers having higher unobserved abilities than publicly recruited inventors.

This paper is related to two strands of literature. First, it is related to the empirical labor literature that 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 (Loury, 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) and 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. Pellizzari (2004) finds that, using the data of European Union countries, both wage premiums and penalties exist for referred workers across countries and industries. Antoninis (2006) studies the labor market of the Egyptian manufacturing sector and finds that referred workers take wage penalties in the case of recruitment to low-skilled jobs; however, if workers are referred by individuals who have direct working experience with them, they can obtain wage premiums in both low- and high-skilled jobs. Finally, Loury (2006) shows that only young males who are referred by older-generation male relatives enjoy higher wages; however, no significant job reference effect exists for other groups of workers. It should be noted that 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 a job search for "scientific researchers".

Our paper departs from these empirical studies in that we study inventors who actively engage in research activities, and we 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 productivity, 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 flow. 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 in 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 for 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 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 US 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 examined in 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 maximizes his expected sum of discounted wages given by:

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

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

We assume that inventor i's match productivity at firm j is given by θ_{ij}, which is unknown to both the inventor and the firm in period $t = 0$. They can observe the noise-ridden version of the true match value, which is given by $\theta_{ij} + \varepsilon_i$, where ε_i is white noise. It is also assumed that they can observe the true match value θ_{ij} after the inventor works at the firm for one period. The firm chooses the pay of 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 strategies 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, because 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:

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

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 of the future wage flow 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:

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

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

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

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:

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

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

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

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 previously collaborated. 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; i.e., $\sigma^2_{\varepsilon N} < \sigma^2_{\varepsilon P}$. 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 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 an increasing function of $\sigma^2_{\varepsilon k}$. Because $\sigma^2_{\varepsilon N} < \sigma^2_{\varepsilon P}$, publicly recruited inventors are more likely to leave the employed firm than network-recruited inventors. This observation leads to the following proposition 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, employed through a collaboration network, he 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 above 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.[3] Then, the value of unemployment, W, is given by:

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

where $\sigma^2_{qk} = \sigma^4_\theta / (\sigma^2_{\varepsilon k} + \sigma^2_\theta)$ 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

[3] We do not explicitly model which firm uses employees' referral in hiring an inventor because it is beyond the focus of the current paper. However, the existing theoretical works, (e.g., Saloner, 1985; Montgomery, 1991) suggest that firms with productive employees will hire through referral, while those without such employees, do not. It is also possible that the current employees of the firm do not have useful connections with others (Casella and Hanaki, 2008). Because we do not assume a productivity difference among workers, the probability p with which a firm hires a referral worker can be interpreted as the probability at which the current employees of the firm have meaningful connections with other inventors.

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 a 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.

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

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 *Network-recruited inventors exhibit a higher initial productivity than 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:

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

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

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

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 $\sigma_{\varepsilon N}^2 \to 0$, while $\sigma_{\varepsilon P}^2$ is strictly positive for the publicly recruited inventors. Noting that $s_N^2 = (1/\sigma_\theta^2 + 1/\sigma_{\varepsilon N}^2)^{-1}$, $\sigma_{\varepsilon N}^2 \to 0$ implies $s_N^2 \to 0$. Furthermore, $\sigma_{\varepsilon N}^2 \to 0$ implies $\sigma_{qN}^2 \to 0$, 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 *Publicly recruited inventors have higher productivity growth than network-recruited inventors as tenure increases.*

The intuitive reason why the average productivity growth is higher for publicly recruited inventors than for 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 average 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*.[4] 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 addresses of inventors, the type of assignee, and the technological category of the patent. We supplement the month of the patent application with the *USPTO PatentBIB* database. The *NBER Patent Data File* contains the patent citations for patents 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.[5] Therefore, 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

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

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

[5]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.

the patents, but also patent citations, and inventors' addresses, while allowing for the possibility of spelling errors in names.[6] In addition, to increase the accuracy of matching individual inventors, we focus on the inventors whose addresses are in the US.

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 periods 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 US.[7]

Let us now describe, in detail, how we construct the employment histories for 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's job spell (CJS).[8]

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.[9] (2) Among the remaining CJSs,

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

[7] 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.

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

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

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 this rule because our aim is not to have a complete employment history of all the inventors, but rather 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.[10] It is found that more than 95 percent of those inventors only had either two or three job spells.

3.2 Recruitment Method

We can obtain information concerning the recruiting method, whether network recruited or publicly recruited, from the patent collaboration histories of 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 been 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 generate more meaningful referral. Therefore, in the analyses below, we also consider more restricted

[10]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.

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 networks for the first jobs, we examine this hypothesis only for *subsequent* jobs of inventors who switched their jobs at least once. Therefore, 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 job spell data are arbitrary censored,[11] we employ a nonparametric 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.

[11] Our job spell data are arbitrarily 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 $(l_2 - r_2) < t_2 < (l_3 - r_1)$.

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 a 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, network-recruited inventors are less likely to leave the employed job than publicly recruited inventors. As other explanatory variables, X_{if}, we include the years of research experience before being employed by firm f. This is given by the number of years since the inventor i applied for patents for the first time until the time when he is employed by firm f, which is called *research experience* in the regression. 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 electronics, mechanical, and others.[12] 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 for before joining firm f, which are called *total and average past patent productivities* in the regression. They are used as proxies for the 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, the coefficient δ is negative and statistically significant, and thus the network recruitment method significantly decreases the hazard of leaving the employment. Therefore, the network-recruited inventors are likely to stay longer at the firm than the publicly recruited inventors.

[12] We follow the technological category definitions of Hall, Jaffe, and Trajtenberg (2001).

In columns (3)–(5), we use various network- recruitment measures that limit the intervals after the collaborations were made. The estimates of the coefficients of network-recruited dummies are significantly negative in all specifications. These estimates imply that network-recruited inventors are about 40 percent less likely to leave the job than publicly recruited inventors.

4.2 Productivity Results

Our theoretical model presents two main empirically testable hypotheses about inventors' productivity. The first hypothesis, given by Proposition 2, is that network-recruited inventors have a higher initial productivity than publicly recruited inventors, on average. The second hypothesis, given by Proposition 4, is 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. Thus, the initial productivity advantage of network-recruited inventors over publicly recruited inventors disappears as tenure progresses. 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 a *Poisson-based* specification as in Hausman, Hall, and Griliches (1984) and 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 by:

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

where X_{ift} is a vector of individual-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 *match premium* for network-recruited inventors over publicly recruited inventors. According to Proposition 2, the network- recruited inventors can obtain the information about their match values with their potential employers through their collaboration network, and thus have better initial match values than publicly recruited inventors. We thus expect that the match premium is positive in the early stage of tenure.

As presented in the introduction, however, the role of collaboration networks may not be confined to reducing match uncertainty between inventors and firms. It is argued by previous studies that network references may act as a screening device in the selection of high-ability workers. Knowing that referees tend to refer others who are similar to themselves, firms have incentives to select inventors who were referred by high-productivity referees rather than those who were referred by low-productivity referees. Therefore, if the collaboration network works as a screening device, the productivity of a network-recruited inventor will be positively correlated with the productivity of the referee who referred the inventor to the firm.

