Microeconomic Essays on Technology, Labor Markets and Firm Strategy

by

Simona Lup

A Dissertation Submitted to the Faculty of the

Department of Economics

In Partial Fulfillment of the Requirements
For the Degree of

Doctor of Philosophy

In the Graduate College

The University of Arizona

2 0 0 5

THE UNIVERSITY OF ARIZONA
GRADUATE COLLEGE

As members of the Dissertation Committee, we certify that we have read the dissertation

prepared by Simona Lup

entitled Microeconomic Essays on Technology, Labor Markets and Firm Strategy

and recommend that it be accepted as fulfilling the dissertation requirement for the

Degree of Doctor of Philosophy.

____ Date: 07/01/05
Ronald L. Oaxaca

____ Date: 07/01/05
Gary D. Libecap

____ Date: 07/01/05
Stanley S. Reynolds

____ Date: 07/01/05
Alfonso Flores-Lagunes

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

____ Date: 07/01/05
Dissertation Director:
Ronald L. Oaxaca

STATEMENT BY AUTHOR

This dissertation has been submitted in partial fulfillment of requirements for an advanced degree at The University of Arizona and is deposited in the University Library to be made available to borrowers under rules of the Library.

Brief quotations from this dissertation are allowable without special permission, provided that accurate acknowledgment of source is made. Requests for permission for extended quotation from or reproduction of this manuscript in whole or in part may be granted by the major department of the Dean of the Graduate College when in his or her judgement the proposed use of the material is in the interests of scholarship. In all other instances, permission must be obtained from the author.

SIGNED : ________Simona Lup_______________

AKNOWLEDGEMENTS

This work would not have been possible without the advise, support and great inspiration by my advisor Dr. Ronald L. Oaxaca. He generously shared with me his time, knowledge and creativity. He has been a great mentor as an economist and as a person.

I am also thankful to the members of my dissertation committee, Dr. Gary Libecap, Dr. Stanley Reynolds, Dr. Alfonso Flores-Lagunes and Dr. Rabah Amir who provided me with great guidance throughout my studies at the University of Arizona. Dr. Gary Libecap has generously given me his time and his support on many occasions, and he has provided prompt and valuable feedback to many drafts. Dr. Stanley Reynolds has provided great insights and feedback when most needed, and he has always been very supportive and generous with his time. Dr. Alfonso Flores-Lagunes always had time and patience to listen to my econometric problems and has provided me with many valuable comments. Dr. Rabah Amir's expertise and insights have greatly aided the second essay of this dissertation.

I would also like to thank Dr. Price Fishback for his constant encouragement and valuable advice. Dr. John Drabicki has been an important resource during my graduate studies by providing valuable teaching advice with a great sense of humor and wit.

I am indebted to the rest of the Economics faculty for stimulating discussions during my graduate studies. My life as a graduate student has been made more manageable by my classmates and my other peers. I thank them all for their assistance and camaraderie. I also want to thank the economics staff, especially Mary and Jennie, for their help over the years.

I would like to gratefully acknowledge the NBER - Alfred P. Sloan Foundation for providing the 'Science and Engineering Workforce' dissertation fellowship to support the work included in my second and third chapters.

Finally, I would like to thank my family and friends from near and far, especially my parents, Ioan and Eugenia, and my sister Adriana for their continuous support, love and patience over the years. A special thanks goes to Geoff who has been next to me for from the beginning of this dissertation. His love and support and his great understanding made my graduate years easier and added a new dimension to my life.

DEDICATION

This dissertation is dedicated to the memory of my grandfather, Lup Nicolae 'Dascalu'. He instilled in me the values that guide me now as an economist and as a citizen of this world.

Table of Contents

List of Figures **8**

List of Tables **9**

Abstract **11**

Chapter 1. Technological Change and Gender Wage Differentials[1] **13**

1.1. Introduction 13
1.2. Conceptual Framework 19
1.2.1. A CES Production Function with Non-Neutral Technological Change 19
1.2.2. A New Dimension: Gender Based Discrimination 21
1.2.3. Non-Neutral Technological Change, Controlling for Skills and Potential Discrimination 23
1.3. Data Description 26
1.3.1. Data on Employment and Wages 26
1.3.2. Data on Non-Labor Factor and Factor Price 27
1.4. Empirical Issues 28
1.4.1. Estimation Strategy 28
1.4.2. Normalization and Additional Constraints 30
1.4.3. Direct Measures of Technological Change 31
1.5. Results 33
1.6. Conclusions 37

Chapter 2. Inter-firm Technological Spillovers, Mobility of Scientists and the Organization of R&D **50**

2.1. Introduction 50
2.2. Mobility of Scientists and R&D Collaboration 54
2.3. Data Description 59
2.4. Empirical Issues 62
2.5. Results 65
2.6. Conclusions 69

[1]This chapter is co-authored with Ronald L. Oaxaca.

Table of Contents—*Continued*

Chapter 3. Labor Mobility of Scientists and Engineers and the Pace of Innovation **81**
3.1. Introduction 81
3.2. Literature review 83
3.3. Mobility and Innovation 87
3.3.1. General Setting 87
3.3.2. The Model 88
3.4. Data 94
3.5. Empirical Strategy 98
3.6. Empirical Results 100
3.7. Conclusions 104

References **116**

List of Figures

Figure 2.1. Difference in Profits, relative to the Spillover Parameter, beta . 59
Figure 2.2. Annual Number of R&D Collaborations 79
Figure 2.3. Annual Average Corporate R&D Spending 80

Figure 3.1. Trends in the Labor Mobility of Scientists and Engineers and the Pace of Innovation 108
Figure 3.2. The Mean Backward Citation Lag, Averages by Industry 109
Figure 3.3. The Labor Mobility of Scientists and Engineers, Averages by Industry 110

List of Tables

Table 1.1. Definition of Industry Variables 39
Table 1.2. Definition of Occupation Variables 39
Table 1.3. Description of Variables 40
Table 1.4. Summary Statistics 41
Table 1.5. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, Industries 1 to 4 42
Table 1.6. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, Industries 5 to 8 43
Table 1.7. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), Industries 1 to 4 44
Table 1.8. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), Industry 5 to 8 45
Table 1.9. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, using RD, Industries 1 to 4 . 46
Table 1.10. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, using RD, Industries 5 to 8 . 47
Table 1.11. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), using RD, Industries 1 to 4 48
Table 1.12. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), using RD, Industries 5 to 8 49

Table 2.1. Industry Standard Classification Codes 71
Table 2.2. Number of RD Collaborations in the Sample, by Year 72
Table 2.3. Annual Average Company RD, by Industry, in million dollars 2000 73
Table 2.4. Annual Average Number of RD Collaborations in the Sample, by Industry 74
Table 2.5. Average Labor Mobility Rates for Scientists and Engineers, by Industry 75
Table 2.6. Summary Statistics for the Sample 76
Table 2.7. Poisson Regressions, Random Effects 77
Table 2.8. Poisson Regressions, Random Effects, continued 78

Table 3.1. Definition of Industry Variables 107

LIST OF TABLES—*Continued*

TABLE 3.2. Summary Statistics 111
TABLE 3.3. Pooled Ordinary Least Squares Results 112
TABLE 3.4. Fixed Effects and Random Effects Estimation Results 113
TABLE 3.5. Generalized Least Squares and Between Effects Results 114
TABLE 3.6. Generalized Least Squares with Dummy Variables Results 115

Abstract

This dissertation consists of three essays in applied microeconomics. These essays investigate different aspects of the impact of technology on labor market outcomes and firm strategy. The first essay, co-authored with Ronald L. Oaxaca, is in the area of labor economics and it investigates the relation between non-neutral technological change and the gender gap in wages. This essay is the first to address the issue of the recent narrowing of the gender wage gap in the context of technological change by using a novel approach to separately estimate the effects of technological change and discrimination on the gender wage gap. Using a constant elasticity of substitution production function and Current Population Survey data on employment and wages by industry and occupation, the results show that changes in non-neutral technological change explain between 5% and 9% of the narrowing of the wage gap between 1979 and 2001. The latter two essays span topics across applied industrial organization, firm strategy and labor economics. The second component of my dissertation investigates the relation between technological knowledge diffusion through the labor mobility of scientists and the organization of R&D activities by innovative firms. Using a labor mobility measure from the Current Population Survey March Supplements as a measure for inter-firm technology spillovers and a panel of R&D alliance data for 18 U.S. industries between 1989 and 1999, a Poisson estimation shows that firms facing a 10% increase in the labor mobility of scientists have a 5% increase in the annual number of R&D collaborations. The third essay is an empirical analysis of the impact of knowledge dissemination generated by the labor mobility of scientists and engineers on a measure of the pace of innovation. Using an unbalanced panel of firms containing patent data matched with firm data across eight innovative industries, from 1989 to 1998, along with a measure of the labor mobility of scientists and engineers, this essay provides evidence that firms in industries exposed to levels of labor mobility

of scientists and engineers that differ by 1%, have an expected time lag between sequential generations of technologies that differs by 0.56 years.

Chapter 1

Technological Change and Gender Wage Differentials[1]

1.1 Introduction

The effect of new technologies on wages and employment is a question that has always interested economists. This topic has received considerable attention as the wage inequality in the U.S. labor market has experienced a dramatic increase from the late 70's into the 90's, an increase believed to be associated with new technologies adopted by firms during this period of time. As summarized by Katz and Autor (1999), the main changes that took place in the U.S. wage structure during the 1980's and 1990's are translated into large increases in wage differentials between blue-collar and white-collar workers and by much greater residual inequality, that is, larger within-group wage dispersion. The wage dispersion increased substantially for both men and women – the weekly earnings of the 90^{th} percentile worker relative to the 10^{th} percentile worker increased by over 25% for both men and women from 1979 to 1995. The wage differentials by education, occupation and experience have increased as well – the relative earnings to college graduates and those with advanced degrees increased dramatically in the 1980s. At the same time, the employment shares of less skilled workers appear to have fallen relative to those of more skilled workers (Berman, Bound and Griliches, 1994). This recent rise in wage inequality has been primarily attributed in the literature to increased relative demand for highly educated and 'more skilled' workers, driven by skill-biased technological change, largely associated with the new information technology.[2]

[1] This chapter is co-authored with Ronald L. Oaxaca.

[2] Bound and Johnson (1992), and Berman et al. (1994), attribute wage structure changes to an increased rate of growth of the relative demand for highly educated and 'more skilled' workers driven

The major exception from this pattern of a widening wage structure has been the substantial narrowing of wage differentials between men and women during the last couple of decades. The statistical data show that gender wage differentials declined both overall and for all age and education groups in the 1980s and 1990s.

Historical trends on the gender wage gap show that there is essentially no significant change in the gender gap in the period immediately following World War II, explained by the failure of women's skills to increase relative to men's (Goldin, 1990). During the 1960s and 1970s, the apparent failure of the gender gap to narrow surprised economists, since during this period of time a significant increase in women's labor force participation was documented. However, starting with the 1980's, the gender gap narrowed at a rapid pace through the early 1990s, and then slowed somewhat during the mid-1990s. The rapid convergence in the gender gap during this period surprised many observers, especially in the light of the earlier lack of convergence. Today, women's pay still lags men's in virtually every sector of the economy. Full-time female workers earned 77.5 percent of what their male counterpart did in 2001, according to the Bureau of Labor Statistics.

There is a large literature in labor economics that attempts to explain the trends in gender wage differentials. However, this literature is largely independent of the literature on non-neutral, skill-biased technological change and continues to leave open the question of the effect of new technologies on the gender wage gap. This essay attempts to contribute to the labor literature by investigating the recent narrowing of the gender wage gap in the context of technological change. Previous literature (Berman et. al. 1994) shows that during the last couple of decades technological change significantly raised the return to skill, including unobserved skills. But is the

by skill-biased technological changes, largely associated with the spread of computers (information technologies) in the workplace. When the explanatory power of technological change proxies is considered (investment in computers, employee computer use, R&D, R&D intensity) the results are even more convincing, showing that technological change has significantly affected the skill composition of the labor force and the wage dispersion. See Card, D., DiNardo, J. E.(2002) for a survey of the literature in this area.

return to skill rising equally for men and women? This essay argues that technological change, associated primarily with new information technology, might enable female workers in possibly different ways than men. One would think that new technologies would at least continue to take away from the emphasis on the physical strength for some jobs. However, this is not the only way technology might affect the relative wages of female and male workers. It might be possible that women have unobserved skills that are more compatible with computer use than men, generating a faster rise in the return to unobservables for women relative to men, as a result of the impact of technological change. The literature on the technological gender gap emphasizes the different approach of women to technology (i.e. use of computers), relative to men. This difference is observed starting with middle school, among boys and girls.[3] While men are more interested in the computer as a 'machine', a bundle of hardware and software, women on average are more interested in the functions of computers, approaching technology as a way to better handle tasks, as means of integrating information, increasing communication with clients, improving work and inter-personal relations. One high profile example of such different approaches to computers is that of Bill Gates of Microsoft and Meg Whitman, the CEO of pioneering online auctioneer eBay Inc. The approach of Bill Gates to information technology is driven by the goal of building faster, more capable computers. Meg Whitman, as described by the BusinessWeek magazine[4], uses the new technologies, combined with a great brand and consumer instinct, leading to the eBay's continuing expension. This essay argues that the different approach to the use of new technologies might generate different returns to skill and computer use for women and men. Bresnahan (1997) introduces the idea of an organizational complementarity between computers and workers who posses both greater skills, but also greater 'people' skills, or 'soft' skills. If educated

[3] C. Brunner, 1999, Merrow Report, Center for Children and Technology, part of the Bank Street College of Education in New York City, as cited by Becky Whittenburg "The Technology Gender Gap. How Are We Doing?", Gray Matters Vol. 3 (3), May 2000.

