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Labor Mobility of Scientists and Engineers and the Pace of Innovation

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ABSTRACT

This paper presents a first empirical estimate of the relation between the labor mobility of research personnel, as a measure of knowledge spillovers, and the pace of innovation, measured by the mean backward lag in patent citations. Using an unbalanced panel of firms across eight U.S. industries with the highest rate of innovation as measured by patents granted from 1984 to 1999, the cross-sectional results show evidence of a positive relation between the rate at which scientists and engineers change jobs and the pace of innovation within each industry. When the relation is estimated with industry fixed effects, the estimate on the labor mobility is not longer significant. Therefore, this paper presents an initial cross-sectional result that establishes a stylized fact between labor mobility of research personnel and the pace of innovation that requires further investigation.

Key Words: knowledge spillover, labor mobility of scientists and engineers, pace of innovation, patenting

JEL Classification: O32, L24, J63

I. INTRODUCTION

Decision makers have always been concerned with issues related to innovation, potential spillovers and their impact on the incentives and capacity to innovate. At least since Scotchmer and Green (1990), economists have accepted the idea that current research can build on the pool of existing technological knowledge, and the pace of innovation depends critically on the amount of knowledge transferred among firms. There are many channels through which knowledge spreads. One channel is the labor movement of scientists and research personnel from one firm to another. This idea was articulated in Arrow's 1962 article on the public good aspect of information, writing that "no amount of labor protection can make a thoroughly appropriable commodity of something so intangible as information. The very use of information in any productive way is bound to reveal it, at least in part. Mobility of personnel among firms provides a way of spreading information" (p. 615). In her 1994 book, Saxenian argues that frequent social and professional meetings of Silicon Valley engineers and the ease with which workers can change jobs led to the rapid dissemination and cross fertilization of ideas which fueled innovation in Silicon Valley.

The theoretical literature on labor mobility and knowledge diffusion is growing. Some studies focus on labor mobility and patenting, (Kim and Marschke, 2005), endogenous R&D and employment decisions (Gersbach and Schmutzler, 2003), labor mobility and spinouts (Franco and Filson, 2006). However, empirical research in this area is just beginning to take off. The main difficulty faced by the empirical literature is the lack of appropriate data.

This paper contributes to the empirical literature on knowledge spillovers and innovation by presenting the first empirical test of the relation between labor mobility of research personnel and the pace of innovation. The pace of innovation is defined as the time lag between two consecutive generations of technology and it is measured by the mean backward lag in patent citations.

The empirical test uses patent citation data from the NBER/ Western Reserve University data on all utility patents granted by the U.S. Patent Office between 1963 and 1999, matched with Compustat firm data for an unbalanced panel of firms across eight U.S. highly innovative industries. The labor mobility is given by the rate of scientists and engineers that change jobs within a year, and it is constructed from the U.S. Bureau of Labor Statistics, the Current Population Survey March Supplements. The cross-sectional results show evidence that an increase in the annual measure of the labor mobility of scientists and engineers is significantly associated with an increase in the measure of the pace of innovation. While this establishes a stylized fact of the relation between labor mobility and the pace of innovation, the fixed effects estimation make the relation disappear, requiring improved data and further research into the relation between the labor mobility and innovation.

The rest of the paper is organized as follows. The next section describes the data, section III presents the empirical strategy and discusses the empirical results, and section IV concludes.

II. DATA

The data set used in this paper is an unbalanced panel of innovative firms across eight innovative U.S. industries, observed between 1984 and 1999, matched with an industry measure of the labor mobility of scientists and engineers. The measure of the pace of innovation is based on patent citations. A key data item in the patent document is "References Cited -- U.S. Patent Documents". The references cited, known in the literature as patent citations, include previous patents and other published material (e.g. scientific literature) that identify aspects of the relevant technology that were previously publicly known. The patent applicant has a legal duty to disclose any knowledge of the "prior art" contained in such patents or other published materials. As a result, patent citations serve an important legal function as they delimit the scope of the property rights awarded by the patent. If a patent issued in year *t*, P_t cites a previous patent issued in year *t-s*, $P_{t-s,}$ it implies that patent P_{t-s} represents a piece of previously existing knowledge upon which patent P_t builds, and over which P_{t-s} cannot have a claim. For this reason, patent citations are considered informative of links between patented innovations, providing direct observations of technological impact and innovation dynamics.