To capture the screening effect through the collaboration network, the regression variables, X_{ift}, include the productivity of the referee inventor who referred inventor i to firm f (we call this the *referee's productivity*). For network-recruited inventor i, we define his referee as one of the past collaborators who was employed by firm f in year t. We measure the referee's productivity by the total number of patents that he had applied for at firm f before inventor i switched to the firm. For publicly recruited inventor i, because he was not referred by anybody at the job switch, the referee's productivity variable is set to be zero. If the screening mechanism works for the collaboration network, it is predicted that the referee's productivity will be positively related to network-recruited inventor i's productivity, and thus the sign of the estimated coefficient of the referee's productivity will be positive. It should be noted that the screening effect is not captured by the match premium ρ of the coefficient of NET_{if}. The job match hypothesis implies that the match premium will be positive $\rho > 0$ *no matter who is the referee*. In other words, a network-recruited inventor is able to obtain information about his match value with the potential employer even though the referee exhibits low patent productivity. Therefore, the job match hypothesis alone cannot explain positive association in productivity between the referee inventors and referred inventors.

As other variables for X_{ift}, we include the years of potential research experience since inventor i applied for patents for the first time (we call this the *total research experience*), and the years of tenure at firm f (we call this the *within-firm research experience*). Both years of experience are measured as of period t. While the years of total research experience are accumulated over time, the years of within-firm experience are reset to be zero whenever the inventor switched his jobs. We also include *research field dummies* for $m = 6$ categories, and the total number of patents that the inventor i has applied for before firm f (we call this the *past patent productivity*) in the regression.[13] As in the hazard regression, it is used as a proxy for the inventor's innate research ability. In addition, we include the total number of patents that were applied for by all inventors employed at firm f during year t (we call this the *firm's patent productivity*). This variable is considered to be a proxy for the research capacity of the firm. It is expected that the higher the

[13] Given that the average number of patents is more susceptible to interval censoring of employment duration than the total number of patents, we use the total number of previously applied patents as a proxy for inventors' ability in what follows.

firm's research capacity, the more patents the firm produces, and vice versa.[14] Finally, following the previous literature (e.g., Hall and Ziedonis, 2001), we include annual dummies, which account 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 his first job. It thus implies that we estimate the effect of referrals on inventors' productivity *after switching firms*.[15] 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.

Table 4 presents the estimation results of the baseline model.[16] In addition to the variables that are explained above, we included the first-year tenure dummy that takes a value of one for an 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.[17]

Column (1) shows the estimation result using the network-recruited dummy constructed from the overall collaboration network. It is found that the estimates of match premium of the network-recruited inventors, ρ, is positive and statistically significant. Columns (2)–(4) present the estimation results in which collaborations only from limited intervals before the job switch are considered. It is also found consistently that the estimated values of ρ are positive and statistically significant. All these findings confirm that network-recruited inventors are more productive than publicly recruited inventors. More interestingly the match premium 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. These findings are consistent with our view that the collaboration network is a method by which agents obtain information about unobserved match quality, and the more recent the information, the more

[14]Often the 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.

[15]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) and Loury (2006).

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

[17]See **?** for a detailed discussion.

certain they are about the quality of their match.

The estimation results also show that the coefficients of referees' productivity are positive and statistically significant, predicting that inventors who were referred by higher-productivity referees tend to be more productive than those who were referred by lower-productivity referees. This suggests that firms may use the referee's productivity to select high-ability inventors among potential employees. Nevertheless, the fact that a substantial match premium remains after controlling for the network screening effect seems to support the job match hypothesis. These findings thus indicate that the collaboration network has *two* roles at the same time: one is to provide firms with the information to screen inventor's ability, and the other is to provide firms and inventors with information about their match quality.

As for the other control variables, many of the estimates confirm our prior expectation. As one expects, the coefficients of the past patent productivity are positive and statistically significant, suggesting that inventors who had applied for more patents tend to produce more patents after their job changes. Furthermore, the coefficients of the firm's patent productivity are, as expected, positive and statistically significant. Though somewhat puzzling, the change in productivity is found to follow a *convex* relationship with the total and within-firm research experiences. We recognize that these research experience variables might be correlated with the *unobserved* ability of the inventor, and thus may be endogenous[18]. Therefore, these results about research experiences should be taken with caution. In the next section, we consider more seriously the problem of the individual unobserved factors that make some explanatory variables endogenous.

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:

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

where $Tenure_{iftk}$ is the kth tenure year dummy for inventor i at firm f, and takes a value of one if inventor i is employed in the kth year by firm f. In this within-firm productivity growth regression, the coefficient ρ_k of the interaction term cap-

[18]For example, a person with a higher ability will stay being an active patent inventor longer, so that his research experience will increase. 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.

tures the productivity premium for network-recruited inventors over publicly recruited inventors observed in the kth tenure year. A positive value of ρ_k means that 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 theoretical model considered above assumes that agents learn about the true match value 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 publicly recruited inventors than for network-recruited inventors, we predict that the coefficient ρ_k is weakly *decreasing* with tenure year k; i.e., $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_K$.

Columns (5)–(8) in Table 4 present 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 presented in the appendix.

The estimates overall deliver similar quantitative results as the productivity regression reported in columns (1)–(4). The coefficient ρ_k of the interaction terms are positive and statistically significant for the first six to eight tenure years in all specifications. Few estimates are found to be negative and significant for tenure years greater than nine; however, no positive significant estimates are found. It is also apparent that the magnitude tends to decrease as tenure year k increases, though the declining pattern is not necessarily uniform. This means that the initial productivity advantage of network-recruited inventors over publicly recruited inventors diminishes with tenure years, and disappears eventually. These findings are consistent with the proposition that publicly recruited inventors have a steeper tenure-productivity profile than network-recruited inventors, and thus supports the job match hypothesis presented by our theoretical model.

4.3 Robustness Check

The estimation results presented above indicate that the positive-match premium of network-recruited inventors is consistent with our theory that a reference through collaboration network may create better matches between inventors and firms. However, alternative explanations to such an interpretation are possible. First, higher-ability workers may receive more referral offers, and thus referrals may be correlated with the unobserved ability of the inventor. If this is the case, the observed productivity difference between network-recruited and publicly recruited inventors can be explained by the unobserved difference in abilities between these groups. Second, the cost of patent production per inventor may decline with the number of coauthors per patent. Therefore, inventors who tend to work in groups or collaborate on projects might appear to be more productive than those who do not, simply because they have many coauthors and thus devote relatively less time to produce one patent. In this sense, the patent productivity computed by the number of granted patents may be "inflated" by the coauthorship. This problem may be serious when network-recruited inventors are more likely to work in projects than the publicly recruited inventors. If this happens, network-recruited inventors appear to be more productive than the publicly recruited inventors, not because of their higher match value, but because of their sheer tendency to work in groups.

In what follows, we examine closely these two alternative hypotheses to ensure that the estimated productivity difference between the network- recruited and publicly recruited inventors is actually driven by a higher match value, as implied by the job match hypothesis that we maintain.

To begin with, we point out that unobserved productivity cannot explain the difference in productivity-tenure profiles between network-recruited inventors and publicly recruited inventors. As already discussed in Simon and Warner (1992), it is explained consistently by the fact that publicly recruited inventors are more likely to leave firms, because of job mismatch, than network-recruited inventors. Thus, the previous finding on different within-firm productivity growth pattern may support the job match hypothesis.

Furthermore, a more direct support for the job match hypothesis can be presented. Given the panel structure of our dataset, we may be able to control for time-invariant unobserved individual factors, including inventors' innate research abilities, by incorporating a fixed effect in the productivity regression. For that purpose, we augmented the baseline regression model (13) by adding an individual time-invariant fixed effect:

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

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

Table 5 presents the estimation results from the fixed-effect specifications.[19] Columns (1)–(4) present the estimation results for the baseline model, while columns (5)–(8) present the estimation results for the within-firm productivity growth model.