[4] Kerstetter, Jim. "Meg Whitman", BusinessWeek, May 15, 2000.

women are more likely to have these 'soft' skills than educated men, the return to computer use will be larger for women than men.

A few papers indirectly point to non-neutral technological change as a potential factor that might explain some of the gender wage narrowing trends. O'Neill and Polachek (1993) analyzed the trend of the gender wage gap in the 1980s, when the gender gap experienced the sharpest change, and found that convergence in measurable work-related characteristics (schooling and work experience) explains one-third to one-half of the narrowing. The remainder is attributed to declining wages of blue-collar workers, who are disproportionately male. These declining wages of blue-collar workers have been considered by later work (Berman et al. 1994) to be driven by skill-biased technological change.

Blau and Kahn (2000) uses a labor supply approach to investigate the effect of gender-specific factors (including gender differences in qualifications, and discrimination) and the overall wage structure on the recent changes in the gender pay gap in the United States. Their test of the effect of technological change on the gender pay gap uses the overall wage structure changes as an explanation for the gender wage differences. They attribute the declining gender differentials primarily to gender-specific factors, specifically the convergence of work-related skills.

In the light of the recent changes in the wage structure, the narrowing of the gender wage gap during the last couple of decades has puzzled economists. Previous results, cited by Blau and Kahn, 1994, suggest that, on average, women tend to be less skilled than men and to be located in lower-paying industries and occupations. This will imply that an increase in the return to experience would cause the gender wage gap to rise, even if women's relative level of experience and their gender-specific treatment by employers remained the same. Similarly, an increase in the return to better paid, 'male' occupations and industries would widen the gender wage gap. As formulated in Card and DiNardo (2002), the trends in the gender wage gap are believed to pose "problems and puzzles" for different versions of the non-neutral technological change hypothesis. The narrowing of the wage gap in the 1980s is considered a problem for the rising return-to-skill version of non-neutral technological change, which predicts that technological change raises the return to skill, including the unobserved skills that are usually hypothesized to explain the gender gap. If women use computers on the job more than men, the narrowing gap is consistent with the computer-use-skill-complementarity version of non-neutral technological change. But this cannot explain the similarity of the trends in the gender wage gap for different levels of education, since well-educated women are documented to actually be less likely to use computers than well-educated men.

A previous paper by Allen (2001) reports evidence on how technological change is related to changes in wage differences by schooling, experience and gender. Using individual level data from the 1979 and 1989 Current Population Survey (CPS), combined with industry level data on technology for 39 industries, Allen (2001) finds that levels and changes in the return to schooling and experience are significantly related to R&D, tech capital and K/L acceleration. Concerning gender wage differentials, Allen (2001) reports that the gender gap narrowed more in industries that most intensively used high-tech capital in 1979. He also reports that wage growth rises with schooling and experience and is greater for women than for men.

This essay attempts to shed some light on these issues by directly investigating the narrowing of the gender wage gap in the context of technological change. The investigation is conducted at a more disaggregated level, by occupation and industry, to capture any potential differences in the effect of new technologies on the relative wages of female workers, both in the manufacturing and non-manufacturing sectors, from 1979 to 2001. These years cover the period of time that witnessed the most significant narrowing trend of the gender wage gap. The relation between non-neutral technological change and the gender wage differentials is modeled through a constant elasticity of substitution (CES) production function that incorporates male and female labor inputs by occupation in each industry, a non-labor input and a productivity parameter function that captures non-neutral technological change. The relation between technological change and gender relative wages is identified by using a novel approach that permits the separate estimation of the effects of technological change and discrimination on the gender wage gap. Specifically, a gender based wage discrimination factor is introduced, along with non-neutral technological change, to further explore the narrowing of the gender wage gap. If the unexplained differences in the gender wage gap (discrimination) are not considered, the estimated elasticity of factor substitution is biased.

The key results of this essay provide evidence that non-neutral technological change had an impact on the narrowing of the gender wage gap during the last two decades, with differences across industries and occupations. The robustness of the results is tested by using direct measures of technological change. When such direct measures of technological change are used the coefficients show a similar sign and significance. This essay also brings evidence that ignoring the unexplained component of the gender wage differentials could result in a biased estimation of the effect on non-neutral technological change on the gender wage gap.

The rest of the chapter is organized as follows: section 1.2. presents the conceptual framework, section 1.3. is concerned with empirical issues, section 1.4. describes the data used in the analysis, section 1.5. presents the results and section 1.6. presents the conclutions. ables with the definition of variables, descriptive statistics and results follow at the end of the chapter.

1.2 Conceptual Framework

1.2.1 A CES Production Function with Non-Neutral Technological Change

To illustrate the concept of non-neutral technological change in relation to gender wage differentials, assume that non-neutral technological change can be modeled as a shift in an industry-wide production technology that can be characterized by a constant elasticity of substitution (CES)[5] production function of the following form:

$$Q_t = A(t)\left[\sum_{j=1}^{J} \alpha_j(t) L_{jt}^{\rho} + \left(1 - \sum_{j=1}^{J} \alpha_j(t)\right) K_t^{\rho}\right]^{\frac{\phi}{\rho}}, \tag{1.1}$$

where Q_t is a measure of output in quarter t, $A(t)$ is a scale parameter that captures neutral technological change, L_{jt} represents employment in quarter t of the j^{th} category of labor (where categories are defined by gender and four occupations within each industry), J is the number of distinct labor inputs, defined by gender and occupation, within each industry, t stands for quarters, K_t is a measure of non labor inputs in quarter t, and $\alpha_j(t)$ is a productivity parameter function that captures technological change by measuring the savings in one factor input relative to the others. The specification of $\alpha_j(t)$ will be discussed below. Note that ϕ is the returns to scale parameter and $\rho = \frac{\sigma-1}{\sigma}$, where σ is the elasticity of substitution among inputs.

The marginal products can be derived as:

$$MP_{L_{jt}} = \phi A^{\frac{\rho}{\phi}}(t) \alpha_j(t) L_{jt}^{\rho-1} Q_t^{1-\frac{\rho}{\phi}} \tag{1.2}$$

and

$$MP_{Kt} = \phi A^{\frac{\rho}{\phi}}(t)\left[1 - \sum_{j=1}^{J} \alpha_j(t)\right] K_t^{\rho-1} Q_t^{1-\frac{\rho}{\phi}}. \tag{1.3}$$

Assuming cost minimization, the marginal products will be equated with the factor

[5] Using Cobb-Douglas or Leontief production technologies, as special cases of the CES production function, would not yield identifiable biases because the elasticity of substitution in these cases is either unity or zero.

input prices:

$$\frac{MP_{L_{jt}}}{MP_{L_{ht}}} = \frac{w_{jt}}{w_{ht}}, \quad j \neq h \tag{1.4}$$

and

$$\frac{MP_{Kt}}{MP_{Ljt}} = \frac{r_t}{w_{jt}}. \tag{1.5}$$

By substituting (1.2) and (1.3) into (1.4) and (1.5), and by normalizing relative to the h^{th} labor input (i.e. L_{ht}, and w_{ht}) one will obtain the following:

$$\frac{\alpha_j(t) L_{jt}^{\rho-1}}{\alpha_h(t) L_{ht}^{\rho-1}} = \frac{w_{jt}}{w_{ht}}, \ j \neq h \tag{1.6}$$

and

$$\frac{\left[1 - \sum_{j=1}^{J} \alpha_j(t)\right] K_t^{\rho-1}}{\alpha_h(t) L_{ht}^{\rho-1}} = \frac{r_t}{w_{ht}}. \tag{1.7}$$

Taking the log of the above relations the following set of equations result:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \ln\left(\frac{\alpha_j(t)}{\alpha_h(t)}\right) + (\rho - 1)\ln\left(\frac{L_{jt}}{L_{ht}}\right), \ j \neq h \tag{1.8}$$

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \ln\left(\frac{\left[1 - \sum_{j=1}^{J} \alpha_j(t)\right]}{\alpha_h(t)}\right) + (\rho - 1)\ln\left(\frac{K_t}{L_{ht}}\right). \tag{1.9}$$

The specification of the $\alpha_j(t)$ functions is given by a multinomial logit form, as:

$$\alpha_j(t) = \frac{e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right) + \epsilon_{jt}}}{1 + \sum_{j=1}^{J} e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right) + \epsilon_{jt}}}, \ j = 1, ..., J \tag{1.10}$$

and

$$\alpha_{J+1}(t) = 1 - \sum_{j=1}^{J} \alpha_j(t) = \frac{1}{1 + \sum_{j=1}^{J} e^{\alpha_{j0} + \alpha_{j1}\left(\frac{1}{t}\right) + \epsilon_{jt}}}, \tag{1.11}$$

where $0<\alpha_j<1$, $\sum_{j=1}^{J+1} \alpha_j(t) = 1$ (the last restriction being necessary for the identification of the $\alpha's$), and ϵ_{jt} is a random error term distributed N(0, σ_ϵ^2).

Given the specification of the $\alpha_j(t)$ functions, the equations (1.8) and (1.9) become estimating equations of the following form:

$$\ln\left(\frac{w_{jt}}{w_{ht}}\right) = \beta_{j0} + \beta_{j1}\frac{1}{t} + (\rho-1)\ln\left(\frac{L_{jt}}{L_{ht}}\right) + \epsilon_{jht}, \; j \neq h, \tag{1.12}$$

and

$$\ln\left(\frac{r_t}{w_{ht}}\right) = \beta_{h0} + \beta_{h1}\frac{1}{t} + (\rho-1)\ln\left(\frac{K_t}{L_{ht}}\right) + \epsilon_{ht}, \tag{1.13}$$

where $\beta_{j0} = \alpha_{j0} - \alpha_{h0}$, $\beta_{j1} = \alpha_{j1} - \alpha_{h1}$ with $j \neq h$, and $j = 1, ..., J$ for equations (1.12), and $\beta_{h0} = -\alpha_{h0}$ for equation (1.13). In this specification, the effect of the non-neutral technological change is going to be captured by the coefficients on $\frac{1}{t}$. It is not necessary to sign the β_{j1} parameters that capture the technological change. With the above specification the $\alpha_j(t)$ functions capture the savings in one labor or non-labor input relative to another, while the inverse of t insures a bounded measure of such savings. $(\rho-1)$ will allow us to estimate the elasticity of substitution between factors of production, since the factor elasticity of substitution in each industry (σ) is equal to $\frac{1}{1-\rho}$.

1.2.2 A New Dimension: Gender Based Discrimination

The issue of gender based discrimination has been extensively documented in the labor literature and thus it cannot be ignored as a potential major factor that shapes the gender wage gap. In this section a framework for incorporating the gender discrimination component is proposed. This framework allows us to measure any potential gender based discrimination.

Generalizing Gary Becker's (1971) decomposition of the relative wage gap between groups of workers into marginal product and discrimination components, let the wage w_{ijt}^m of male workers in quarter t , industry i, occupation j be given by the corresponding marginal product:

$$w_{ijt}^m = MP_{L_{ijt}}^m. \tag{1.14}$$

Let the wage w_{ijt}^f of female workers in quarter t , industry i, occupation j be given by the corresponding marginal product, discounted by a discrimination index d_{ijt}:

$$w_{ijt}^f = \frac{MP_{\underset{Lijt}{f}}}{(1 + d_{ijt})}, \tag{1.15}$$

where

$$\ln(1 + d_{ijt}) = d_{0i,j-h} + \frac{d_{1i,j}}{t} - d_{2ij} \ln(\frac{L_{ijt}^f}{L_{ijt}^m}) + u_{ijt} \ . \tag{1.16}$$

The wage equations for male workers in any industry, occupation j, normalized to the wage of male workers in industry i, occupation h, where $j \neq h$, can be written as:

$$\ln(\frac{w_{jt}^m}{w_{ht}^m}) = \alpha_{0,j-h}^{mm} + \frac{\alpha_{1,j-h}^{mm}}{t} + (\rho - 1) \ln(\frac{L_{jt}^m}{L_{ht}^m}) + \epsilon_{j-h,t}^{mm}. \tag{1.17}$$

Note that the industry index, i, was suppressed in the expression above and will be suppressed for simplicity from here on. In the wage equation above there is no gender based discrimination.

The wage equations for female workers in any industry, occupation j, normalized to the wage of male workers in industry i, occupation h will take into account potential gender based discrimination, and can be written as:

$$\begin{aligned}
\ln(\frac{w_{jt}^f}{w_{ht}^m}) &= \ln\left(\frac{MP_{jt}^f}{w_{ht}^m}\right) - \ln(1 + d_{jt}) \\
&= \left(\alpha_{0,j-h}^{fm} - \alpha_{0,j-h}^{mm} - d_{0j}\right) + \left(\alpha_{1,,j-h}^{fm} - \alpha_{1,j-h}^{mm} - d_{1j}\right)\frac{1}{t} \\
&\quad + (\rho - 1)\ln\left(\frac{L_{jt}^f}{L_{ht}^m}\right) + d_{2,j-h}\ln\left(\frac{L_{jt}^f}{L_{jt}^m}\right) + \\
&\quad + \ \epsilon_{j-h,t}^{fm} - \epsilon_{j-h,t}^{mm} - u_{jt} \ ,
\end{aligned} \tag{1.18}$$

where

$$\ln(\frac{MP^f_{jt}}{w^m_{jt}}) = \alpha^{fm}_{0,,j-h} + \frac{\alpha^{fm}_{1,,j-h}}{t} + (\rho-1)\ln(\frac{L^f_{jt}}{L^m_{ht}}) + \epsilon^{fm}_{j-h,t} \ , \tag{1.19}$$

for j, h =1,... ,4 occupation index.