The patent citation data come from the NBER/Case Western Reserve University data on all utility patents granted by the U.S. Patent Office between 1963 and 1999, matched with Compustat firm data. The measure of the pace of innovation captures the length of the technology cycle by identifying the time lag between prior art and the current generation of technology. Specifically, it measures the mean backward lag in citations, computed as the mean lag in years between the grant year of the citing patent and the grant year of the cited patents. The backward lags are computed from the grant year of the citing patent to the grant year of the cited patent. Assume that patent issued in year *t*, $P_{t,}$ cites patent, $P_{t-s,}$ previously issued in year *t-s*. The lag in years between the grant year of patent P_t and the grant year of patent P_{t-s} is *t-s* years. In any given industry, the shorter the mean backward lag in citation, the shorter the technology cycle length is.

The measure of the labor mobility of scientists and engineers (MOB) used in this paper is constructed from the Current Population Survey (CPS), the Annual March Supplements. MOB, the rate of scientists and engineers that changed employers during the previous year of the survey in each industry and year, is defined by occupation according with the three-digit 1980 Standard Occupational Classification: Engineers, 044-059; Mathematical and Computer Scientists, 064-068; Natural Scientists, 069-083; Clinical laboratory technologists and technicians, 203; Engineers and related technologists and technicians 213-216; Science technicians, 223-225; Computer programmers, 229. The CPS March dataset offers the advantage that the labor mobility can be consistently defined in each year since 1979, and that the CPS data is based on a survey that represents a national population. The average annual mobility rate for the entire sample is 9.14 percent, reflecting the turnover rate of scientists who changed employers at least once during the previous year of the survey. The average mean age of the scientists in the sample is 34.

The full sample used in this study contains firm level data for 531 firms in eight industries (Aerospace, Automotive, Biotech/Pharmaceuticals, Chemicals, Computers, Instruments, Semiconductors, and Telecommunications), in an unbalanced panel, extending from 1984 to 1999. The full sample has 5024 firm-year observations. The data set contains information on the number of patents granted to firm *i*, counted by the application year, (PATENTCOUNTS) and the mean backward lag in citations for each patent granted to a firm *i*, in year *t* (BACKLAG). If a firm had successfully applied for more than one patent in year *t*, the BACK_LAG variable for firm *i*, year *t* is calculated as an average BACK_LAG for each of the patents granted to firm *i* in year *t*. Additional firm level data come from the annual Compustat data set, matched with the patent data. These firm level data include variables such as annual R&D expenditure (R&D), annual sales (SALES) and the number of employees (EMPL), as well as Plant and Equipment (K). Based on these data, one can construct new variables, such as annual R&D intensity (RDI), capital intensity (K/L) and the Herfindahl Index (HERF). After eliminating data on firms with missing observations of R&D expenditure, the working sample contains data on 481 firms in an unbalanced panel from 1984 to 1999. The working sample has 3983 firm-year observations. Table 1 reports summary statistics of the mobility variable (MOB) and the measure of the pace of innovation (BACKLAG), along with the other variables used. From the sample, the industry with the shortest lag between sequential generations of technologies is Semiconductors, with a mean BACKLAG of 7.1 years, followed by Computers and Telecommunications, with 8.7 and 9.7 years, respectively. The longest lag is recorded for Automotive and Aerospace, with 14.9 and 16.2 years, respectively. In the sample used, the industry with the highest labor mobility is Semiconductors, with an annual turnover rate of 11.40 percent, while the lowest mobility measure is for Automotive, with a 6.1 percent annual turnover rate.

Table 1: Summary Statistics

	Working Sample			
Variables	Mean	Std. Dev	Min	Max
MOB	0.09	0.05	0.00	0.26
BACK_LAG	11.27	5.85	0.00	71.83
RD	216.82	687.76	0.03	9483.22
SALES	3928.29	14088.53	0.00	179535.6
EMPL	18.33	59.62	0.01	876.80
K/L	45.57	42.17	0.00	514.13
HERF	0.18	0.12	0.07	0.65
No. of Firms	481 firms (3983 firm-year observations)			

a. MOB = the share of scientists who changed their employers at least once within a year, by industry
b. BACK_LAG = the mean backward lag in citations for each patent granted, by firm and year
c. R&D = annual research and development expenses at firm level [million, in constant 2000 dollars]
d. Sales = annual sales at firm level [million, in constant 2000 dollars]
e.EMPL = employment [in thousands]
f. K/L = plant and equipments [million, in constant 2000 dollars]/ Employment [in thousands]
g. AGE = average age of scientists and engineers, by industry and year
h. HERF =the Herfidahl Index, sum of squared market shares based on sales