The results in columns (1)–(4) show that, for all specifications of network-recruitment dummies, the match premiums are again positive and statistically significant. Furthermore, the match premium increases among the more recent collaborations, as was previously found in Table 4. Thus, we find evidence that the collaboration networks bring about better matches between inventors and firms even after controlling for unobserved heterogeneity among inventors.

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

From the estimated coefficients of the interaction term, ρ_k, reported in columns (5)–(8), it is found that the interaction terms up to the eighth tenure year are positive and statistically significant in all specifications. The estimation results show that the match premium declines monotonically after the early tenure years, and disappears as tenure progresses. These results confirm that network-recruited inventors are initially more productive than publicly recruited inventors; however, the productivity advantage declines with tenure, and the convergence of productivity occurs between the two groups. It thus suggests that inventors learn their match productivity rather quickly after moving into a new firm.

These fixed-effect estimates in Table 5 are generally comparable to those in Table 4. However, one significant difference between the pooled and fixed-effect regressions is found in the estimated coefficient of the past patent productivity. The estimates are negative and statistically significant under the fixed-effect specification, while they are positive and significant under the pooled regression in which we ignore unobserved individual heterogeneity. The change in the sign of the estimates might be partly explained by the fact that past patent productivity, which is used to proxy for an inventor's research ability, captures some part of the inventor's individual heterogeneity, and is absorbed by the fixed-effect term. Furthermore, the effect of so-called "regression toward the mean" might explain the negative coefficient of the past patent productivity. Once both the observed and unobserved characteristics of inventors are controlled by regressors and the fixed effect, the numbers of patents applied in two successive job spells are thought to follow the same probability distribution. Therefore, inventors who are far from the mean productivity in the first job spell will tend to be closer to the mean productivity in the second job spell, and thus there will be a negative association between before-job-change productivity and after-job-change productivity.

It should be also noted in the estimates presented in Table 5 that there is a significant positive relationship between patent productivity and total research experience, suggesting that the inventors with longer research experience tend to produce more patents. Interestingly, patent productivity is also associated with within-firm research experience, yet the relationship is found to be concave.

We now turn to checking whether the positive-match value premium of network-recruited inventors, $\rho > 0$, is because of the fact that the productivity is "inflated" by coauthorships. Assuming that the coauthors contribute equally to patent production, individual contribution by each inventor to each patent is given by the inverse of the number of coauthors of the patent. Therefore, coauthorship-adjusted productivity is given by the annual sum of the inventor's patent contributions per coauthor. To be more precise, suppose that inventor i applied for a total of M_{it} patents in year t. Let N_m be the number of coauthors of the mth patent for $m = 1, \cdots, M_{it}$. Then the coauthorship-adjusted productivity of inventor i in year t is give by $P_{it} = \sum_{m=1}^{M_{it}} 1/N_m$. Using this "weighted" productivity measure as the dependent variable, we reestimate the regressions. Because the dependent variable is no longer integer-valued, we can use the linear regression model with or without fixed effects.

Table 6 presents the estimation results of the fixed-effect regression.[20] As presented, the estimates yield similar results to those from the Poisson regressions that do not take into account the individual-based contribution to each patent. In particular, the estimated match premium and their cross-terms with tenure dummies exhibit the same signs and statistical significance in all specifications of the collaboration network. Thus we can say that coauthorship does not play a big role in explaining the observed productivity difference between network-recruited inventors and publicly recruited inventors.

5 Conclusion

This paper developed a simple model of job search and matching 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 parent database. The empirical analysis supports the prediction of the theoretical model. It is found that network-recruited inventors who moved to companies where their research collaborators were employed had significantly longer tenure than publicly recruited inventors who moved to companies with which they had no personal connections. Moreover, the former group produced substantially more patents than the latter group for several years after their job switches; however, the productivity gap between the two groups declined as tenure years progressed. These findings can be consistently explained by the matching mechanism of the informal networks that reduce uncertainty in job matches between employers and employees. Interestingly, there is also evidence that informal networks work as a screening mechanism, and it enables firms to extract information about the potential employee's unobserved ability through their referee's observed abilities. Finally, fixed-effect regression results showed that unobserved individual characteristics cannot explain all of the productivity differences between network-recruited inventors and publicly recruited inventors.

The finding that network-refereed workers were more productive than non-referred workers is generally consistent with the existing literature, especially of those studying the role of informal job networks in high-paying sectors, (e.g., Si-

[20]The estimation results of the pooled regression are quite comparable to those of the fixed-effect regression, so the conclusion that we draw from the fixed-effect regression results still holds. The estimation results of the pooled regression are available upon request from the authors.

mon and Warner, 1992; Kugler, 2003; Antoninis, 2006; Loury, 2006). This paper further presented new empirical evidence that workers and firms may rely on two mechanisms of the informal networks at the same time in their job search and hiring processes; that is, workers use the network to reduce the uncertainty in their match value with potential employers, and firms use the network to select high-ability workers who are referred by high-ability referees. Of course, the evidence described above is derived from the labor market of patent inventors who have very high skills in general, and thus the implications may not be as valid for the labor markets of low-skilled workers. Although we expect the difference will be only a matter of degree, additional empirical evidence is necessary to ensure that the network mechanisms described here still work in the more general labor market setting.

The results of this paper have several implications for future research. First, although it is consistently suggested that the network- recruitment method enables firms to hire better-matched inventors than the publicly recruitment method does, it is found that many inventors were not necessary recruited through network reference. This raises the possibility that firms self-select themselves into segregated labor markets in which some firms use the network-recruitment method and other firms use the public recruitment method. This paper assumes that firms' choice of recruitment method is exogenously given by some process unrelated to search and matching, and thus does not explicitly account for firms' endogenous use of employees' referral in hiring inventors. Therefore, future work is needed to address this issue.

Second, our findings indicated that firms may use interfirm R&D networks not only as a way of exploiting external knowledge, as previously reported by the industrial organization literature (e.g., Singh, 2005), but also as a way of recruiting inventors with good match values and high research abilities through inventors' referrals. This unique role of R&D networks, which was downplayed by previous studies, may explain the observed relationship between firms' inventive productivity and their network position in R&D networks (Ahuja, 2000; Schilling and Phelps, 2007). The empirical finding of this paper suggests that firms with higher connectivity in R&D networks can recruit better-matched inventors than those with low connectivity, because the former firms can use more interfirm referrals than the latter firms in their hiring processes. Thus, a future extension of this paper will examine this hypothesis, and it will be a step forward in understanding the mechanism of how the global R&D network structure influences firm-level innovation.