In the case where $j = h$, one has:

$$\begin{aligned}\ln(\frac{w^f_{jt}}{w^m_{jt}}) &= \ln\left(\frac{MP^f_{jt}}{w^m_{jt}}\right) - \ln(1+d_{jt}) \\ &= \left(\alpha^{fm}_{0,j-j} - \alpha^{mm}_{0,j-j} - d_{0j}\right) + \left(\alpha^{fm}_{1,j-j} - \alpha^{mm}_{1,j-j} - d_{1j}\right)\frac{1}{t} \\ &\quad +[(\rho-1)+d_{2,j-h}]\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right) + \epsilon^{fm}_{j-j,t} - \epsilon^{mm}_{j-j,t} - u_{jt} \ . \end{aligned} \tag{1.20}$$

If one believes that there is potential gender based wage discrimination in the occupations considered, ignoring it could lead to estimating an ‘apparent’ elasticity of substitution σ between female and male labor inputs. This apparent estimated elasticity of substitution between female and male labor inputs without taking into account the potential discrimination is smaller than the actual elasticity of substitution, showing a diminished substitutability of female and male workers within the same occupation by potential gender based wage discrimination. Although the parametr $d_{2,j-h}$ varies across occupations, consider as a first approximation that $\frac{-1}{\sigma}+d_{2,j-h} = -\frac{1}{\tilde{\sigma}}$. Since $d_{2,j-h} < 0$, this implies that $\frac{1}{\sigma}<\frac{1}{\tilde{\sigma}}$. Thus, in the presence of discrimination, the estimated elasticity of factor substitution $\tilde{\sigma}$ is smaller than the true estimated σ, measuring the factor elasticity of substitution when there is no discrimination.

1.2.3 Non-Neutral Technological Change, Controlling for Skills and Potential Discrimination

Here we introduce a framework that allows us to estimate the effect of non-neutral technological change apart from the potentially confounding effects of changes in discrimination. By using data on individual characteristics (schooling, potential experience, potential experience squared), aggregated each quarter, by industry and occupation, a measure of discrimination can be derived.

Consider first the wage equation for a male worker k, in any industry[6], in occupation j, quarter t,

$$\ln w^m_{jtk} = X^m_{jtk}\hat{\beta}^m_{jt} + \upsilon^m_{jtk}. \tag{1.21}$$

Similarly, consider the wage equation for a female worker k, in any industry, in occupation j, quarter t,

$$\ln w^f_{jtk} = X^f_{jtk}\hat{\beta}^f_{jt} + \upsilon^f_{jtk}. \tag{1.22}$$

By using the estimated coefficients of the male and female workers' wage equations, the wage gap between female and male workers can be decomposed by using the Oaxaca decomposition (Oaxaca, 1973) as:

$$\ln(w^m_{jtk} - w^f_{jtk}) = (\overline{X}^m_{jt} - \overline{X}^f_{jt})\hat{\beta}^m_{jt} + \overline{X}^f_{jt}(\hat{\beta}^m_{jt} - \hat{\beta}^f_{jt}), \tag{1.23}$$

where the first term represents the wage gap due to differenc in skills and the second term represents the wage gap due to discrimintion.

Using the decomposition above, a measure of unexplained differences (discrimination) can be obtained as:

$$\ln(1 + d_{jt}) = \overline{X}^f_{jt}(\hat{\beta}^m_{jt} - \hat{\beta}^f_{jt}), \tag{1.24}$$

where $\overline{X}^f_{jt}$ is the sample average of workers' characteristics, $\overline{X}^f_{jt} = \sum_{k_f}(X^f_{jtk}) * weight^f_{jtk}$[7].

[6] The industry index, i, is supressed for simplicity.

[7] Alternatively, the discrimination can be estimated by using the method proposed by Oaxaca & Ransom (1994). First, estimate a common wage structure for both male and female workers:
$lnw^m_{ijtk} = X^m_{ijtk}\tilde{\beta}^m_{ijt} + \upsilon^m_{ijt}$
Then, measure the discrimination as:
$ln\,(1 + D_{ijt}) = \overline{X}^m_{ijt}(\hat{\beta}^m_{ijt} - \tilde{\beta}_{ijt}) + \overline{X}^f_{ijt}(\tilde{\beta}_{ijt} - \hat{\beta}^f_{ijt})$
where $\overline{X}^m_{ijt}$ is the sample average, $\overline{X}^m_{ijt} = \sum_{k_m}(X^m_{ijtk}) * weight^m_{ijtk}$
and $\overline{X}^f_{ijt}$ is the sample average, $\overline{X}^f_{ijt} = \sum_{k_f}(X^f_{ijtk}) * weight^f_{ijtk}$. However, this alternative requires a larger number of estimations, so it is more costly.

The weights are provided by the Bureau of Labor Statistics with the Current Population Survey data.

Following Oaxaca (1973), the wage of a female worker relative to the wage of a male worker can be written as the difference between their relative marginal products and an index of discrimination:

$$\ln(\frac{w^f_{jt}}{w^m_{jt}}) = \ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) - \ln(1+d_{jt}). \tag{1.25}$$

Thus, the relative marginal products can be written as:

$$\ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) = \ln(\frac{w^f_{jt}}{w^m_{jt}}) + \ln(1+d_{jt}). \tag{1.26}$$

By replacing $ln\,(1+d_{jt})$ from equation (1.24), the following relation is obtained for the relative wages of male and female workers:

$$\ln(\frac{w^f_{jt}}{w^m_{jt}}) + \overline{X}^f_{jt}(\hat{\beta}^m_{jt} - \hat{\beta}^f_{jt}) = \alpha_{0jt} + \alpha_{1jt}\frac{1}{t} + (\rho-1)\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right) + \epsilon_t. \tag{1.27}$$

Thus equation (1.26) above can be re-written in relative marginal products as:

$$\ln\left(\frac{MP^f_{jt}}{MP^m_{jt}}\right) = \alpha_{0jt} + \alpha_{1jt}\frac{1}{t} + (\rho-1)\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right) + \epsilon_t. \tag{1.28}$$

Equation (1.28) above allows for the measurement of the impact of non-neutral technological change on the gender wage differentials, controlling for the unexplained wage gap (potential gender based discrimination).

1.3 Data Description

1.3.1 Data on Employment and Wages

In order to investigate the impact of non-neutral technological change on the gender wage gap, data from the Current Population Survey (CPS) on quarterly hourly wage and employment are used, for the years 1979 to 2001. The Data Appendix provides a description of the Current Population Survey. The data used here come from the National Bureau of Economic Research (NBER) extracts of the CPS files. The extracts include micro data for approximately 30,000 individuals each month. About fifty variables each month are selected for continuity across years. For the purpose of this study quarterly employment and hourly wages data are used for full time employees, 16 years or over, aggregated quarterly by gender, industry and occupation. Tables 1.1. and 1.2. list the industry and occupation variables. There are eight major industries considered (Agriculture, Mining, Construction, Manufacture, Transportation, Trade, Finance and Services) and four major occupations (Executive and managerial occupations; Technical, sales and administrative support; Service occupations, mechanics and repairers; Machine Operators, laborers and farmers). Table 1.3. provides a description of the variables used in the estimations, and Table 1.4. provides summary statistics.

Based on the CPS data used in this essay, the overall ratio of women's wages to men's wages changed from 0.67 in the beginning of 1979 to 0.80 at the end of 2001. This represents a percentage change in the relative wages of 19.4% during this period of time. During the same time, the employment ratio of female to male workers went up from 0.57 to 0.70.

1.3.2 Data on Non-Labor Factor and Factor Price

Data on the non-labor input come primarily from the National Income and Product Accounts (NIPA) tables of the Bureau of Economic Analysis (BEA). The series on K_t, the non-labor input, was obtained from recursive equations, given initial conditions for K_t, and a certain rate of capital depreciation δ_t in each industry. To obtain series on r_t, the user cost of capital is used.

Here is how the data on the non-labor factor were obtained. Starting from the following accounting relation:

$$P_tQ_t = w_tL_t + r_tK_t \ , \tag{1.29}$$

data for P_tQ_t were obtained from the NIPA Table 6.1, on National Income Without Capital Consumption Adjustment by Industry Group, while data on w_tL_t came from BEA Table SQ7 (State Quarterly Income Estimates).

Data on $\delta_t r_{t-1} K_{t-1}$ can be retrieved from NIPA Tables 6.13 and 6.22, Noncorporate and Corporate Capital Consumption Allowances by Industry Group, while data on $r_{t-1}K_{t-1}$ can be retrieved from NIPA Table 3.3ES, Historical-Cost Net Stock of Private Fixed Assets by Industry. Accordingly δ_t can be backed out.

Assuming zero profits, the user cost of capital can be calculated as follows:

$$r_t = (i_t + \delta_t)pd_t \ , \tag{1.30}$$

where i_t is the quarterly interest rate is from the Federal Reserve Historical Statistics, δ_t is the depreciation rate, calculated above, and pd_t is a price deflator, from NIPA table 7.6, Chain-Type Quantity and Price Indexes for Private Fixed Investment by Type. The K_t series can be recovered from (27):

$$K_t = \frac{(P_tQ_t - w_tL_t)}{r_t}. \tag{1.31}$$

By treating K_t this way, internal consistency of the data is insured.

1.4 Empirical Issues

1.4.1 Estimation Strategy

Given the conceptual framework proposed in section 3, first subsection, the empirical investigation of the effect of non-neutral technological change on the gender wage differences involves estimating a set of equations as described in (1.12) and (1.13).

The identification strategy for the coefficients will have to take into account some specific issues that this model involves:

(a) cross-equation restrictions on ρ;

(b) endogeneity of the $\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right)$ variables, which requires proper instrumental variables.

The cross-equations restrictions on the ρ parameters results from the functional form of the production function, which implies an elasticity of substitution that does not vary with time, and it is the same for all pairs of labor, non-labor factors, for each industry. Thus, ρ will be restricted to have the same value across all equations, in each industry.

In the standard elasticity of substitution equations the dependent variable is the factor intensity in logs, $\ln\left(\frac{L^f_{jt}}{L^m_{jt}}\right)$, and the independent variable is $\ln\left(\frac{w^f_{jt}}{w^m_{jt}}\right)$. That is, $\ln\left(\frac{w^f_{jt}}{w^m_{jt}}\right)$ is usually considered exogenous since firms are assumed to be competitive in the factor market. However, at the industry level, the factor price ratios might be considered endogenous. Here, the focus is on the impact of technological change on gender wage differentials, thus, the factor price ratio is normalized as the dependent variable. Hence, the right hand side factor intensity variable is endogenous. In order to obtain consistent estimators it is necessary to consider estimation by instrumental variables. The instrumental variables used to solve the endogeneity problem are variables aggregated at the industry level that are believed to be correlated with the employment ratio, but uncorrelated with the error term.

The following instrumental variables are considered:

- the ratio of year-round, full time employed women to employed men (fwm);
- year-round, full time employed women to employed men in industry i (fwm_i);
- year-round, part time employed women to employed men (pwm);
- quarterly dummies ($d_{1,}d_{2,}d_3$);
- 3-month T-bill rates, quarterly averages (i_t).

It is reasonable to consider that fwm, fwm_i and pwm are correlated with the ratio of full-time female-to-male workers in each industry, in occupation j, and uncorrelated with the error term. That is, it is reasonable to assume that changes in the gender composition of employment at the economy or industry level are correlated with the gender composition of the employment within an occupation, and uncorrelated with the specific wages of female and male workers within an occupation. A Hausman specification test with the null hypothesis that the Instrumental Variable estimator is consistent, and the OLS estimator is efficient and consistent but inconsistent under the alternative hypothesis rejects the null hypotheses and justifies the use of instrumental variable methods in 84% of the equations. An overidentification test for the instrumental variables, with the joint null hypothesis that the excluded instruments are valid instruments, i.e., uncorrelated with the error term and correctly excluded from the estimated equation, does not reject the null, supporting the validity of the instruments. The first stage results are not reported. The F-statistic for the excluded instruments passes the significance test for 86.11% of the equations.

The equations (1.12) and (1.13) are estimated by Non-Linear Two Stage Least Squares (NL2SLS), the non-linearity being in coefficients. This is necessary for incorporating the cross-equations restriction mentioned above, plus the additional constraints that are due to the internal logic of the model. To understand the need for such additional constraints, it is useful to look at the normalization and identification issues that come with the estimation of these demand equations, as described in the subsection below.

1.4.2 Normalization and Additional Constraints

The normalization used to derive equations (1.12) and (1.13) is relative to the labor input h, but the model can be specified as relative to any of the factor inputs. Staying with the normalization on the h^{th} labor input, it is straightforward to back out the effects on any set of wage differentials from the estimated model.