III. EMIRICAL STRATEGY AND RESULTS

The early economic literature on innovation and patenting (Dasgupta and Stiglitz, 1980), considers the pace of innovation as determined by each firm's rate of investment and by the number of firms that enter the patent race. Thus, the explanatory variables include the firm's R&D investment and a measure of firm concentration (the Herfindahl Index, constructed as a sum of the squared market shares of sales). However, later literature (Scotchmer and Green, 1990) emphasizes that the pace of innovation depends critically on the amount of knowledge transferred among firms since current research can build on the previous technological knowledge disclosed. In order to capture this knowledge flow, the rate of the labor mobility of scientists and engineers is added to the regressors list, while

Therefore, the empirical test of the relation between knowledge spillover generated by the labor mobility of research personnel and the pace of innovation uses the following estimation equation:

$$BACKLAG_{it}=\alpha_i+\varphi RD_{it}+\lambda HERF_{jt}+\gamma MO_{jt}+\theta X_{it}+\varepsilon it,$$

where $BACKLAG_{it}$ is the measure of the pace of innovation of firm *i*, year *t*; RD_{it} is the research and development expenditure of firm *i*, in year *t*; $HERF_{jt}$ is the Herfindahl index for industry *j* which contains firm *i*, in year *t* , MOB_{jt} measures the labor mobility of scientists and engineers in industry *j* to which mobility firm *i* is exposed in year *t*; and X_{it} is a 1xK vector of firm *i*'s characteristics in year *t*, ε_{it} is the error term, assumed to be independent and identically distributed as a normal. Evidence suggests that larger firms are, on average, slightly quicker innovators than smaller firms (see "Serial Innovators: The Small Firm Contribution to Technical Change", CHI Research, prepared for the Office of Advocacy, Small Business Administration, Order No. SBAHQ-01-C-0149). Therefore, X_{it} includes SALES, as a measure of the size of the firm, to account for economies of scale in innovation. An alternative measure of the size of the firm is EMPL, the number of employees for each firm. A capital-labor ratio, K/L, is also included, measured as the deflated plant and equipment over the number of employees. Firms that are less capital intensive might be more flexible in the innovation process and more prepared to embrace new technologies. The estimation method relies on panel data estimation techniques.

The pooled Ordinary Least Squares (OLS) results for the unbalanced panel of 481 firms, with a total of 3983 firm-year observations, are shown in Table 2.

The dependent variable is $BACKLAG_{it}$, the mean backward lag in citations received by all the patents successfully applied for by firm *i*, in year *t*. The results show a significant and negative coefficient for the measure of the labor mobility of scientists and engineers, MOB, for all specifications. This coefficient shows that a 10 percentage point increase in the annual measure of the labor mobility of scientists and engineers is associated with a 1.1 years decrease in the lag between the grant year of a patent and the grant years of the cited patents. The elasticity calculated at the sample mean is -0.88.

Table 2: Labor Mobility and the Pace of Innovation, Pooled OLS estimates

Dependent Variable: BACK_LAG

	[1]	[2]	[3]	[4]	[5]
RD	-0.005*	-0.003*	-0.005*	-0.005*	-0.005*
	(0.0001)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
MOB	-11.300*	-12.054*	-10.830*	-11.141*	-11.245*
	(2.049)	(2.058)	(2.009)	(2.008)	(2.008)
No. Firms	0.010**	0.013*			
	(0.005)	(0.005)			
SALES	0.0002*		0.0002*	0.0002*	0.0002*
	(0.0001)		(0.0001)	(0.0001)	(0.0001)
HERF			-2.520*	-3.115*	-3.059*
			(0.763)	(0.780)	(0.780)
EMPL		0.0299*			
		(0.003)			
K/L				-0.008*	-0.007*
				(0.002)	(0.002)
T					-0.044**
					(0.002)
F-test	43.25	31.02	45.1	38.69	32.87
P Value	0.000	0.000	0.000	0.000	0.000
No. of Obs.	3983	3983	3983	3983	3983

Note: (Std. error)