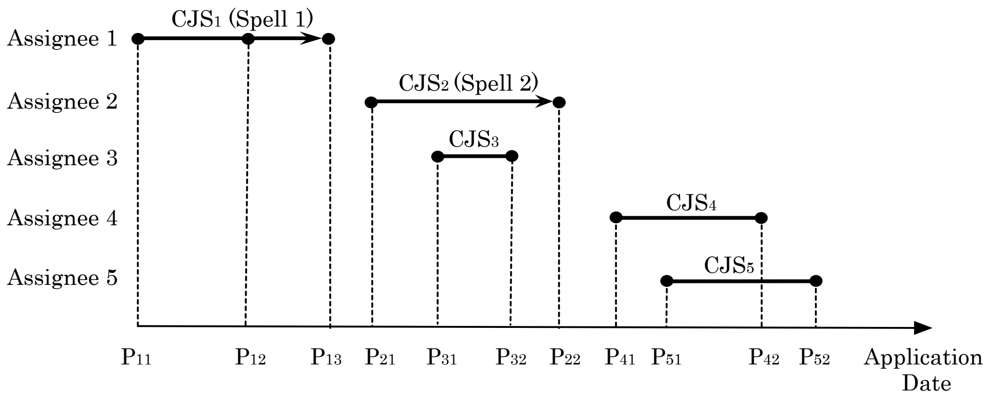

Figure 1: The Construction of Job Spells

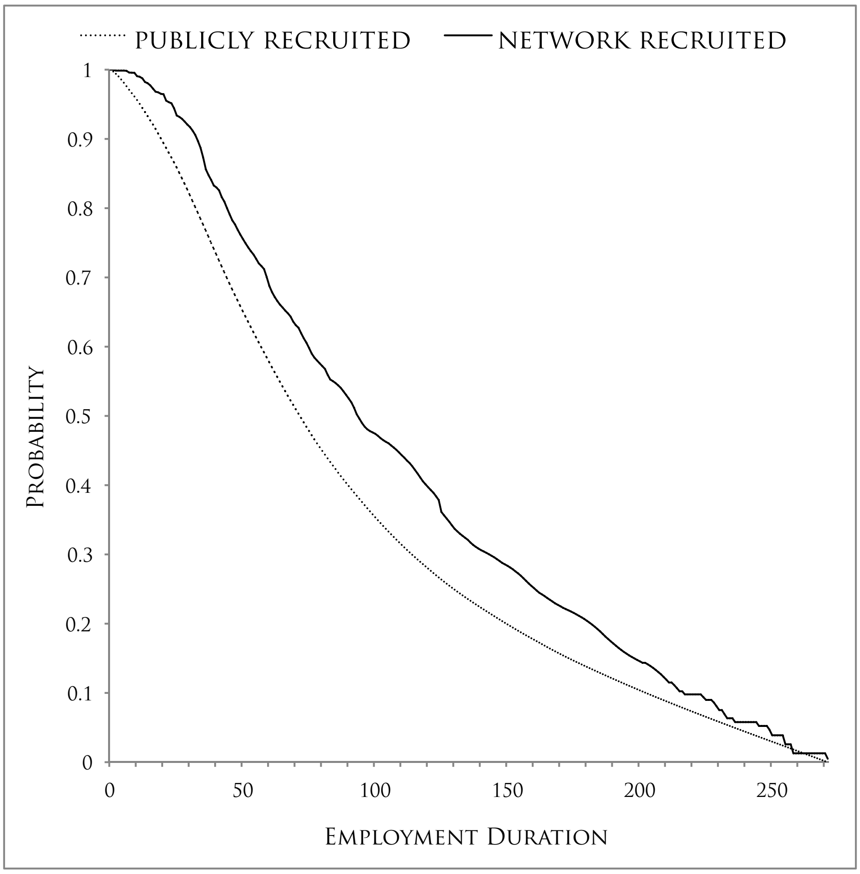

Figure 2: Survival Curves for Employment Duration after Job Transition

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
	$(.031)$	$(.030)$	$(.030)$	$(.030)$	$(.030)$
Past productivity:					
Total	$.0287$		$.0273$	$.0269$	$.0259$
	$(.002)$		$(.002)$	$(.002)$	$(.002)$
Average		$.0326$			
		$(.004)$			
Research experience	$-.0893$	$-.0819$	$-.0965$	$-.0958$	$-.0900$
	$(.009)$	$(.009)$	$(.009)$	$(.009)$	$(.009)$
(Research experience)^2	$.0036$	$.0035$	$.0039$	$.0039$	$.0037$
	$(.000)$	$(.000)$	$(.000)$	$(.000)$	$(.000)$
$\log \alpha$ [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	ALL SAMPLES	NETWORK RECRUITED	PUBLICLY RECRUITED
Number of patents made by	1.003	1.126	0.989
an individual in a year	(1.08)	(1.21)	(1.07)
Network referral dummies:			
overall	0.102	–	–
	(.303)		
within 36 months	0.064	–	–
	(.245)		
within 24 months	0.050	–	–
	(.217)		
within 12 months	0.026	–	–
	(.159)		
Referee's productivity	1.826	17.831	0.000
	(10.615)	(28.544)	(.000)
Past productivity	1.716	4.769	1.368
	(3.706)	(6.338)	(3.087)
Total research experience	5.713	8.109	5.439
	(5.353)	(5.269)	(5.294)
Within-firm research experience	3.344	3.045	3.378
	(3.176)	(2.653)	(3.229)
Firm's productivity†	0.088	0.078	0.090
	(.185)	(.183)	(.186)
Research field dummies:			
Chemical	0.316	0.349	0.312
	(.465)	(.477)	(.463)
Comp.& Comm.	0.194	0.182	0.195
	(.395)	(.386)	(.396)
Drugs & Medical	0.131	0.178	0.125
	(.337)	(.383)	(.331)
Elec. & Electronics	0.288	0.248	0.293
	(.453)	(.432)	(.455)
Mechanical	0.307	0.273	0.311
	(.461)	(.446)	(.463)
Others	0.295	0.265	0.298
	(.456)	(.441)	(.458)
N	286954.000	29393.000	257561.000

NOTE.– The statistics are computed for both the aggregated samples and disaggregated samples by recruitment method. The standard errors are in parentheses.
† The unit of firm's productivity is in thousand.

Table 4: Baseline Regression Estimates

	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network referral dummy: ρ	0.0554^{***}	0.0685^{***}	0.0733^{***}	0.0733^{***}				
	(0.0072)	(0.0082)	(0.0092)	(0.0122)				
Interaction terms of network and tenure dummies: ρ_k								
year 1					0.0355^{***}	0.0368^{***}	0.0425^{***}	0.0437^{***}
					(0.0074)	(0.0089)	(0.0102)	(0.0145)
year 2					0.0493^{***}	0.0994^{***}	0.1040^{***}	0.1245^{***}
					(0.0182)	(0.0219)	(0.0248)	(0.0351)
year 3					0.1449^{***}	0.1883^{***}	0.1909^{***}	0.1911^{***}
					(0.0198)	(0.0245)	(0.0266)	(0.0332)
year 4					0.1103^{***}	0.1288^{***}	0.1258^{***}	0.1191^{***}
					(0.0247)	(0.0297)	(0.0333)	(0.0435)
year 5					0.0743^{**}	0.0728^{*}	0.0707	−0.0195
					(0.0323)	(0.0422)	(0.0499)	(0.0477)
year 6					0.0731^{**}	0.0675	0.0471	0.0574
					(0.0371)	(0.0468)	(0.0559)	(0.0775)
year 7					0.0700	0.0264	−0.0147	−0.0760
					(0.0503)	(0.0660)	(0.0810)	(0.0840)
year 8					0.0723	0.0817	0.0888	0.0988
					(0.0522)	(0.0681)	(0.0691)	(0.0906)
year 9					−0.0732	−0.0688	0.0165	0.0070
					(0.0650)	(0.0788)	(0.0884)	(0.1264)
year 10					−0.0768	−0.0332	−0.0208	−0.1360
Referee's productivity	0.0014^{***}	0.0015^{***}	0.0016^{***}	0.0018^{***}	0.0014^{***}	0.0015^{***}	0.0016^{***}	0.0018^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Past patent productivity	0.0103^{***}	0.0102^{***}	0.0102^{***}	0.0103^{***}	0.0102^{***}	0.0102^{***}	0.0102^{***}	0.0103^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Overall research experience	-0.0108^{***}	-0.0101^{***}	-0.0098^{***}	-0.0097^{***}	-0.0109^{***}	-0.0103^{***}	-0.0099^{***}	-0.0097^{***}
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
(Overall research experience)^2	0.0003^{***}	0.0003^{***}	0.0002^{***}	0.0002^{***}	0.0003^{***}	0.0003^{***}	0.0002^{***}	0.0002^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Within-firm research experience	−0.0039	−0.0044	−0.0046	−0.0048	−0.0034	−0.0028	−0.0034	−0.0038
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0035)	(0.0035)	(0.0034)	(0.0034)
(Within-firm research experience)^2	0.0003^{*}	0.0003^{*}	0.0004^{*}	0.0004^{*}	0.0004^{*}	0.0003	0.0004^{*}	0.0003^{*}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
The first tenure year dummy	0.4603^{***}	0.4601^{***}	0.4600^{***}	0.4592^{***}	0.4687^{***}	0.4709^{***}	0.4681^{***}	0.4643^{***}
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0080)	(0.0078)	(0.0077)	(0.0076)
Firm's productivity	0.1685^{***}	0.1692^{***}	0.1691^{***}	0.1681^{***}	0.1680^{***}	0.1679^{***}	0.1679^{***}	0.1670^{***}
	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)
Constant	-0.3314^{***}	-0.3320^{***}	-0.3313^{***}	-0.3286^{***}	-0.3402^{***}	-0.3444^{***}	-0.3408^{***}	-0.3350^{***}
	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0130)	(0.0128)	(0.0127)	(0.0126)
Log-likelihood	-355398.98	-355393.13	-355395.49	-355410.54	-355355.05	-355346.29	-355358.24	-355384.75
Observations	286954	286954	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. 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. Robust standard errors are in parentheses. $*\, p < .1$. $**\ p < .05$. $***\, p < .01$.