For example, if the h^{th} labor input corresponds to male workers in occupation 4 and the estimating equations (1.12) and (1.13) are written relative to the h^{th} labor input which corresponds to male workers in occupation 4, then the female/ male wage differential for occupation 1 can be recovered as:

$$\ln\left(\frac{w_{1t}^{f}}{w_{1t}^{m}}\right) = \left(\widehat{\beta}_{0,1-4}^{fm} - \widehat{\beta}_{0,1-4}^{mm}\right) + \frac{\left(\widehat{\beta}_{1,1-4}^{fm} - \widehat{\beta}_{1,1-4}^{mm}\right)}{t} + (\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{f}}{L_{1t}^{m}}\right) + \widehat{\epsilon}_{1t}^{fm} - \widehat{\epsilon}_{1t}^{mm}\ , \tag{1.32}$$

where the coefficients $\widehat{\beta}_{v,1-4}^{fm}, \widehat{\beta}_{v,1-1}^{mm}$, with $v = 0, 1$, are from the following two equations of the type (1.12):

$$\ln\left(\frac{w_{1t}^{f}}{w_{4t}^{m}}\right) = \widehat{\beta}_{0,1-4}^{fm} + \frac{\widehat{\beta}_{1,1-4}^{fm}}{t} + (\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{f}}{L_{4t}^{m}}\right) + \widehat{\epsilon}_{1-4,t}^{fm}\ , \tag{1.33}$$

and

$$\ln\left(\frac{w_{1t}^{m}}{w_{4t}^{m}}\right) = \widehat{\beta}_{0,1-4}^{mm} + \frac{\widehat{\beta}_{1,1-4}^{mm}}{t} + (\widetilde{\rho}-1)\ln\left(\frac{L_{1t}^{m}}{L_{4t}^{m}}\right) + \widehat{\epsilon}_{1-4,t}^{mm}. \tag{1.34}$$

With this demand equation model, one needs $n-1$ equations to be able to span the entire system of equations, where n is the number of factor inputs. If non-neutral technological change narrows the gender wage gap among skilled workers, we would expect $\widehat{\beta}_{1,1-4}^{fm} - \widehat{\beta}_{1,1-4}^{mm} < 0$. One problem is that the estimated parameters would not be invariant with respect to the normalization; in other words, if the wage differentials were estimated relative to say wages of skilled females, one would have different estimates.

The skilled female/skilled male wage differential (female employed in occupation 1, Executive and managerial occupations) can also be directly estimated by:

$$\ln\left(\frac{w_{1t}^{f}}{w_{1t}^{m}}\right) = \widehat{\delta}_{0,1-1}^{fm} + \widehat{\delta}_{1,1-1}^{fm}\frac{1}{t} + (\widehat{\rho}-1)\ln\left(\frac{L_{1t}^{f}}{L_{1t}^{m}}\right) + \widehat{\nu}_{1t}^{fm} \ . \tag{1.35}$$

However, in general $\widehat{\delta}_{0,1-1}^{fm} \neq \left(\widehat{\beta}_{0,1-4}^{fm} - \widehat{\beta}_{0,1-4}^{mm}\right)$, $\widehat{\delta}_{1,1-1}^{fm} \neq \left(\widehat{\beta}_{1,1-4}^{fm} - \widehat{\beta}_{1,1-4}^{mm}\right)$, $\widetilde{\rho} \neq \widehat{\rho}$, $\widehat{\nu}_{1t}^{fm} \neq \widehat{\epsilon}_{1t}^{fm} - \widehat{\epsilon}_{1t}^{mm}$.

This necessitates estimating $\binom{9}{2} = 36$ equations for all possible wage differential pairings with cross-equation restrictions in order to uniquely identify the estimated parameters. However, the residual variance/covariance matrix will be singular because the error terms will be perfect linear combinations of one another. Thus, a seemingly unrelated estimation (SURE) cannot be performed for all 36 equations simultaneously. This problem can be avoided by using a Non-Linear Two Stage Least Squares (NL2SLS) estimation method. The NL2SLS is used for all 36 possible pairings. However, because any 8 equations can span the rest of the 28 equations, for internal consistency, additional constraints are imposed on the constant term and the coeficient of the time variable are imposed. These constraints insure invariance of the estimating coefficients to the choice of any 8 equations.

Since the focus of this chapter is on estimation of the effect of non-neutral technological change on gender wage differentials, only the estimation results pertinent to the relative gender wages in each one of the occupations considered are reported and discussed. The other results are available upon request from the authors.

1.4.3 Direct Measures of Technological Change

To directly test the power of specific factors in explaining the trends in the gender wage differentials in the recent past, proxies of technological change are considered.

The measurement of technology is a problem inherent in all empirical work. This has long been the subject of investigation and controversy. Among the several measures for technological change, R&D is the most popular. Other measures have been constructed and used, such as investment in computers, employee computer use, R&D intensity, capital intensity, K/L growth and total factor productivity (Berman et al. 1994, Allen, 2001, Card, D., DiNardo, J. E. 2002).

This essay employs as measures of technological change annual R&D investment, number of patents granted each year, and R&D employment. These measures are chosen because of availability of consistent data for the years that this investigation considers. The summary statistics of these measures are listed in Table 1.4. Only the results using R&D are reported.

1.5 Results

The first set of results, reported in Tables 1.5. and 1.6., show the estimated values of the impact of the non-neutral technical change on the gender wage differentials, without taking account of the possibility of discrimination. These estimates are obtained by using a Non-Linear Two Stage Least Squares (NL2SLS) estimation technique.

Before discussing these results, note that if non-neutral technological change has an effect on relative wages, this will translate into a statistically significant coefficient on $\frac{1}{t}$. Also, because of the link to the elasticity of factor substitution, the coefficient $(\rho - 1)$ on $\frac{L_{jt}^{f}}{L_{jt}^{m}}$ is expected to be negative and significant. Although estimated coefficients are obtained for all possible pairings of relative factor price ratios, only the results pertinent to the gender relative wages for each occupation in each industry are presented here. This is motivated by the focus of this essay on the effect of non-neutral technological change on the relative wages of female workers within four distinct occupations. The other results are available upon request from the authors.

The results shown in Tables 1.5. and 1.6. provide evidence that non-neutral technological change narrows the gender based wage differentials for all four occupations in all industries. The strongest impact, in terms of the magnitude, is found at the level of managerial, scientific and professional specialty occupations, occupation 1, where all the coefficients on $\frac{1}{t}$ are negative and statistically significant across all industries. This implies that new technologies adopted by firms had contributed to the narrowing of the gender wage gap in the managerial and professional occupations, in all industries in the sample. At this occupational level, at the mean, changes in the non-neutral technology adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between .09% and .05%. The negative and strongly significant coefficients on $\frac{1}{t}$ suggest that, after controlling for skill, the non-neutral technological change is associated with a faster increase in the return to unobservables for women, relative to men, contributing to the narrowing of the gender gap.

The smallest impact was found at the lowest pay occupation levels, operators and laborers, occupation 4, where changes in non-neutral technology adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between 0.05% and 0.008% while the gap narrowed at average annual rate of about 1%. For Technical, Sales and Administrative occupations (occupation 2) the effect of non-neutral technological change is mixed across industries. The estimates show no significant effect on the gender relative wages in agriculture, mining and finance. However, new technologies are associated with a decreasing gender wage gap in manufacturing and construction, while in transportation and trade the gender wage gap becames larger.

Tables 1.7. and 1.8. present the estimated coefficients of the effect of non-neutral technological change, controlling for skills and discrimination, using the identification strategy presented in section 2. The sign and significance of the coefficients on $\frac{1}{t}$ remain largely the same as in Tables 1.7. and 1.8. However, the magnitude of these coefficients is different. This suggests that, controlling for skills and potential discrimination changes the portion of the narrowing gender gap explained by the effect of non-neutral technological change, depending on the sign of the unexplained gender wage differences. For example, in Table 1.6, for industry 5, occupation 1, the coefficient on the inverse of t is -0.367. If skills and potential discrimination are considered, the coefficient on the inverse of t is smaller, at -0.254, as shown in Table 1.8. This is interpreted as a reduction in discrimination, which, once accounted for, reveals a smaller effect of the non-neutral technological change on the gender wage gap. However, for industry 5, occupation 3, the coefficients on the inverse of t from Table 1.6 is -0.321. If skills and potential employer discrimination are considered, the coefficient on the inverse of t in Table 1.8 is larger, at -0.325. This is interpreted as an increase in discrimination, which, once accounted for, shows a larger impact of the non-neutral technological change on the narrowing of gender wage gap.

In Table 1.6 all coefficients on $\frac{1}{t}$ for occupation 1 retain the same sign and significance, however, the magnitude of the coefficients is smaller for all industries. This suggests that part of the narrowing of the gender wage gap is in fact explained by changes in discrimination. As discussed in section 2, not taking into account the unexplained wage differences may lead to an 'apparent' estimated σ, which is downward biased. By comparing the values of σ reported in Tables 1.5. and 1.6. and Tables 1.7. and 1.8., the values of σ are largely the same, with the exception of manufacturing, where, by controlling for unexplained wage differences (discrimination), the value of the factor elasticity of substitution is higher. For agriculture and construction however, the values of σ are larger when controlling for discrimination. This might be explained for agriculture by the positive coefficients on $\frac{1}{t}$ for occupations 1 and 2, and no significance of this coefficient for occupation 3, as reported in Tables 1.7. and 1.8., suggesting that in fact technological change has contributed to an increase on the wage gap. With this in mind, looking at the same coefficients for agriculture, but in Tables 1.5. and 1.6., it may be inferred that in fact discrimination had a narrowing effect on the gender wage gap (decreasing discrimination). This may explain why the value of the factor elasticity of substitution in Tables 1.7. and 1.8. is smaller than the one reported in Tables 1.5. and 1.6.. For constructions, one can see that the sign, significance and magnitude of the coefficients on $\frac{1}{t}$ in Tables 1.5. and 1.6. and Tables 1.7. and 1.8. are essentially the same.

When direct measures of technological change are used, such as Total R&D expenditure in industry (from National Science Foundation Tables) the results, as reported in Tables 1.9. and 1.10. are similar, with a few exceptions, to those reported for regressions using $\frac{1}{t}$. The impact of R&D investment shows the largest effect on the relative wages of women in managerial and professional occupations (occupation 1). The smallest effect on the gender wage ratio is found for occupations 2 and 4, Technical, Sales and Administrative Support, and Operators, Laborers respectively. For occupation 2, the sign on the inverse of RD is positive for Transportation, Finance and Services. Specifically, changes in the R&D expenditure by firms are raising the quarterly female-to-male wage ratio in occupation 1 at an annualized rate that varies between 0.035% and 0.008%. The smaller rate growth of women's wages attributed to R&D expenditure, compared to the growth rate based on the pure time trend may be explained by the fact that R&D expenditure is only one of the multi-dimensions of technological change. In terms of elasticities, the effects on $\frac{1}{t}$ and $\frac{1}{RD}$ are very similar. For occupation 1, the elasticity of the gender relative wages with respect to non-neutral technological change ranges between 0.011 and 0.006, while the elasticity with respect to R&D ranges between 0.011 and 0.002. The values of these elasticities seem small, but they reflect responses of the relative wage to quarterly changes in non-neutral technological change and R&D, respectively.

When the effect of R&D expenditure is estimated, controlling for skills and unobserved differentials, the value of the coefficients on R&D are smaller. These results are reported in Tables 1.11. and 1.12.. The reduced magnitude of the coefficient is consistent again with the explanation that the 'apparent' effect of R&D on relative wages in fact was combined with the effect of changes in discrimination.

1.6 Conclusions

This essay provides evidence of the impact of non-neutral technological change on the gender wage gap during the last two decades. The results suggest that changes in non-neutral technologies acquired by firms partially explain the documented narrowing of the gender wage differentials even after controlling for unexplained differences in gender relative wages (discrimination). Specifically, changes in non-neutral technological change explain between 5 % and 9 % of the overall increase of women's wages relative to men's in the sample.

To obtain these estimated effects, the relation between non-neutral technological change and wages was modeled through a constant elasticity of substitution production function that incorporates male and female labor inputs by occupation in each industry, a non-labor input and a productivity parameter function that captures non-neutral technological change. The estimation employs quarterly CPS data on employment and wages, by industry and occupation, from 1979 to 2001. The model was estimated with a Non-Linear Two Stage Least Squares estimation method that incorporates cross-equation restrictions.

The results suggest that changes in non-neutral technology contributed to the changes in the gender wage differentials differently across occupations. Specifically, non-neutral technological change contributed the most to changes in the gender wage gap at the level of managerial and professional occupations. These results are robust across all industries and specifications (controlling for unexplained differences in gender relative wages or using R&D, as a direct measure of technological change). For these managerial and professional occupations, at the sample mean, changes in non-neutral technologies adopted by firms are raising the quarterly female-to-male wage ratio at an annualized rate that varies between 0.09% and 0.05% while the gap narrowed at average annual rate of about 1%.

The smallest impact was found at the lower pay occupations (operators and laborers), where, at the mean, the quarterly female-to male wage ratio is raising at an annualized rate that varies between 0.05% and 0.008%. These results are robust across industries and specifications.

Non-neutral technological change influenced the relative wages in favor of women in managerial and professional occupations (occupation 1) and service occupations, precision, craft and repair (occupation 3). However, for technical, sales and administrative occupations (occupation 2) the effect of the non-neutral technological change on relative wages contributed to a wider gender wage gap in some industries. This is an interesting result, since the documented narrowing trend of the gender wage ratio is very similar for different age and education groups. This suggests that different factors contributed in different proportions and directions to the narrowing trend of the gender wage ratio. It also suggests that the investigation of the narrowing trend of the gender wage gap would gain additional insight from an investigation at a more disaggregated level.