* significant at the 1% level, two tailed t-test

** significant at the 5% level, two tailed t-test

The estimate for research and development, R&D, is negative and significant, which is consistent with the theoretical literature predictions. This coefficient indicates that an increase in the amount spent on R&D decreases the mean back lag in citations. On average, an additional billion dollars in research and expenditure is associated with a reduction in the back lag of 5 years. The elasticity at the sample mean is -0.1. In Table 2, the coefficient on the number of firms in the industry, NoFirms, is significant and positive. This result might seem counter intuitive. The theoretical literature on innovation predicts that the pace of innovation depends on the number of firms that compete. However, the number of firms does not offer a good indication of the market structure. When a Herfindahl index is used instead of the number of firms in order to capture the effect of the competition on the pace of the innovative process, the coefficient on the Herfindahl index, HERF is negative and significant. This suggests that the more concentrated the market, the shorter the lag between sequential generations of technological advancement. SALES and EMPL are used as alternative controls for the size of the firm. The coefficient on SALES (EMPL) is positive and significant, suggesting diseconomies of scale. On average, an increase in the employment level by 100,000 workers generates an increase of the backward lag in citations of 2.9 years. Similarly, an increase in the annual net sales by 1 billion dollars is associated with an increase in the average lag in backward citations by 0.2 years. The pooled OLS results for the industry aggregates are similar in sign and significance. A time trend, T, is used to test the sensitivity of the results to a time trend. As shown in Table 2, column 5, the coefficient on MOB is negative and significant. The coefficient on the capital-labor ratio, K/L is also significant. This suggests that firms that more labor intensive can potentially be more flexible in the innovation process, and eventually faster innovators.

Firm fixed-effect estimates, not presented, show insignificant coefficients for all independent variables, except the constant. Indeed, the F-test doesn't reject the null hypothesis that all coefficients are jointly zero. A random-effect model has a better fit, although in this case too, the F-test doesn't reject the null hypothesis that all coefficients are jointly zero. A Hausman specification test suggests that the fixed-effects model should be used over the random-effect model. However, as described above, the firm fixed effect estimates are not significant. One potential explanation is the large number of dummy variables used for the individual firm effects (there are 481 firms in the panel) relative to number of time periods. Another issue is the variability of MOB, which has no variation across firms within one industry. An alternative specification is the between effects (BE) model, presented in Table 3.

Table 3: Labor Mobility and the Pace of Innovation, BE estimates

Dependent Variable: BACK_LAG	
RD	-0.008*
	(0.002)
MOB	-34.194*
	(9.105)
SALES	0.0004*
	(0.0001)
HERF	-2.642*
	(1.897)
K/L	-0.008
	(0.006)
F-test	8.31
P value	0.000
No. of Obs.	3983

Note: (Std. error)
* significant at the 1% level, two tailed t-test
** significant at the 5% level, two tailed t-test

The BE estimates use the cross-sectional information reflected in changes between firms. The BE estimates for the labor mobility measure, MOB, are negative and significant showing that, if two firms are exposed to levels of labor mobility of scientists and engineers that differ by 10 percentage points, the expected difference in the backward lag in citations for those firms is 3.4 years. At the sample mean, the elasticity is -2.7. This result has an additional interpretation in the context of the data set used in this paper, primarily because of the source of variation of the MOB variable. The labor mobility varies only by industry and year, it is not firm specific. Thus, firms exposed to different levels of labor mobility are necessarily in different industries, which makes the BE estimator a FE for the industry.

Table 4: Labor Mobility and the Pace of Innovation, GLS Estimates

Dependent Variable: BACK_LAG	(1)	(2)	(3)	(4)
RD	-0.004*	-0.001*	-0.005*	-0.0007*
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
MOB	-9.009*	-3.074	-5.848*	-1.072
	(1.907)	(1.742)	(1.742)	(0.909)
SALES	0.0002*	0.0001	0.0002*	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HERF	-5.696*	-0.834	-5.863*	-1.489
	(0.696)	(2.122)	(0.696)	(2.353)
K/L	-0.009*	-0.009*	-0.008*	-0.009*
	(0.696)	(0.002)	(0.002)	(0.002)
Log Likelihood	-12459.05	-12013.8	-12443.65	-12007.51
Chi2	236.07	1645.07	273.36	1652.41
P-value	0.000	0.000	0.000	0.000
No. of Obs.	3983	3983	3983	3983

Note: (Std. error)
* significant at the 1% level, two tailed t-test
(2) includes industry dummies
(3) includes year dummies
(4) includes industry and year dummies

To test for potential heteroskedasticity, a Breusch-Pagan/Cook-Weisberg test is employed. The test indicates at a 1 percent level of significance that the regression results are indeed heteroskedastic. To address this issue, a Generalized Least Squares (GLS) estimator for panel data is used. The estimates are presented in Table 4. The MOB coefficient indicates a negative relation between the labor mobility variable and the pace of innovation, as measured by the lag in backward citations. The magnitude is slightly smaller than the pooled OLS estimates. In Table 4, columns 2 to 4 present the estimates from a panel GLS estimator with industry and/ or year fixed effects. The sign of the MOB coefficient is negative and significant only for the specification with year fixed effects. Although negative, the estimates for MOB are not significant when industry fixed effects are present.

Therefore, the results discussed here show a cross-sectional result that establishes a stylized fact of the relation between the labor mobility of scientists and engineers and the pace of innovation. However, when the relation is estimated with industry fixed effects, the estimate on the labor mobility is not longer significant.