Table 5: Fixed-effect Regression Estimates

	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network referral dummy: ρ	0.1023^{***}	0.1270^{***}	0.1551^{***}	0.1806^{***}				
	(0.0104)	(0.0117)	(0.0129)	(0.0169)				
Interaction terms of network and tenure dummies: ρ_k								
year 1					0.0801^{***}	0.0935^{***}	0.1195^{***}	0.1368^{***}
					(0.0120)	(0.0138)	(0.0154)	(0.0208)
year 2					0.1323^{***}	0.1844^{***}	0.2133^{***}	0.2599^{***}
					(0.0172)	(0.0199)	(0.0220)	(0.0287)
year 3					0.2166^{***}	0.2640^{***}	0.2865^{***}	0.3101^{***}
					(0.0186)	(0.0221)	(0.0244)	(0.0322)
year 4					0.1589^{***}	0.1794^{***}	0.1980^{***}	0.2250^{***}
					(0.0226)	(0.0279)	(0.0312)	(0.0417)
year 5					0.1026^{***}	0.1120^{***}	0.1329^{***}	0.0793
					(0.0271)	(0.0338)	(0.0384)	(0.0525)
year 6					0.0907^{***}	0.1111^{***}	0.1238^{***}	0.1755^{***}
					(0.0320)	(0.0406)	(0.0468)	(0.0613)
year 7					0.0619	0.0385	0.0426	0.0224
					(0.0377)	(0.0488)	(0.0569)	(0.0784)
year 8					0.0571	0.0865	0.1331^{**}	0.1784^{**}
					(0.0436)	(0.0541)	(0.0617)	(0.0816)
year 9					-0.1158^{**}	-0.0836	0.0167	0.0399
					(0.0549)	(0.0678)	(0.0751)	(0.1014)
year 10					-0.1161^{*}	-0.0655	-0.0398	-0.1252
					(0.0631)	(0.0759)	(0.0865)	(0.1262)
Referee's productivity	0.0012^{***}	0.0014^{***}	0.0014^{***}	0.0017^{***}	0.0011^{***}	0.0014^{***}	0.0014^{***}	0.0017^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Past productivity	-0.0394^{***}	-0.0395^{***}	-0.0395^{***}	-0.0392^{***}	-0.0395^{***}	-0.0396^{***}	-0.0396^{***}	-0.0392^{***}
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Total research experience	0.0159^{***}	0.0167^{***}	0.0170^{***}	0.0177^{***}	0.0153^{***}	0.0162^{***}	0.0167^{***}	0.0175^{***}
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
(Total research experience)^2	0.0011^{***}	0.0010^{***}	0.0010^{***}	0.0010^{***}	0.0011^{***}	0.0011^{***}	0.0011^{***}	0.0010^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Within-firm research experience	0.0062^{**}	0.0053^{*}	0.0052^{*}	0.0048	0.0101^{***}	0.0086^{***}	0.0076^{**}	0.0066^{**}
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0033)	(0.0032)	(0.0032)	(0.0031)
(Within-firm research experience)^2	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}	-0.0006^{***}	-0.0008^{***}	-0.0007^{***}	-0.0007^{***}	-0.0007^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
The first tenure year dummy	0.5396^{***}	0.5394^{***}	0.5396^{***}	0.5390^{***}	0.5569^{***}	0.5548^{***}	0.5515^{***}	0.5465^{***}
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0076)	(0.0074)	(0.0073)	(0.0072)
Firm's productivity	0.3045^{***}	0.3061^{***}	0.3072^{***}	0.3074^{***}	0.3024^{***}	0.3036^{***}	0.3055^{***}	0.3054^{***}
	(0.0172)	(0.0173)	(0.0173)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)
Log-likelihood	-236433.22	-236423.18	-236410.06	-236425.31	-236363.28	-236356.18	-236358.39	-236393.13
Observations	286954	286954	286954	286954	286954	286954	286954	286954

NOTE.– Dependent variable is the number of patents applied by inventor. All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C1. 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 Regression Using Coauthorship-Adjusted Productivity

	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network referral dummy: ρ	0.0586^{***}	0.0564^{***}	0.0732^{***}	0.0937^{***}				
	(0.0071)	(0.0081)	(0.0089)	(0.0117)				
Interaction terms of network and tenure dummies: ρ_k								
year 1					-0.0115	-0.0189^{*}	-0.0072	0.0009
					(0.0086)	(0.0100)	(0.0113)	(0.0154)
year 2					0.1125^{***}	0.1213^{***}	0.1384^{***}	0.1674^{***}
					(0.0108)	(0.0128)	(0.0142)	(0.0188)
year 3					0.1558^{***}	0.1651^{***}	0.1789^{***}	0.1971^{***}
					(0.0121)	(0.0147)	(0.0163)	(0.0217)
year 4					0.1466^{***}	0.1404^{***}	0.1587^{***}	0.1875^{***}
					(0.0145)	(0.0181)	(0.0203)	(0.0273)
year 5					0.1165^{***}	0.0974^{***}	0.1148^{***}	0.1106^{***}
					(0.0171)	(0.0215)	(0.0244)	(0.0325)
year 6					0.1071^{***}	0.0922^{***}	0.0985^{***}	0.1104^{***}
					(0.0202)	(0.0256)	(0.0293)	(0.0390)
year 7					0.0926^{***}	0.0723^{**}	0.0776^{**}	0.0866^{*}
					(0.0239)	(0.0305)	(0.0349)	(0.0471)
year 8					0.1299^{***}	0.1321^{***}	0.1716^{***}	0.1862^{***}
					(0.0278)	(0.0348)	(0.0399)	(0.0535)
year 9					0.0287	0.0140	0.0757	0.1106^{*}
					(0.0330)	(0.0408)	(0.0469)	(0.0636)
year 10					0.0352	0.0471	0.0766	-0.0155
					(0.0381)	(0.0464)	(0.0531)	(0.0736)
Referee's productivity	0.0010^{***}	0.0013^{***}	0.0013^{***}	0.0014^{***}	0.0010^{***}	0.0013^{***}	0.0013^{***}	0.0014^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Past productivity	-0.0355^{***}	-0.0354^{***}	-0.0355^{***}	-0.0354^{***}	-0.0358^{***}	-0.0356^{***}	-0.0356^{***}	-0.0354^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Total research experience	0.0045^{***}	0.0051^{***}	0.0052^{***}	0.0055^{***}	0.0053^{***}	0.0053^{***}	0.0053^{***}	0.0055^{***}
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
(Total research experience)^2	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}	0.0005^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Within-firm research experience	0.0009	0.0003	0.0003	0.0001	0.0014	0.0013	0.0010	0.0007
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
(Within-firm research experience)^2	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
The first tenure year dummy	0.3475^{***}	0.3471^{***}	0.3472^{***}	0.3470^{***}	0.3672^{***}	0.3612^{***}	0.3583^{***}	0.3535^{***}
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0047)	(0.0046)	(0.0045)	(0.0045)
Firm's productivity	0.1334^{***}	0.1346^{***}	0.1349^{***}	0.1348^{***}	0.1324^{***}	0.1330^{***}	0.1337^{***}	0.1336^{***}
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
Log-likelihood	-249117.45	-249129.52	-249118.27	-249120.36	-248953.42	-249003.83	-249015.49	-249052.41
Observations	286954	286954	286954	286954	286954	286954	286954	286954