The results of this essay, providing estimates of the effect of non-neutral technological change on the gender wage gap by industry and occupation, bring additional insight to the question of the impact of technology on the gender wage gap. The significance, sign and magnitude of these estimates could guide further research to point to specific versions of non-neutral technological change, which might solve some of the 'problems and puzzles' summarized by Card and DiNardo (2002).

In the area of the technology effect on the gender wage differences, a more flexible modeling approach that would relax the assumption of a constant elasticity of substitution across all factors could allow for a finer estimation of the impact of technology on the narrowing of the gender wage gap. This is left for future research.

Table 1.1. Definition of Industry Variables

I. **Industry Categories**
I1 Agriculture, Forestry and Fisheries
I2 Mining
I3 Construction
I4 Manufacturing
I5 Transportation, Communications & Utilities
I6 Wholesale and Retail Trade
I7 Finance, Insurance and Real Estate
I8 Services

Table 1.2. Definition of Occupation Variables

II. **Occupational Categories**
Oc1 Managerial and Professional Specialty
Oc2 Technical, Sales and Administrative Support
Oc3 Service Occupations and Precision Production, Craft and Repair
Oc4 Operators, Fabricators and Laborers, Farming, Forestry and Fishing

Table 1.3. Description of Variables

Variable	**Description**
w_{ijt}^{f}	Hourly wage of full time female worker in industry i, occupation j, quarter t
w_{ijt}^{m}	Hourly wage of full time male worker in industry i, occupation j, quarter t
L_{ijt}^{f}	Employment of full time female worker in industry i, occupation j, quarter t
L_{ijt}^{m}	Employment of full time male worker in industry i, occupation j, quarter t
PTL_{it}^{f}	Employment of part time female worker in industry i, quarter t
PTL_{it}^{m}	Employment of part time male worker in industry i, quarter t
FTL_{it}^{f}	Employment of full time female worker in industry i, quarter t
FTL_{it}^{m}	Employment of full time male worker in industry i, quarter t
r_{it}	Non-labor Input factor price, in industry i, quarter t
K_{it}	Non-labor Input, in industry i, quarter t
i_{t}	3-months T-bill
QS_{it}	Share of Industry i Output in the Total Economy Output, in quarter t
RD_{it}	Total R&D expenditure for industry i, quarter t [millions]
P_{t}	Total count of granted patents in quarter t
RDE_{it}	Total R&D Employment for industry i, quarter t

TABLE 1.4. Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**No. of Obs.**
L_t^f	1.28e+07	1113089	1.37e+07	1.77e+07	92
L_t^m	1.57e+07	71215.6	345375.2	661084.7	92
PTL_t^f	1886043	702460.3	30874.8	3968063	92
PTL_t^m	2246369	634580.8	1391054	1.53e+07	92
FTL_t^f	1.09e+07	1060273	8817634	1.26e+07	92
FTL_t^m	1.35e+07	758889.1	1.18e+07	1.48e+07	92
i_t	6.78263	2.914583	1.906	15.053	92
RD_t [thousands]	33426.02	8417.57	18695.35	50227.8	92

TABLE 1.5. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, Industries 1 to 4

Industry 1 - Agriculture, Forestry and Fisheries								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.131*	(.016)	-.027*	(.012)	-.351*	(.025)	-.188*	(.017)
$\frac{1}{t}$	-.404*	(.073)	-.064*	(.045)	.168*	(.074)	-.049*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.175*	(.021)	-.175*	(.021)	-.175*	(.021)	-.175*	(.021)
$\sigma_1 = \frac{1}{(1-\rho)}$	5.71							
No. Obs. 87								

Industry 2 – Mining								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.169*	(.019)	-.125*	(.006)	-.209*	(.031)	-.194	(.023)
$\frac{1}{t}$	-.408*	(.199)	-.003	(.069)	-.322*	(.125)	.121	(.104)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.098*	(.016)	-.098*	(.016)	-.098*	(.016)	-.098*	(.016)
$\sigma_2 = \frac{1}{(1-\rho)}$	10.20							
No. Obs. 72								

Industry 3 - Construction								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.038*	(.017)	-.106*	(.004)	-.423*	(.026)	-.372*	(.023)
$\frac{1}{t}$	-.390*	(.091)	-.133*	(.021)	-.285*	(.033)	-.081*	(.033)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.188*	(.014)	-.188*	(.014)	-.188*	(.014)	-.188*	(.014)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.31							
No. Obs. 92								

Industry 4 - Manufacturing								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.050*	(.013)	-.136*	(.001)	-.403*	(.008)	-.235*	(.003)
$\frac{1}{t}$	-.413*	(.091)	-.028*	(.010)	-.245*	(.015)	.003	(.007)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.337*	(.010)	-.337*	(.010)	-.337*	(.010)	-.337*	(.010)
$\sigma_4 = \frac{1}{(1-\rho)}$	2.96							
No. of Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.6. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, Industries 5 to 8

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.069*	(.013)	-.093*	(.002)	-.460*	(.013)	-.578*	(.016)
$\frac{1}{t}$	-.367*	(.088)	.031*	(.016)	-.321*	(.028)	-.163*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)
$\sigma_5 = \frac{1}{(1-\rho)}$	2.39							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.131*	(.011)	-.189*	(.002)	-.266*	(.005)	-.309*	(.010)
$\frac{1}{t}$	-.389*	(.082)	.048*	(.015)	-.122*	(.017)	-.086*	(.014)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)
$\sigma_6 = \frac{1}{(1-\rho)}$	3.25							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.182*	(.013)	-.054*	(.004)	-.537*	(.009)	-.545*	(.014)
$\frac{1}{t}$	-.507*	(.098)	.018	(.020)	-.030	(.036)	-.275*	(.073)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)
$\sigma_7 = \frac{1}{(1-\rho)}$	1.79							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.249*	(.011)	.201*	(.004)	-.112*	(.001)	-.358*	(.004)
$\frac{1}{t}$	-.280*	(.083)	.083*	(.015)	.013	(.011)	-.018	(.018)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.66							
No. Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.7. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), Industries 1 to 4

Industry 1 - Agriculture, Forestry and Fisheries								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.242*	(.011)	-.021*	(.012)	-.391*	(.024)	-.226*	(.016)
$\frac{1}{t}$	-.176*	(.048)	.110*	(.048)	.166*	(.079)	-.047	(.032)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.246*	(.019)	-.246*	(.019)	-.246*	(.019)	-.246*	(.019)
$\sigma_1 = \frac{1}{(1-\rho)}$	4.06							
No. Obs. 87								

Industry 2 – Mining								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.186*	(.012)	-.100*	(.012)	-.182*	(.030)	-.175*	(.027)
$\frac{1}{t}$	-.138*	(.079)	-.038	(.078)	-.212*	(.113)	.076	(.097)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.091*	(.015)	-.091*	(.015)	-.091*	(.015)	-.091*	(.015)
$\sigma_2 = \frac{1}{(1-\rho)}$	10.98							
No. Obs. 72								

Industry 3 - Construction								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.296*	(.010)	-.068*	(.004)	-.443*	(.022)	-.391*	(.019)
$\frac{1}{t}$	-.308*	(.030)	-.113*	(.024)	-.234*	(.031)	-.087*	(.030)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.211*	(.011)	-.211*	(.011)	-.211*	(.011)	-.211*	(.011)
$\sigma_3 = \frac{1}{(1-\rho)}$	4.71							
No. Obs. 92								

Industry 4 - Manufacturing								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.180*	(.005)	-.060*	(.003)	-.206*	(.006)	-.089*	(.005)
$\frac{1}{t}$	-.315*	(.014)	-.226*	(.011)	-.418*	(.013)	-.331*	(.013)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.242*	(.009)	-.242*	(.009)	-.242*	(.009)	-.242*	(.009)
$\sigma_4 = \frac{1}{(1-\rho)}$	4.13							
No. of Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.8. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), Industry 5 to 8

Industry 5 - Transportation, Communications & Utilities								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.272*	(.006)	-.075*	(.002)	-.468*	(.013)	-.580*	(.015)
$\frac{1}{t}$	-.254*	(.025)	.056*	(.021)	-.325*	(.013)	-.138*	(.023)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.439*	(.012)	-.439*	(.012)	-.439*	(.012)	-.439*	(.012)
$\sigma_5 = \frac{1}{(1-\rho)}$	2.27							
No. Obs. 92								
Industry 6 - Wholesale and Retail Trade								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.186*	(.003)	-.165*	(.003)	-.229*	(.004)	-.297*	(.008)
$\frac{1}{t}$	-.266*	(.021)	.068*	(.022)	-.090*	(.020)	-.078*	(.019)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.332*	(.012)	-.332*	(.012)	-.332*	(.012)	-.332*	(.012)
$\sigma_6 = \frac{1}{(1-\rho)}$	3.01							
No. Obs. 92								
Industry 7 - Finance, Insurance and Real Estate								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.172*	(.003)	-.042*	(.004)	-.507*	(.009)	-.531*	(.014)
$\frac{1}{t}$	-.377*	(.027)	.027	(.023)	-.049	(.035)	-.270*	(.070)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.559*	(.011)	-.559*	(.011)	-.559*	(.011)	-.559*	(.011)
$\sigma_7 = \frac{1}{(1-\rho)}$	1.78							
No. Obs. 88								
Industry 8 - Services								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.071*	(.002)	.227*	(.004)	-.076*	(.002)	-.333*	(.004)
$\frac{1}{t}$	-.135*	(.019)	.105*	(.017)	.022	(.018)	.001	(.021)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.607*	(.007)	-.607*	(.007)	-.607*	(.007)	-.607*	(.007)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.64							
No. Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.9. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, using RD, Industries 1 to 4

Industry 1 - Agriculture, Forestry and Fisheries

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.361*	(.044)	.111*	(.026)	-.334*	(.041)	-.166*	(.021)
$\frac{1}{RD}$	-.745*	(.137)	-.479*	(.063)	.065	(.108)	-.013	(.034)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.150*	(.024)	-.150*	(.024)	-.150*	(.024)	-.150*	(.024)
$\sigma_1 = \frac{1}{(1-\rho)}$	6.66							
No. Obs. 87								

Industry 2 – Mining

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.371*	(.060)	-.154*	(.018)	.209*	(.031)	.033	(.045)
$\frac{1}{RD}$	-.243	(.176)	.005	(.055)	-.287*	(.108)	.389*	(.100)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.103*	(.018)	-.103*	(.018)	-.103*	(.018)	-.103*	(.018)
$\sigma_2 = \frac{1}{(1-\rho)}$	9.7							
No. Obs. 72								

Industry 3 - Construction

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.271*	(.042)	-.029*	(.012)	-.258*	(.034)	-.335*	(.048)
$\frac{1}{RD}$	-.784*	(.132)	-.267*	(.029)	-.535*	(.048)	-.101*	(.048)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.183*	(.019)	-.183*	(.019)	-.183*	(.019)	-.183*	(.019)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.46							
No. Obs. 92								

Industry 4 - Manufacturing

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.315*	(.041)	-.140*	(.005)	-.288*	(.007)	-.261*	(.007)
$\frac{1}{RD}$	-.990*	(.127)	.529	(.022)	-.529*	(.022)	.033*	(.012)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.389*	(.014)	-.389*	(.014)	-.389*	(.014)	-.389*	(.014)
$\sigma_4 = \frac{1}{(1-\rho)}$	2.57							
No. of Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.10. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, using RD, Industries 5 to 8

Industry 5 - Transportation, Communications & Utilities

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.330*	(.040)	-.130*	(.006)	-.270*	(.016)	-.370*	(.020)
$\frac{1}{RD}$	-.756*	(.124)	.107*	(.021)	-.364*	(.040)	-.349*	(.028)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.328*	(.018)	-.328*	(.018)	-.328*	(.018)	-.328*	(.018)
$\sigma_5 = \frac{1}{(1-\rho)}$	3.04							
No. Obs. 92								

Industry 6 - Wholesale and Retail Trade

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.351*	(.037)	-.170*	(.006)	-.103*	(.009)	-.174*	(.011)
$\frac{1}{RD}$	-.651*	(.116)	-.037*	(.018)	-.388*	(.020)	-.087*	(.016)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.153*	(.017)	-.153*	(.017)	-.153*	(.017)	-.153*	(.017)
$\sigma_6 = \frac{1}{(1-\rho)}$	6.53							
No. Obs. 92								

Industry 7 - Finance, Insurance and Real Estate

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.428*	(.044)	-.125*	(.008)	-.378*	(.019)	-.233*	(.030)
$\frac{1}{RD}$	-.812*	(.136)	.041*	(.024)	-.020	(.042)	-.378*	(.080)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.346*	(.020)	-.346*	(.020)	-.346*	(.020)	-.346*	(.020)
$\sigma_7 = \frac{1}{(1-\rho)}$	2.89							
No. Obs. 88								

Industry 8 - Services

	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.425*	(.038)	.113*	(.007)	-.101*	(.004)	-.330*	(.009)
$\frac{1}{RD}$	-.603*	(.116)	.192*	(.018)	-.043*	(.014)	-.015	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.542*	(.012)	-.542*	(.012)	-.542*	(.012)	-.542*	(.012)
$\sigma_8 = \frac{1}{(1-\rho)}$	1.84							
No. Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.11. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), using RD, Industries 1 to 4