IV. CONCLUSIONS

The theoretical literature on labor mobility and knowledge diffusion is growing. However, empirically, little is known about the implications of this increased mobility of scientists on innovative firms and the innovation process itself. One of the main problems in this area is the difficulty of obtaining reasonably good data to be able to test the theoretical predictions and to provide guidance for better conceptual models that connect the labor mobility and the innovation process.

This paper contributes to the empirical literature on knowledge spillovers and innovation by presenting a first empirical test of the relation between knowledge dissemination generated by labor mobility of research personnel, and the pace of innovation. The pace of innovation is given by the mean backward lag in citation, which is the mean lag between the grant year of patent applications submitted by firms each year and the grant year of the patents cited. This measure is based on the legal function represented by the patent itself, that of delimiting the scope of the property rights awarded by the patent relative to prior art.

The data used come from three data sets. The patent and patent citation data come from the NBER/Case Western Reserve University data set on all utility patents granted by the U.S. Patent Office matched with Compustat, with additional financial firm level data supplemented from Compustat. The data on the labor mobility of scientists and engineers are collected from the Current Population Survey March Supplements. The resulting data set is an unbalanced panel of 481 firms across eight industries, between 1984 and 1999.

The cross sectional results reported in the paper show a significant effect of the labor mobility of the pace of innovation. A pooled OLS coefficient shows that a 10 percentage point increase in the annual measure of the labor mobility of scientists and engineers is associated with a 1.1 years increase in the pace of innovation. The elasticity calculated at the sample mean is -0.88. A between panel estimator suggests specifically that firms in different industries, exposed to levels of labor mobility of scientists and engineers that differ by 10 percentage point, have an expected difference in the backward lag in citations of 3.4 years. At the sample mean, the elasticity is -2.7. Taking into account heteroskedasticity lowers the magnitude of the labor mobility estimate to a 0.9 years increase in the pace of innovation given a 10 percentage point increase in the labor mobility rate. These cross-sectional results establish a stylized fact between the growth in the labor mobility of research personnel and a growth in the pace of innovation. When the relation is estimated with industry fixed effects, the estimate on the labor mobility is not longer significant. One possible explanation is a limitation of this study in that the measure of the labor mobility of scientists and engineers does not vary within industry. The results presented here lead to some initial findings about the role of the labor mobility of research personnel on innovation and growth. Additional research, using better data, is required to further advance the knowledge in this field by continuing to test the theoretical predictions and providing guidance for improved conceptual models that connect knowledge spillovers and the innovation process.

REFERENCES

Almeida, P., Kogut, B., 1999. Localization of Knowledge and the Mobility of Engineers in Regional Networks, Management Science, 45(7) 905-917

Arrow, Kenneth J., 1962. Economic Welfare and the Allocation of Resources for Inventions, in "The Rate and Direction of Inventive Activity: Economic and Social Factors", edited by R.R. Nelson. University-National Bureau Conference Series no. 13, Princeton, N.J., Princeton University Press

Dasgupta, P., Stiglitz, J., 1980. Uncertainty, Industrial Structure, and the Speed of R&D. Bell Journal of Economics, Vol. 11, No. 1

Franco, A. M., Filson, D., 2006. Spinouts: Knowledge Diffusion through Employee Mobility. The RAND Journal of Economics, Vol. 37(4), 841-860.

Gersbach, H, Schmutzler, A., 2003. Endogenous Technological Spillovers: Causes and Consequences, Journal of Economics and Management Strategy, Vol. 12(2), 179-205

Grilliches, Z. (ed.), 1984. R&D, Patents, and Productivity. NBER Conference Proceedings. University of Chicago Press.

Grilliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature, Vol. 25, 1661-1707

Hall, B. H., A. B. Jaffe, and M. Tratjenberg, 2001. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." NBER Working Paper 8498.

Kim, J., Marschke, G., 2005. Labor Mobility of Scientists, Technological Diffusion, and the Firm's Patenting Decision, The RAND Journal of Economics, Vol. 36(2), 298-317

Levin, R. C., Kletorick, A.K., Nelson, R.R., and Winter, S.G., 1987. Appropriating the Returns from Industrial Research and Development, Brookings Papers on Economic Activity 3

Saxennian, A., 1994. Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard Business School Press.

Scotchmer, S., Green, J., 1990. Novelty and Disclosure in Patent Law, The RAND Journal of Economics, Vol. 21(1), 131-146

_______ Serial Innovators: The Small Firm Contribution to Technical Change, CHI Research, prepared for the Office of Advocacy, Small Business Administration, Order No. SBAHQ-01-C-0149.