NOTE.– Dependent variable is the annual sum of inventor's per coauthor contribution to patent. Fixed effect regressions are used. All estimation results are presented in Appendix C. Other variable included in each column are the same as those in Table C1. 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. Robust standard errors are in parentheses. $*\, p < .1$. $**\ p < .05$. $***\, p < .01$.

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.[21] 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.[22] 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-

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

[22] 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: Baseline Regression: All Estimation Results

	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network referral dummy: ρ	0.0554^{***}	0.0685^{***}	0.0733^{***}	0.0733^{***}				
	(0.0072)	(0.0082)	(0.0092)	(0.0122)				
Interaction terms of network and tenure dummies: ρ_k								
year 1					0.0355^{***}	0.0368^{***}	0.0425^{***}	0.0437^{***}
					(0.0074)	(0.0089)	(0.0102)	(0.0145)
year 2					0.0493^{***}	0.0994^{***}	0.1040^{***}	0.1245^{***}
					(0.0182)	(0.0219)	(0.0248)	(0.0351)
year 3					0.1449^{***}	0.1883^{***}	0.1909^{***}	0.1911^{***}
					(0.0198)	(0.0245)	(0.0266)	(0.0332)
year 4					0.1103^{***}	0.1288^{***}	0.1258^{***}	0.1191^{***}
					(0.0247)	(0.0297)	(0.0333)	(0.0435)
year 5					0.0743^{**}	0.0728^{*}	0.0707	−0.0195
					(0.0323)	(0.0422)	(0.0499)	(0.0477)
year 6					0.0731^{**}	0.0675	0.0471	0.0574
					(0.0371)	(0.0468)	(0.0559)	(0.0775)
year 7					0.0700	0.0264	−0.0147	−0.0760
					(0.0503)	(0.0660)	(0.0810)	(0.0840)
year 8					0.0723	0.0817	0.0888	0.0988
					(0.0522)	(0.0681)	(0.0691)	(0.0906)
year 9					−0.0732	−0.0688	0.0165	0.0070
					(0.0650)	(0.0788)	(0.0884)	(0.1264)
year 10					−0.0768	−0.0332	−0.0208	−0.1360
					(0.0723)	(0.0916)	(0.1106)	(0.1507)
year 11					−0.0263	−0.0626	0.0028	0.0957
					(0.0960)	(0.1291)	(0.1172)	(0.1594)
year 12					−0.1136	−0.1473	−0.1543	−0.1058
					(0.1008)	(0.1282)	(0.1506)	(0.1868)
year 13					−0.1558	−0.1953	−0.1009	−0.1950
					(0.1085)	(0.1336)	(0.1560)	(0.2086)
year 14					−0.1398	−0.1900	−0.2250	−0.2290
					(0.1482)	(0.1492)	(0.1862)	(0.2663)
year 15					−0.1647	−0.2366	−0.1947	−0.0582
					(0.1762)	(0.1876)	(0.2131)	(0.2711)
year 16					0.3348	−0.1901	−0.3310	−0.1520
					(0.3904)	(0.2933)	(0.3322)	(0.4880)
year 17					-0.4982^{**}	-0.4558^{*}	-0.6362^{**}	−0.5160
					(0.2080)	(0.2406)	(0.2670)	(0.3618)
year 18					−0.1268	−0.1412	0.0136	−0.4545
					(0.2017)	(0.2261)	(0.2186)	(0.4116)
year 19					-0.6782^{*}	-0.6764^{*}	−0.9025	−0.6961
					(0.3818)	(0.3819)	(0.6033)	(0.5643)
year 20					−0.1027	−0.0990	−0.0953	−0.0515
					(0.0993)	(0.0994)	(0.0995)	(0.1085)
year 21					-1.0322^{*}	-1.0263^{*}	-1.0217^{*}	-1.0143^{*}

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	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					(0.5547)	(0.5547)	(0.5547)	(0.5546)
year 22					−0.3985**	−0.3920**	−0.3870**	−0.3775**
					(0.1598)	(0.1599)	(0.1598)	(0.1599)
Referee's productivity	0.0014***	0.0015***	0.0016***	0.0018***	0.0014***	0.0015***	0.0016***	0.0018***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Past productivity	0.0103***	0.0102***	0.0102***	0.0103***	0.0102***	0.0102***	0.0102***	0.0103***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Total research experience	−0.0108***	−0.0101***	−0.0098***	−0.0097***	−0.0109***	−0.0103***	−0.0099***	−0.0097***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
(Total research experience)^2	0.0003***	0.0003***	0.0002***	0.0002***	0.0003***	0.0003***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Within-firm research experience	−0.0039	−0.0044	−0.0046	−0.0048	−0.0034	−0.0028	−0.0034	−0.0038
	(0.0033)	(0.0033)	(0.0033)	(0.0033)	(0.0035)	(0.0035)	(0.0034)	(0.0034)
(Within-firm research experience)^2	0.0003*	0.0003*	0.0004*	0.0004*	0.0004*	0.0003	0.0004*	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
The first tenure year dummy	0.4603***	0.4601***	0.4600***	0.4592***	0.4687***	0.4709***	0.4681***	0.4643***
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0080)	(0.0078)	(0.0077)	(0.0076)
Firm's productivity	0.1685***	0.1692***	0.1691***	0.1681***	0.1680***	0.1679***	0.1679***	0.1670***
	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)
Field dummies:								
Chemical	0.2910***	0.2910***	0.2911***	0.2912***	0.2915***	0.2916***	0.2916***	0.2916***
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Comp.& Comm.	0.2304***	0.2304***	0.2304***	0.2303***	0.2306***	0.2306***	0.2306***	0.2304***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Drugs & Medical	0.2885***	0.2882***	0.2880***	0.2882***	0.2888***	0.2884***	0.2880***	0.2882***
	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)	(0.0075)
Elec. & Electronics	0.1908***	0.1908***	0.1907***	0.1908***	0.1910***	0.1909***	0.1909***	0.1909***
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)
Mechanical	0.1888***	0.1889***	0.1889***	0.1890***	0.1891***	0.1892***	0.1892***	0.1891***
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
Others	0.1790***	0.1790***	0.1791***	0.1789***	0.1793***	0.1792***	0.1792***	0.1788***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Annual dummies								
year 2	−0.1430***	−0.1421***	−0.1427***	−0.1444***	−0.1406***	−0.1388***	−0.1400***	−0.1427***
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
year 3	−0.1929***	−0.1923***	−0.1929***	−0.1943***	−0.1897***	−0.1883***	−0.1898***	−0.1926***
	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0145)
year 4	−0.2377***	−0.2372***	−0.2378***	−0.2391***	−0.2344***	−0.2335***	−0.2349***	−0.2375***
	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
year 5	−0.2435***	−0.2431***	−0.2436***	−0.2450***	−0.2405***	−0.2399***	−0.2411***	−0.2434***
	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)
year 6	−0.2665***	−0.2661***	−0.2666***	−0.2679***	−0.2637***	−0.2632***	−0.2643***	−0.2665***
	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)	(0.0135)
year 7	−0.2905***	−0.2903***	−0.2909***	−0.2921***	−0.2878***	−0.2874***	−0.2885***	−0.2906***
	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0130)
year 8	−0.3261***	−0.3257***	−0.3262***	−0.3275***	−0.3236***	−0.3232***	−0.3241***	−0.3263***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0123)	(0.0123)	(0.0123)	(0.0122)
year 9	−0.3439***	−0.3437***	−0.3442***	−0.3454***	−0.3418***	−0.3415***	−0.3423***	−0.3444***
	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)
year 10	−0.3476***	−0.3474***	−0.3479***	−0.3492***	−0.3456***	−0.3451***	−0.3459***	−0.3480***