Industry 1 - Agriculture, Forestry and Fisheries								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.207*	(.022)	.015	(.027)	-.341*	(.025)	-.176*	(.023)
$\frac{1}{RD}$	-.051	(.073)	-.180*	(.067)	.065	(.113)	-.042	(.045)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.192*	(.023)	-.192*	(.023)	-.192*	(.023)	-.192*	(.023)
$\sigma_1 = \frac{1}{(1-\rho)}$	5.20							
No. Obs. 87								

Industry 2 – Mining								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.107*	(.025)	-.132*	(.022)	.114*	(.046)	-.052	(.040)
$\frac{1}{RD}$	.002	(.070)	.048	(.066)	-.244*	(.105)	.270*	(.089)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.132*	(.015)	-.132*	(.015)	-.132*	(.015)	-.132*	(.015)
$\sigma_2 = \frac{1}{(1-\rho)}$	7.57							
No. Obs. 72								

Industry 3 - Construction								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.126*	(.011)	-.018	(.012)	-.250*	(.031)	-.299*	(.029)
$\frac{1}{RD}$	-.484*	(.048)	-.202*	(.032)	-.439*	(.044)	-.114*	(.043)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.175*	(.018)	-.175*	(.018)	-.175*	(.018)	-.175*	(.018)
$\sigma_3 = \frac{1}{(1-\rho)}$	5.71							
No. Obs. 92								

Industry 4 - Manufacturing								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	-.121*	(.007)	-.126*	(.008)	-.262*	(.008)	-.238*	(.008)
$\frac{1}{RD}$	-.674*	(.027)	.036	(.020)	-.502*	(.025)	.072*	(.019)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.384*	(.014)	-.384*	(.014)	-.384*	(.014)	-.384*	(.014)
$\sigma_4 = \frac{1}{(1-\rho)}$	2.60							
No. of Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

TABLE 1.12. NL2SLS with cross-equation restrictions for the estimation of the impact of non-neutral technological change, taking into account the unexplained gender wage gap (discrimination), using RD, Industries 5 to 8

Industry 5 - Transportation, Communications & Utilities								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.069*	(.013)	-.093*	(.002)	-.460*	(.013)	-.578*	(.016)
$\frac{1}{RD}$	-.367*	(.013)	.031*	(.028)	-.321*	(.028)	-.163*	(.024)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)	-.417*	(.013)
$\sigma_5=\frac{1}{(1-\rho)}$	2.39							
No. Obs. 92								
Industry 6 - Wholesale and Retail Trade								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.131*	(.011)	-.189*	(.002)	-.266*	(.005)	-.309*	(.010)
$\frac{1}{RD}$	-.389*	(.082)	.048*	(.015)	-.122*	(.017)	-.086*	(.014)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)	-.307*	(.014)
$\sigma_6=\frac{1}{(1-\rho)}$	3.25							
No. Obs. 92								
Industry 7 - Finance, Insurance and Real Estate								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.182*	(.013)	-.054*	(.004)	-.537*	(.009)	-.545*	(.014)
$\frac{1}{RD}$	-.507*	(.098)	.018	(.020)	-.030	(.036)	-.275*	(.070)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)	-.557*	(.011)
$\sigma_7=\frac{1}{(1-\rho)}$	1.79							
No. Obs. 88								
Industry 8 - Services								
	Wf1/Wm1		Wf2/Wm2		Wf3/Wm3		Wf4/Wm4	
Const.	.249*	(.011)	.201*	(.007)	-.112*	(.001)	-.358*	(.004)
$\frac{1}{RD}$	-.280*	(.083)	.192*	(.018)	.013	(.011)	-.018	(.018)
$\ln\left(\frac{L_j^f}{L_j^m}\right)$	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)	-.600*	(.007)
$\sigma_8=\frac{1}{(1-\rho)}$	1.66							
No. of Obs. 92								

Note: * Significant at a 5% level. Standard errors in parentheses.

Chapter 2

Inter-firm Technological Spillovers, Mobility of Scientists and the Organization of R&D

2.1 Introduction

Knowledge spillovers have played a central role in the theoretical analysis of R&D investments and cooperative R&D. One of the key results in this literature is that when firms perform research and development activities and when R&D by one firm spills over to other firms, private incentives to conduct R&D are reduced by a free-riding effect. This makes the ability to maintain proprietary rights over the scientific knowledge resulting from own R&D activities a key determinant of the private return to R&D investment of firms. If firms were to cooperate in R&D and choose R&D investment levels jointly, spillovers would be internalized. Cooperation results in an increased effective R&D investment and raises welfare.

In the early 1980s, there were concerns that U.S. firms were losing their competitiveness in global markets (especially to Japanese firms in high-tech industries) because they avoided cost-saving collaborative activities, such as joint R&D, due to fears of U.S. antitrust enforcement. The National Research Cooperation Act, signed by President R. Reagan in October 11, 1984, offered reduced antitrust liability to firms participating in joint research and development projects for the purpose of cost-sharing, reduced duplication, efficient use of scarce resources and research personnel, and economies of scale. Especially after the passage of the National Research Cooperation Act, the subject of knowledge spillovers and R&D investment witnessed a very high level of interest, with the seminal work of Katz, 1986, d'Aspremont and

Jaquemin, 1988, Kamien et al., 1992, followed by numerous other papers[1]. This literature has emphasized the idea that spillovers drive a wedge between private and social returns, leading to inefficient R&D levels and the need for cooperation.

The effect of spillovers on R&D investment and R&D cooperation, extensively treated in the theoretical literature, represents a major chasm between the theoretical contributions and the empirical research. The empirical literature has not been able to adequately investigate the validity of the emphasis of the theory on spillovers and to test their effect on R&D investment. One challenge facing this literature is the difficulty of empirically measuring spillovers. Economists have tried different proxies for spillovers. Veugelers and DeBondt (1992) test whether R&D cooperation occurs more in high spillover industries by using a survey based classification of industries according to the importance of spillovers, as provided in Levin and Reiss (1988). They find evidence of a significantly larger number of R&D cooperative agreements (joint ventures, as well as more informal cooperative agreements) occurring in high and medium spillover industries.[2]

Cassiman and Veugelers (2002) use survey data on Belgian manufacturing firms to empirically explore the effects of knowledge flows on R&D cooperation by measuring firm-specific incoming spillovers and outflows. They do find a significant relation between external information flows and the decision to cooperate in R&D. Specifically, firms that rate incoming spillovers as more important inputs to their innovation process are more likely to be actively engaged in cooperative R&D agreements. At the same time, they find that the firms that are more effective in appropriating the results from their innovation process (i.e. lower outgoing spillovers) are also more likely to cooperate in R&D. Cassiman and Veugelers' results suggest that the probability of cooperating in R&D is higher when the appropriability is higher, which is

[1] See DeBondt (1997) for a survey of the literature.

[2] The high spillover industries are telecommunications, semiconductors, instruments, chemicals and electronics, the medium spillover industries include the transportation equipment, and the low spillover industries are food and drink.

contrary to the theoretical results that firms engage in R&D cooperation when they cannot perfectly appropriate the results of their own R&D (i.e. when appropriability is low).

One frequently cited way of spreading the technological knowledge acquired during the research process is through mobility of scientists and research personnel from one firm to another. The link between labor mobility and knowledge spillovers goes back to 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). After Arrow's seminal article, the large literature on R&D spillovers that followed continued to consider labor mobility an important spillover mechanism.[3]

The econometric evidence of knowledge spillovers through labor mobility is increasing. Levin, Klevoric, Nelson and Winter (1987), based on data derived from a survey of high-level R&D executives, find that hiring R&D employees from innovative firms is a significant channel of learning about new processes and products. Almeida and Kogut (1999) investigate the relationship between the mobility of major patent holders and the localization of technological knowledge by looking at patent citations of important semiconductor innovations. They find that the engineers who hold major patents experience a high rate of inter-firm mobility in the semiconductor industry, and empirically show that the inter-firm mobility of engineers influences the local transfer of knowledge. A recent paper by Kim and Marschke (forthcoming) investigates the effect of labor mobility of scientists on the firm's patenting decision. They find evidence that scientists' turnover reduces the firm's R&D expenditures and does partially explain cross-industry patenting variation.

[3] Geroski (1995), Stephan (1996).

Recent evidence from the Bureau of Labor Statistics[4] suggests that mobility of scientists is on the rise, especially among innovative firms. This gives reasons to believe that this channel of spreading technological knowledge may become even more important.

This essay contributes to the empirical literature on R&D collaboration by testing the relation between knowledge diffusion through labor mobility of scientists and engineers and the firm's decision to collaborate in R&D. The firm's decision to engage in cooperative R&D is presented in a context of an oligopoly with cost-reducing R&D opportunities, following the model presented in Amir (2000). This model generates a testable implication which states that the difference in profits between R&D cooperation and R&D competition is not monotonic with respect to the spillover level, but is is U-shaped. This suggests that firms in industries where the spillover levels are either very low, or very high, are more likely to cooperate in R&D, relative to firms in industries with moderate spillovers. This implication is tested by using a measure of labor mobility of scientists constructed from the CPS March Supplements and a panel of R&D alliance data for 18 U.S. manufacturing industries, between 1989 and 1999. However, because of anti-trust regulations, industries with very low levels of spillovers are not expected to show a large number of R&D collaborations. The results provide evidence of a positive and statistically significant relationship between the measure of labor mobility of scientists and the number of R&D collaboration agreements, suggesting that the labor mobility of research personnel generates knowledge externalities among firms, externalities that are internalized through alliances.

The chapter is organized as follows: section 2.2. details the theoretical background and presents the testable implication. Section 2.3. presents the data, with a discussion of the empirical strategy in section 2.4. Section 2.5. presents the results and section 2.6. concludes.

[4] BLS (2000), Labor Force Statistics from the Current Population Survey, at http://stats.bls.gov/cps_over.htm.

2.2 Mobility of Scientists and R&D Collaboration

This part draws from a specialized case of the Kamien, Muller and Zang (1992) model, presented in Amir (2000)[5], where in a two stage symmetric duopoly each firm produces a single homogeneous good and faces a linear inverse demand function:

$$P_i = a - b\sum_i q_i, \tag{2.1}$$

where a is the demand intercept, and q_i the output of firm i, with i=1, 2. The two firms have identical initial unit-costs, c, and have zero fixed costs. Without loss of generality, let b=1.

The model is formulated as a two period game, under two different regimes:

1. Under the first regime, 'non-cooperative R&D', firms compete in R&D in the first stage, and then compete in quantities (Cournot competition) in the second stage.

2. Under the second regime, 'cooperative R&D', firms collaborate in R&D in the first stage by choosing jointly the R&D levels that maximize the sum of their payoffs, and then compete in quantities in the second stage.

In period one, each firm decides to invest in an R&D project that would lead to an autonomous cost reduction. To obtain this cost reduction, each firm hires a scientist and spends $x_i \geq 0$ in autonomous R&D expenditure. The scientist participates in the R&D project and contributes to the generation of an autonomous cost reduction $\sqrt{\frac{2}{\gamma}x_i}$ for firm i. Assume that there are inter-firm spillovers, with $\beta \in$[0,1] being the spillover parameter, defined as the proportion of autonomous cost reduction of firm j which enters the effective cost reduction of firm i. Thus, the effective cost reduction of firm i is $\sqrt{\frac{2}{\gamma}(x_i + \beta x_j)}$, where γ is a large positive number. The spillover parameter β is considered exogenous in this model. One can think about β as a measure of the

[5] The model presented in Amir (2000) encompasses both d'Apremont and Jacquemin (1988), and Kamien, Muller and Zang (1992).

level of labor mobility, the strength of the property rights regime, the possibilities of reverse engineering, etc.

The unit cost of firm i, considering the effective cost reduction, is given by the following relation:

$$c_i = c - \sqrt{\frac{2}{\gamma}(x_i + \beta x_j)}. \tag{2.2}$$

The profit function of firm i is then given by the following:

$$\pi_i = (a - \sum_i q_i - (c - \sqrt{\frac{2}{\gamma}(x_i + \beta x_j)})q_i - x_i. \tag{2.3}$$

At the end of the R&D project, the scientist acquired additional knowledge that makes him valuable to a rival. Part of this additional knowledge is general knowledge, part is knowledge specific to the R&D process utilized by firm i. At the end of the first period, the scientist has the choice of staying with the initial firm or joining or setting up a rival.

In the first period, the decision regarding the level of R&D investment is made independently or jointly, depending on whether the regime is 'non-cooperative R&D' or 'cooperative R&D'.

In the second period, each firm produces and markets a homogeneous product, without the scientist's help, and competes in the product market in a Cournot oligopoly. Assume that the life of the product ends at the end of the second period, when all the revenues from the product market are realized. Also, assume that the firms and the scientists are risk neutral profit and earnings maximizers, respectively.

As usual in these types of models, the solution is the subgame perfect equilibrium by backward induction. In the second stage, the firms compete in the product market a la Cournot, choosing the output such that they maximize profits:

$$\pi_i = (a - \sum_i q_i - (c - \sqrt{\frac{2}{\gamma}(x_i + \beta x_j)})q_i. \tag{2.4}$$

Thus,

$$q_i^* = \frac{1}{3}[(a - c) + 2\sqrt{\frac{2}{\gamma}(x_i + \beta x_j)} + \sqrt{\frac{2}{\gamma}(x_j + \beta x_i)}]. \tag{2.5}$$

In the first stage, firms choose the R&D investment, either independently, or cooperatively.

1. If the firms are competing in R&D, each firm chooses x_i to maximize its profits:

$$\pi_i^n = q_i^2 - x_i. \tag{2.6}$$

This gives a symmetrical equilibrium, where the autonomous non-cooperative cost reduction x^n is given by:

$$x_i^n = x_j^n = \frac{2(a-c)^2(\beta-2)^2}{(1+\beta)(9\gamma+2\beta-4)^2}. \tag{2.7}$$

The profit for R&D non-cooperative firms is given by the following:

$$\pi_i^n = \frac{2(a-c)^2\gamma(\beta-2)^2}{(1+\beta)(2\beta+9\gamma-4)^2} + \frac{1}{9}(a-c+\frac{2(a-c)(\beta-2)}{(9\gamma+2\beta-4)})^2. \tag{2.8}$$

2. If the firms are cooperating in R&D, they choose their autonomous cost reductions x_i and x_j such that they maximize their joint profits:

$$\pi_T^c = q_i^2 - x_i + q_j^2 - x_j. \tag{2.9}$$

This gives a symmetrical equilibrium, where the autonomous cooperative cost reduction x^c is given by:

$$x_i^c = x_j^c = \frac{2(a-c)^2(1+\beta)\gamma}{(2\beta-9\gamma+2)^2}. \tag{2.10}$$

The profit for R&D cooperative firms is given by:

$$\pi_i^c = \frac{1}{9}(a-c+2\sqrt{\frac{(a-c)^2(1+\beta)^2\gamma}{\gamma(2\beta-9\gamma+2)^2}})^2 - \frac{2(a-c)^2(1+\beta)\gamma}{(2\beta-9\gamma+2)^2}. \tag{2.11}$$

R&D cooperation is always more profitable for firms than R&D competition, that is $\pi_i^c > \pi_i^n$. This result holds for both the d'Aspremont and Jaquemin (1988), and Kamien, Muller and Zang (1992) models. However, the relation between the difference in profits from R&D cooperation relative to profits from R&D competition is not monotonic in β.

Proposition 1. *The difference in profits between R&D cooperation and R&D competition, π_i^c - π_i^n, is not monotonic with respect to the spillover parameter, β. Cooperation in R&D is most profitable for very low (i.e. close to zero) and very large (i.e. close to one) spillover levels, and it is minimum for a value of $\beta = \frac{1}{2}$. The difference in profits, π_i^c - π_i^n, is U-shaped in the spillover parameter β.*

To show this, consider the difference in cooperation and competition in R&D, π_i^c - π_i^n, given by:

$$\pi_i^c - \pi_i^n = \frac{2(a-c)^2(1-2\beta)\gamma(-16+8\beta^2+45\gamma+2\beta(-4+9\gamma))}{(1+\beta)(2\beta+9\gamma-4)^2(-9\gamma+2\beta+2)}. \tag{2.12}$$

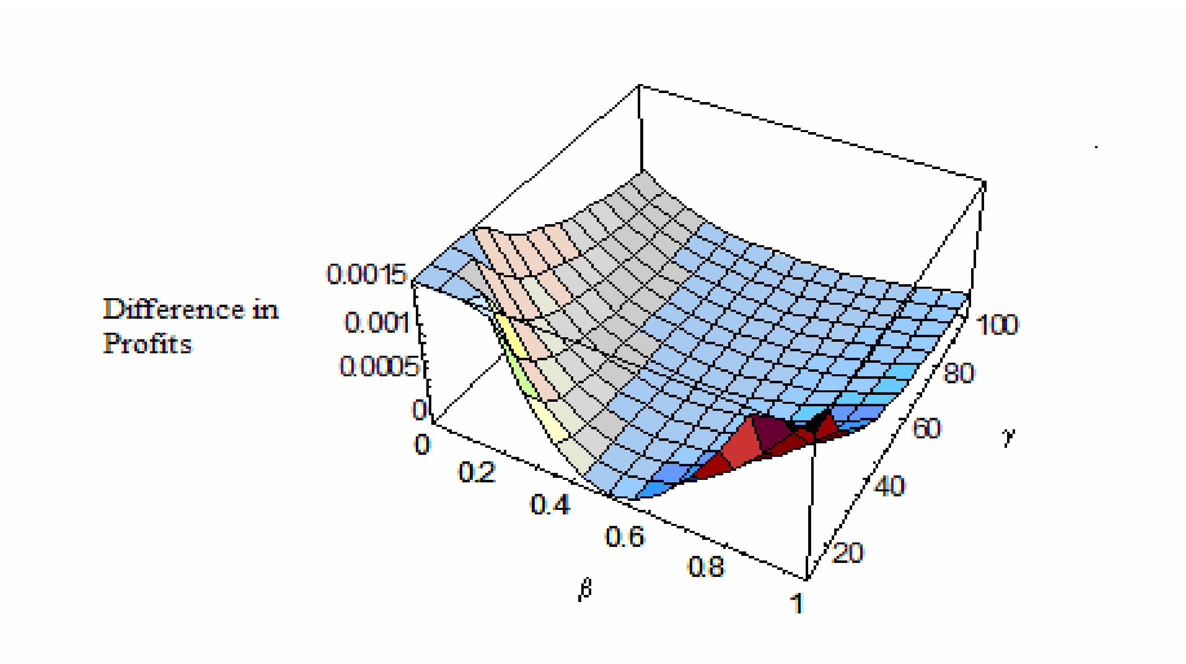
Using the first and second order condition it can be shown that the first derivative of π_i^c - π_i^n with respect to β is negative for $\beta<\frac{1}{2}$, and positive for $\beta>\frac{1}{2}$. Thus, the profit difference π_i^c - π_i^n has a U-shape in β, as shown in the Figure 2.1. below, where π_i^c - π_i^n values are shown on the vertical axes, with horizontal axes displaying values of β, with $\beta \in$ [0,1], and γ, which is a scaling factor that takes large positive values.

This U-shaped graph shows that it is most profitable for firms to cooperate in R&D when spillovers are either very small, or very large. This is a testable implication, suggesting that firms in industries where the spillovers are either very low, or very high, are more likely to cooperate in R&D, relative to firms in industries with moderate spillovers.

One intuitive explanation for a smaller expected number of collaborations in industries with moderate spillover levels could be provided by the cost of collaborating. Hernan, Martin and Siotis (1999) find that past experience in research cooperation greatly enhances the probability of entering a collaborative venture. This suggests that there are fixed costs, as well as learning effects associated with R&D collaborations. Since collaborations in R&D are relatively less profitable when the level of spillover is around $\frac{1}{2}$, it might not always be the case that the profits from cooperating in R&D offset the costs of collaborating.

By using a measure of labor mobility of scientists as a proxy for the level of spillovers, this testable implication will be investigated in the empirical section of this chapter.

FIGURE 2.1. Difference in Profits, relative to the Spillover Parameter, beta



2.3 Data Description

The empirical investigation of the effect of labor mobility of scientists on the firm's decision of engaging in R&D collaborations uses a data set of R&D alliances from the Securities Data Company (SDC) on Joint Venture & Strategic Alliances database, now owned by Thomson Financial, matched with Compustat firm data, for 18 manufacturing industries, as shown in Table 2.1., for the time period between 1989 and 1999.

The SDC database contains information on all types of alliances and is compiled from publicly available sources, including SEC filings, industry and trade journals and news reports. SDC has collected information on alliances starting with 1970. However, consistent data collection efforts by SDC extend primarily starting from 1988. The coverage of alliances formed after 1988, while more comprehensive than before 1988, is still inevitably incomplete since firms are not required to report alliance activities. Nevertheless, the database is among the most comprehensive sources of information on alliances, and is one of the only sources available for large-scale empirical studies on alliance activity.[6]

The alliance sample used in this essay includes all of the alliances that involve R&D activities, either exclusively, or in addition to marketing, production, and/or supply, involving at least one U.S. firm, in the 18 selected industries, between 1989 and 1999. The total number of alliances in the sample is 2672, with a distribution for each year shown in Table 2.2. The sample is restricted to only U.S. firms because, as detailed below, the measure of the labor mobility of scientists is only available for the U.S. labor market.

The measure for the mobility of scientists (MOB) is constructed from the Current Population Survey (CPS), the Annual March Supplements, and it is calculated as the rate scientists and engineers[7] who change employers during the previous year of the survey, for each industry and year in the alliance data set. The CPS March data set has the advantage that mobility can be consistently defined in each year since 1989, and that the CPS data is based on a survey that represents a national population. The CPS March Supplements generate on average annual records on 969 scientists and engineers for the industries in the sample. The average annual mobility rate for the entire sample is 11.51%, reflecting the share of scientists that changed employers at least once during the previous year of the survey. To account for the well accepted fact in the labor literature that inter-firm labor mobility is higher for younger workers, who have fewer skills, a mean age of scientists and engineers (AGE) is calculated, by industry and year. The average mean age of the scientists in the sample is 39.84.

[6] The SDC alliance database was used in Anand and Khanna (2000), and R. Sampson (2003).

[7] Defined by the following occupational categories, 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 alliance data are combined with industry data collected from National Science Foundation (NSF) tables. The variables collected are company-funded R&D (RD), R&D intensity (RDI), which is company-funded R&D as a percent of net sales for R&D performing companies, company domestic net sales ($SALE$) and employment ($EMPL$). Table 2.3. shows the annual average company R&D by industry, while Figure 2.2 shows graphically the distribution across industries of the annual average company R&D. The highest annual average R&D expenditure is recorded for Transportation Equipment, with about 20 billion 2000 dollars, followed by Drugs, Machinery (excluding computers), Professional and Scientific Instruments, and Industrial chemicals. The lowest annual average R&D expenditure is recorded for Paper, Lumber and Primary Metals.

Table 2.4. describes the distribution of the annual average number of R&D collaborations in each industry. The same information is presented graphically in Figure 2.3. The highest counts are for Drugs, with an annual average of 85 R&D alliances, followed by Semiconductors, Communication Equipment and Machinery (excluding computers). The lowest R&D alliances counts are recorded for Lumber, Paper and Textiles, with less than one R&D alliance per year. Table 2.6. presents summary statistics for the sample.

2.4 Empirical Issues

In order to test Proposition 1 which implies that firms in industries with extreme levels of spillovers will find it more profitable to engage in R&D collaborations than firms from industries characterized by medium spillover levels, the following specification is considered. The number of R&D collaborations, the dependent variable, is considered to be a function of the intensity of the research and development activities of the firms in each industry, a measure of labor mobility of scientists and engineers used as a proxy for the inter-firm spillovers, and a set of industry specific variables. In order to assess the impact of these determinants on the number of collaborations, the discrete nature of the dependent variable has to be taken into account. The number of collaborations in each industry and each year is a count variable which takes values of either zero or a positive integer. For instance, as Proposition 1 predicts, at spillover levels close to $\frac{1}{2}$ the difference between cooperative and non-cooperative R&D profits might not be high enough to cover the fixed costs of collaboration. Thus a zero value is a natural outcome of this variable for firms in industries with moderate spillover levels. To accommodate the discrete non-negative nature of the R&D collaborations, the dependent variable is modeled as following a Poisson model specification.

Let $RDCO_{it}$ be the number of R&D collaborations in industry i, year t, where $i = 1, ..., N$ is the index for firms, and $t = 1, ..., T$ is the index for time periods, in this case, years. The $RDCO_{it}$ variable is assumed to be independent and to have a Poisson distribution with parameters λ_{it} (mean and variance of the Poisson distribution). The parameters λ_{it} depend on a set of explanatory variables as follows:

$$\lambda_{it} = exp(\alpha_i + \theta X_{it} + \gamma RDI_{it} + \delta MOB_{it}), \tag{2.13}$$

where X_{it} is a 1xK vector of the industry i characteristics in year t, RDI_{it} is the annual R&D expenditure as the percent of the net sales of R&D performing firms in industry i, and MOB_{it} is a measure of the annual rate of labor mobility of scientists faced by firms in industry i, year t. X_{it} includes corporate research and development expenditure (RD), net sales ($SALE$) and employment ($EMPL$).

The dependent $RDCO$ variable is related to this function through the conditional mean of the Poisson model:

$$E(RDCO_{it}|X_{it}, RDI_{it}, MOB_{it}) = \lambda_{it}. \tag{2.14}$$

The theoretical literature has shown that at sufficient levels of spillovers, cooperation in R&D is associated with higher levels of R&D expenditure than in the competitive case, as a result of internalizing spillovers.[8] This suggests a positive correlation between collaborations in R&D and R&D intensity.

Proposition 1 implies that the coefficient on MOB, the measure of labor mobility of scientists and engineers, is expected to be positive. That is, in the presence of spillovers, firms are more likely to cooperate in R&D. Specifically, Proposition 1 implies a non-monotonic relation between MOB and the number of R&D collaborations, with an expected coefficient of larger magnitude for industries with either the highest or the lowest levels of mobility rates, relative to a smaller magnitude for industries facing medium levels of labor mobility rates. R&D cooperation is welfare enhancing at high enough levels of spillovers. This supports a lenient policy stance regarding cooperation in R&D. However, at low levels of spillovers, given concerns of the anti-trust regulations enforcement regarding R&D collaborations, the propensity to collaborate in R&D is expected to be small. This suggests that the U-shaped relation between spillovers, measured here by the labor mobility rates of scientists and engineers, and the propensity to collaborate in R&D, as implied by Proposition 1, might not be confirmed by the empirical results. Instead, given the anti-trust concerns, the empirical results are expected to show that the propensity to collaborate in R&D is increasing in the measure of the labor mobility of scientists and engineers.