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	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
year 11	−0.3183***	−0.3180***	−0.3185***	−0.3195***	−0.3161***	−0.3157***	−0.3165***	−0.3184***
	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0110)	(0.0110)	(0.0110)	(0.0111)
year 12	−0.3335***	−0.3331***	−0.3335***	−0.3345***	−0.3312***	−0.3307***	−0.3316***	−0.3334***
	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)	(0.0109)
year 13	−0.3144***	−0.3139***	−0.3143***	−0.3150***	−0.3126***	−0.3119***	−0.3126***	−0.3140***
	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)
year 14	−0.2825***	−0.2820***	−0.2825***	−0.2831***	−0.2809***	−0.2799***	−0.2807***	−0.2820***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0104)
year 15	−0.2626***	−0.2620***	−0.2624***	−0.2631***	−0.2607***	−0.2597***	−0.2605***	−0.2618***
	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)
year 16	−0.2540***	−0.2535***	−0.2538***	−0.2543***	−0.2522***	−0.2513***	−0.2520***	−0.2533***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)
year 17	−0.2502***	−0.2498***	−0.2500***	−0.2504***	−0.2488***	−0.2477***	−0.2481***	−0.2494***
	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)
year 18	−0.2361***	−0.2359***	−0.2360***	−0.2362***	−0.2347***	−0.2338***	−0.2340***	−0.2349***
	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
year 19	−0.2074***	−0.2072***	−0.2074***	−0.2070***	−0.2053***	−0.2048***	−0.2054***	−0.2060***
	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)
year 20	−0.1575***	−0.1573***	−0.1573***	−0.1564***	−0.1551***	−0.1550***	−0.1553***	−0.1552***
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
year 21	−0.0033	−0.0037	−0.0036	−0.0022	−0.0007	−0.0008	−0.0012	−0.0005
	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)	(0.0094)
year 22	−0.0465***	−0.0471***	−0.0469***	−0.0455***	−0.0446***	−0.0455***	−0.0455***	−0.0447***
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
Constant	−0.3314***	−0.3320***	−0.3313***	−0.3286***	−0.3402***	−0.3444***	−0.3408***	−0.3350***
	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0130)	(0.0128)	(0.0127)	(0.0126)
Log-likelihood	-355398.98	-355393.13	-355395.49	-355410.54	-355355.05	-355346.29	-355358.24	-355384.75
Observations	286954	286954	286954	286954	286954	286954	286954	286954

NOTE.– Dependent variable is the number of patents applied by inventor. 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. Robust standard errors are in parentheses. $*\, p < .1$. $**\ p < .05$. $***\, p < .01$.

Table C. 2: Fixed-Effect Regression: All Estimation Results

	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network referral dummy: ρ	0.1023^{***}	0.1270^{***}	0.1551^{***}	0.1806^{***}				
	(0.0104)	(0.0117)	(0.0129)	(0.0169)				
Interaction terms of network and tenure dummies: ρ_k								
year 1					0.0801^{***}	0.0935^{***}	0.1195^{***}	0.1368^{***}
					(0.0120)	(0.0138)	(0.0154)	(0.0208)
year 2					0.1323^{***}	0.1844^{***}	0.2133^{***}	0.2599^{***}
					(0.0172)	(0.0199)	(0.0220)	(0.0287)
year 3					0.2166^{***}	0.2640^{***}	0.2865^{***}	0.3101^{***}
					(0.0186)	(0.0221)	(0.0244)	(0.0322)
year 4					0.1589^{***}	0.1794^{***}	0.1980^{***}	0.2250^{***}
					(0.0226)	(0.0279)	(0.0312)	(0.0417)
year 5					0.1026^{***}	0.1120^{***}	0.1329^{***}	0.0793
					(0.0271)	(0.0338)	(0.0384)	(0.0525)
year 6					0.0907^{***}	0.1111^{***}	0.1238^{***}	0.1755^{***}
					(0.0320)	(0.0406)	(0.0468)	(0.0613)
year 7					0.0619	0.0385	0.0426	0.0224
					(0.0377)	(0.0488)	(0.0569)	(0.0784)
year 8					0.0571	0.0865	0.1331^{**}	0.1784^{**}
					(0.0436)	(0.0541)	(0.0617)	(0.0816)
year 9					-0.1158^{**}	-0.0836	0.0167	0.0399
					(0.0549)	(0.0678)	(0.0751)	(0.1014)
year 10					-0.1161^{*}	-0.0655	-0.0398	-0.1252
					(0.0631)	(0.0759)	(0.0865)	(0.1262)
year 11					-0.0867	-0.1216	-0.0300	0.1424
					(0.0717)	(0.0875)	(0.0976)	(0.1320)
year 12					-0.2427^{***}	-0.2580^{**}	-0.2304^{*}	-0.0964
					(0.0906)	(0.1082)	(0.1282)	(0.1786)
year 13					-0.2978^{***}	-0.2851^{**}	-0.1385	-0.1493
					(0.1061)	(0.1253)	(0.1407)	(0.2075)
year 14					-0.2420^{*}	-0.2887^{*}	-0.3027^{*}	-0.1851
					(0.1322)	(0.1498)	(0.1726)	(0.2508)
year 15					-0.3046^{**}	-0.3629^{**}	-0.2603	-0.0940
					(0.1517)	(0.1751)	(0.1893)	(0.2526)
year 16					0.1332	-0.3750^{*}	-0.4957^{**}	-0.2807
					(0.1419)	(0.2029)	(0.2362)	(0.3115)
year 17					-0.7175^{***}	-0.6825^{**}	-0.8391^{***}	-0.6531
					(0.2489)	(0.2740)	(0.3228)	(0.4176)
year 18					-0.1575	-0.1700	0.0813	-0.2941
					(0.2461)	(0.2608)	(0.2713)	(0.4605)
year 19					-0.5998	-0.6160	-0.6960	-0.5140
					(0.4584)	(0.4586)	(0.5896)	(0.5918)
year 20					0.2764	0.2620	0.3017	0.3563
					(0.4309)	(0.4310)	(0.4314)	(0.4731)
year 21					-0.5669	-0.5803	-0.5392	-0.4971

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	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					(1.0226)	(1.0226)	(1.0228)	(1.0235)
year 22					−0.0654	−0.0771	−0.0358	0.0072
					(0.7390)	(0.7390)	(0.7393)	(0.7402)
Referee's productivity	0.0012***	0.0014***	0.0014***	0.0017***	0.0011***	0.0014***	0.0014***	0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Past productivity	−0.0394***	−0.0395***	−0.0395***	−0.0392***	−0.0395***	−0.0396***	−0.0396***	−0.0392***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Total research experience	0.0159***	0.0167***	0.0170***	0.0177***	0.0153***	0.0162***	0.0167***	0.0175***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
(Total research experience)^2	0.0011***	0.0010***	0.0010***	0.0010***	0.0011***	0.0011***	0.0011***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Within-firm research experience	0.0062**	0.0053*	0.0052*	0.0048	0.0101***	0.0086***	0.0076**	0.0066**
	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0033)	(0.0032)	(0.0032)	(0.0031)
(Within-firm research experience)^2	−0.0007***	−0.0007***	−0.0007***	−0.0006***	−0.0008***	−0.0007***	−0.0007***	−0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
The first tenure year dummy	0.5396***	0.5394***	0.5396***	0.5390***	0.5569***	0.5548***	0.5515***	0.5465***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0076)	(0.0074)	(0.0073)	(0.0072)
Firm's productivity	0.3045***	0.3061***	0.3072***	0.3074***	0.3024***	0.3036***	0.3055***	0.3054***
	(0.0172)	(0.0173)	(0.0173)	(0.0172)	(0.0172)	(0.0172)	(0.0172)	(0.0172)
Field dummies:								
Chemical	0.1971***	0.1970***	0.1973***	0.1972***	0.1983***	0.1979***	0.1980***	0.1978***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0101)
Comp.& Comm.	0.1630***	0.1635***	0.1634***	0.1639***	0.1636***	0.1639***	0.1635***	0.1639***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Drugs & Medical	0.1691***	0.1693***	0.1692***	0.1687***	0.1705***	0.1703***	0.1698***	0.1692***
	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0155)
Elec. & Electronics	0.1812***	0.1813***	0.1811***	0.1817***	0.1819***	0.1818***	0.1812***	0.1820***
	(0.0099)	(0.0099)	(0.0099)	(0.0099)	(0.0099)	(0.0099)	(0.0099)	(0.0099)
Mechanical	0.1684***	0.1691***	0.1702***	0.1700***	0.1698***	0.1706***	0.1714***	0.1706***
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
Others	0.1802***	0.1802***	0.1810***	0.1803***	0.1811***	0.1808***	0.1814***	0.1806***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)
Annual dummies								
year 2	0.0104	0.0101	0.0100	0.0096	0.0164	0.0154	0.0142	0.0121
	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)
year 3	−0.0412**	−0.0420***	−0.0421***	−0.0422***	−0.0345**	−0.0362**	−0.0377**	−0.0399**
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)
year 4	−0.1031***	−0.1042***	−0.1046***	−0.1047***	−0.0972***	−0.0993***	−0.1008***	−0.1025***
	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0158)	(0.0157)	(0.0157)	(0.0157)
year 5	−0.1327***	−0.1340***	−0.1342***	−0.1346***	−0.1278***	−0.1300***	−0.1310***	−0.1327***
	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)
year 6	−0.1733***	−0.1746***	−0.1748***	−0.1753***	−0.1692***	−0.1714***	−0.1721***	−0.1736***
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0150)	(0.0150)	(0.0150)	(0.0149)
year 7	−0.2157***	−0.2170***	−0.2172***	−0.2182***	−0.2123***	−0.2141***	−0.2148***	−0.2167***
	(0.0147)	(0.0147)	(0.0147)	(0.0147)	(0.0147)	(0.0147)	(0.0147)	(0.0147)
year 8	−0.2734***	−0.2747***	−0.2747***	−0.2761***	−0.2709***	−0.2725***	−0.2727***	−0.2749***
	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0144)
year 9	−0.3139***	−0.3153***	−0.3156***	−0.3171***	−0.3120***	−0.3134***	−0.3138***	−0.3160***
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)
year 10	−0.3370***	−0.3382***	−0.3385***	−0.3403***	−0.3349***	−0.3362***	−0.3364***	−0.3388***

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	Productivity Regressions				Productivity Growth Regression			
	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12	OVERALL	WITHIN 36	WITHIN 24	WITHIN 12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0140)	(0.0139)	(0.0139)	(0.0139)
year 11	-0.3133^{***}	-0.3143^{***}	-0.3151^{***}	-0.3167^{***}	-0.3114^{***}	-0.3124^{***}	-0.3129^{***}	-0.3151^{***}
	(0.0134)	(0.0134)	(0.0134)	(0.0134)	(0.0135)	(0.0134)	(0.0134)	(0.0134)
year 12	-0.3353^{***}	-0.3361^{***}	-0.3367^{***}	-0.3386^{***}	-0.3334^{***}	-0.3341^{***}	-0.3348^{***}	-0.3374^{***}
	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)	(0.0132)
year 13	-0.3378^{***}	-0.3385^{***}	-0.3390^{***}	-0.3408^{***}	-0.3368^{***}	-0.3370^{***}	-0.3375^{***}	-0.3396^{***}
	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)	(0.0127)
year 14	-0.3164^{***}	-0.3163^{***}	-0.3169^{***}	-0.3191^{***}	-0.3153^{***}	-0.3144^{***}	-0.3150^{***}	-0.3176^{***}
	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0124)	(0.0124)	(0.0124)	(0.0123)
year 15	-0.3081^{***}	-0.3076^{***}	-0.3083^{***}	-0.3108^{***}	-0.3067^{***}	-0.3054^{***}	-0.3062^{***}	-0.3092^{***}
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0121)
year 16	-0.3227^{***}	-0.3221^{***}	-0.3226^{***}	-0.3252^{***}	-0.3214^{***}	-0.3197^{***}	-0.3203^{***}	-0.3236^{***}
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
year 17	-0.3360^{***}	-0.3348^{***}	-0.3356^{***}	-0.3382^{***}	-0.3348^{***}	-0.3324^{***}	-0.3331^{***}	-0.3367^{***}
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
year 18	-0.3353^{***}	-0.3337^{***}	-0.3344^{***}	-0.3375^{***}	-0.3340^{***}	-0.3310^{***}	-0.3316^{***}	-0.3353^{***}
	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)	(0.0119)
year 19	-0.3138^{***}	-0.3118^{***}	-0.3126^{***}	-0.3149^{***}	-0.3119^{***}	-0.3090^{***}	-0.3098^{***}	-0.3133^{***}
	(0.0118)	(0.0118)	(0.0118)	(0.0118)	(0.0118)	(0.0118)	(0.0118)	(0.0118)
year 20	-0.2711^{***}	-0.2689^{***}	-0.2692^{***}	-0.2708^{***}	-0.2688^{***}	-0.2662^{***}	-0.2665^{***}	-0.2689^{***}
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
year 21	-0.1024^{***}	-0.1011^{***}	-0.1017^{***}	-0.1026^{***}	-0.0999^{***}	-0.0980^{***}	-0.0986^{***}	-0.0998^{***}
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
year 22	-0.1516^{***}	-0.1510^{***}	-0.1515^{***}	-0.1516^{***}	-0.1505^{***}	-0.1493^{***}	-0.1497^{***}	-0.1503^{***}
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Log-likelihood	-236433.22	-236423.18	-236410.06	-236425.31	-236363.28	-236356.18	-236358.39	-236393.13
Observations	286954	286954	286954	286954	286954	286954	286954	286954

NOTE.– Dependent variable is the number of patents applied by inventor. 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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