[8] D'Aspremont and Jaquemin (1988) and Kamien, Muller, Zang (1992). Such a results holds for endogenous spillovers and when spillovers are asymmetric, Kamien and Zang (2000), Amir and Wooders (1999).

The business literature stresses that, in order to benefit from cooperative research, firms must have absorptive capacities. The absorptive capacity of each firm is determined by factors such as size, past experience with research collaborations, among other (Kogut, 1991). To control for the effect of size on the propensity of firms to engage in R&D collaborations $SALE$, measured as company domestic net sales, deflated by the GDP Deflation Index, base-year 2000, or $EMPL$, the number of employees, are used as a measures of industry size.

The industry specific intercept, α_i, is assumed to be random and distributed gamma. The estimates are obtained by using a maximum likelihood for the Poisson distribution.

2.5 Results

The results of random effect Poisson model estimations are presented in Table 2.7. The dependent variable is the number of R&D collaborations in year t, industry i, ($RDCO$). The explanatory variables include the measure of labor mobility of scientists and engineers in year t, industry i (MOB), the R&D intensity of firms (RDI) and sales ($SALE$), both measured by industry i, year t. The mean age of scientists and engineers (AGE) employed in year t, industry i is also used as a regressor. This is motivated by the results in the labor literature which suggest a link between age and mobility of workers. Job mobility rates are higher for younger workers, who also have lower cumulated human capital. Thus, using the age as a regressor takes into account the changing distribution of skills in the labor force that might accompany the labor mobility rates of workers. This allows for a more precise estimation of the effect of the labor mobility of scientists and engineers on the decision to engage in R&D collaborations. Note that for the Poisson estimations the link function between $RDCO$ and λ_{it} was the log function. This makes that dependent variable lnRDCO, and thus the estimated models are in semi-log form, because only the dependent variable is in logs. In this case, the coefficients have the interpretations of percentage change in the $RDCO$, as a result of a one unit change in the regressor.

The estimation results are reported for different specifications. Across these specifications, the coefficient on MOB, which is the labor mobility measure, remains positive and significant, implying a positive correlation with the R&D collaborations in the sample used. Specifically, firms facing a 10% increase in the labor mobility of scientists have a 5% increase in the annual number of R&D collaborations. At the sample mean this is equal to 0.7 more collaborations by industry as 6.8 more engineers change their employer. This is consistent with the hypothesis that the labor mobility of research personnel is a channel of diffusion of knowledge spillovers, making the R&D collaborations more profitable to firms than competitive R&D, and thus increasing the firms' propensity to collaborate in R&D. By including the square of MOB among the regressors ($MOB2$), the functional form of the relation between MOB and R&D collaborations is tested. The coefficient on $MOB2$ is not significant. This suggests a positive linear relation between the measure of the labor mobility of scientists and engineers and the propensity of collaborating in R&D. As discussed above, it is not likely to find empirical support for a U-shaped relation as suggested by Proposition 1, due to antitrust enforcement limiting the R&D collusive behavior in industries with low spillovers.

The estimated affect of AGE suggests that scientists with more experience (accumulated human capital) are more likely to increase the propensity of their employers to collaborate in R&D (they are more productive in generating R&D collaborations).

The coefficient on RDI is positive and signifcant, showing that firms that are more intensively involved in R&D activities are more likely to engage in collaborations. While the theoretical literature points to a positive correlation between collaborations in R&D and R&D intensity, the previous empirical evidence is mixed. Piga and Vivarelli (2004) did not find compelling evidence that R&D intensity increases the propensity of firms to engage in R&D collaborations, while Arora and Gambarella (1990) found that the number of agreements concluded by a sample of biotech and pharmaceutical companies is positively correlated with R&D intensity. In this essay, the results show support for a positive correlation between the industry R&D intensity and the propensity of entering collaborative R&D agreements.

$SALE$ has a positive and significant coefficient, supporting the hypothesis that firm size (or absorptive capacities) is an important determinant of the collaborative decisions of innovative firms.

If the variables in the estimation are time trended, the estimated effect of MOB on R&D collaborations may be spurious. Using a time trend T as an additional regressor, the trend effect does not appear to be statistically significant.

Running the estimations using the fixed effects Poisson specification, results not shown, provide similar qualitative and quantitative results. A Hausman specification test rejects the hypothesis that the estimated coefficients for the fixed effects and random effects are significantly different. This points to the RE estimator as the efficient estimator. Also, testing for sensitivity with respect to the distributional assumption of the random effects α_i, the effect of the labor mobility rate on the R&D collaboration using a normal distribution is similar to the one obtained assuming a Gamma distribution. Additional sensitivity test results are shown in Table 2.8. When year dummies are included, instead of a time trend, the estimated coefficients capture only the cross-industry variation in MOB. When industry dummies are included the estimated coefficients capture only the within-industry variation in MOB. The coefficient estimate associated with MOB is positive and significant in both situations, however, it is higher when industry dummies are considered. This suggests that variation in R&D collaborations is driven primarily by cross-industry variation in the labor mobility measure used in this study.

If one is concerned with the potential endogeneity between the measure of labor mobility and R&D intensity, a generalized method of moments estimation (GMM) can be used, as suggested in Windmeijer (2000), allowing one to exploit the panel nature of the data to control for endogeneity. In the Amir (2000) model, firms decide both about the R&D expenditure, and whether to collaborate in R&D. Another concern could be the direction of the causality in the relation between the labor mobility of research personnel and the R&D collaborations. The increase in spillovers through labor mobility make the R&D cooperation more profitable relative to R&D competition. Additionally, it can be suspected that, as labor mobility increases the propensity of firms to collaborate in R&D, collaborations could induce some of the scientists to move. Estimating a multiplicative moment conditions estimation in levels with lagged (once and twice) R&D as instruments for R&D, and AGE and AGE lagged, as well as lagged (once and twice) MOB as instruments for MOB, no evidence of such reversed causality is found. The GMM estimation results show that the coefficient on MOB is still positive and significant, and it does not show a smaller coefficient as it would be expected when the reverse causality is present.

2.6 Conclusions

This essay provides evidence for a significant relationship between a measure of labor mobility of scientists and the number of R&D collaborations in 18 U.S. industries. Empirically, the relation between the labor mobility of scientists and a firm's decision of engaging in cooperative R&D was tested by using R&D alliance data for 18 industries between 1989 and 1999 and a measure of labor mobility of scientists obtained from the CPS March Supplements. Robust to a variety of alternative specifications and sensitivity tests, a positive correlation between the labor mobility rate and the joint R&D agreements is found. Specifically, the main result suggests that firms facing a 10% increase in the labor mobility of scientists have a 5% increase in the annual number of R&D collaborations. At the sample mean this is equal to 0.7 more collaborations by industry as 6.8 more engineers change their employer. This result is in agreement with previous empirical studies, finding support for labor mobility of research personnel as a channel of technology diffusion among firms. Furthermore, this study finds that the knowledge flows generated by the labor mobility of scientists and engineers impact the decision to collaborate in R&D. This offers some empirical evidence for the effects of spillovers on R&D cooperation.

The results presented in this essay strengthen the idea that the mobility of research personnel is a potential direction for future research for a better understanding of the sources of spillovers, as well as their impact on innovation decisions.

This essay opens several venues for future research. One potential venue includes further empirical investigation of the relation between the labor mobility of scientists and the R&D collaborations at the firm level. This requires data on the labor mobility of scientists and engineers at the firm level, with a potential source in the patent files. The patent files provide the names of the innovators. These patent files can be used to follow the innovators as they change employers and match the pattern of cross-firm citations in the patent data[9] with the patterns of R&D alliances. Another line of research is the empirical investigation of the effect of labor mobility of research personnel on the specific form of organizing the joint R&D. These research topics are left for future work.

[9] Patent citations are found in the literature as good indicators of knowledge flows among firms. See Jaffe et al. (1993) and Thompson, P., Fox-Kean, M., (2005).

TABLE 2.1. Industry Standard Classification Codes

Industry	SIC
Food	20, 21
Textiles	22, 23
Lumber, wood, furniture	24, 25
Paper	26
Industrial chemicals	28, without 283
Drugs	283
Petroleum	13, 29
Rubber	30
Stone, clay, glass	32
Primary metals	33
Fabricated metal products	34
Office, computing	357
Other machinery	35, without 357
Communication equipment	366
Electronic components-Semiconductors	367
Other electrical equipment	36, without 366 and 367
Transportation equipment	37
Professional and scientific instruments	38

TABLE 2.2. Number of RD Collaborations in the Sample, by Year

Year	Total R&D Alliances in Sample
1989	74
1990	320
1991	508
1992	302
1993	354
1994	423
1995	307
1996	134
1997	169
1998	51
1999	30

Table 2.3. Annual Average Company RD, by Industry, in million dollars 2000

Industry	Annual Corporate R&D
Food	1,596.06
Textiles	383.12
Lumber, wood, furniture	313.46
Paper	1,525.08
Industrial chemicals	7,341.50
Drugs	10,166.60
Petrolium	2,289.51
Rubber	1,293.62
Stone, clay, glass	597.85
Primary metals	723.47
Fabricated metal products	1,181.40
Office, computing	9,311.36
Other machinery	4,652.62
Communication equipment	5,656.61
Electronic components	7,716.84
Other electrical equipment	3,586.90
Transportation equipment	19,870.70
Instruments	8,658.92

TABLE 2.4. Annual Average Number of RD Collaborations in the Sample, by Industry

Industry	Annual Average Number of R&D Collaborations
Food	1.27
Textiles	1
Lumber	0.09
Paper	0.45
Chemicals	13.45
Drugs	85.18
Petrolium	1.55
Rubber	2.36
Stone Products	1.18
Primary Metals	3.09
Fabricated Metal Products	1.55
Computers	10.45
Machinery, other than computers	27.18
Electrical Equipment*	6.45
Communication Equipment	27.45
Semiconductors	36.55
Transportation Equipment	5.36
Instruments	18.27

*except communication and semiconductors

TABLE 2.5. Average Labor Mobility Rates for Scientists and Engineers, by Industry

Industry Name	Average Mobility Rate (%)
Food	12.44
Textiles	12.03
Lumber, wood, furniture	12.7
Paper	12.41
Industrial chemicals	10.21
Drugs	9.49
Petroleum	6.91
Rubber	10.62
Stone, clay, glass	16.89
Primary metals	13.96
Fabricated metal products	10.55
Office, computing	10.98
Other machinery	14.81
Communication equipment	10.58
Electronic components	13.1
Other electrical equipment	13.2
Transportation equipment	5.76
Professional and scientific instruments	10.44

Table 2.6. Summary Statistics for the Sample

Variables	Mean	Std. Dev.	Min	Max	No. of observations
R&D Collaborations	13.49495	25.3877	0	158	198
RD	4889.148	5186.863	221.7682	24449.3	193
RDI	3.676838	3.543733	0.4	14.9	179
SALE	193292	150138.4	18165.32	804580.4	137
MOB	0.115062	0.082674	0	0.5	198
AGE	39.84845	2.627424	33	51.7	198

Notes:

a. RD is company-funded R&D by industry and year
[in million $ 2000]

b. RDI is company-funded R&D, as a percent of net sales, in R&D performing companies, by industry and year

c. MOB is the share of scientists and engineers who changed employer, by industry and year

d. AGE is the mean age of scientists and engineers by industry and year

e. SALE=Company domestic net sales, by industry and year [in million $ 2000]

TABLE 2.7. Poisson Regressions, Random Effects

Poisson Regressions, Random Effects

Dependent Variable: R&D Collaborations

	[1]		[2]		[3]		[4]		[5]	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z
RDI	0.1731*	6.84	0.1763*	7.03	0.1761*	7.02	0.193*	7.61	0.1928*	7.6
MOB	0.5483**	2.19	0.5694**	2.31	1.4903**	2.07	0.4303*	2.66	0.42***	1.9
MOB2					-2.9159	-1.35				
AGE			0.0517*	5.47	0.0542*	5.6	0.0468*	4.82	0.0473*	4.76
SALE							0.00028*	2.85	0.00029*	2.78
T									-0.0019	-0.25
Constant	2.1311*	8.86	0.0559	0.12	-0.0916	-0.2	-0.0869	-0.18	-0.1046	-0.21
Observations	179		179		179		179		176	
Log Likelihood	-2403.82		-2388.8		-2387.86		-2314.2		-2314.16	
Wald Chi2	51.31		81.82		83.32		88.12		88.13	
Prob > chi2	0		0		0		0		0	

Note : z records the ratios of the coefficient to the standard error.

The random effects follow a Gamma distribution.

The Wald Chi2 statistic is reported for the specification in each column.

Prob > chi2 reported is the p value of the test that coefficients are jointly zero.

* significant at the 1% level for a 2 tailed t-test

** significant at the 5% level for a 2 tailed t-test

*** significant at the 10% level for a 2 tailed t-test

Table 2.8. Poisson Regressions, Random Effects, continued

Poisson Regressions

Dependent Variable: R&D Collaborations

	Pooled Poisson †		RE with Year dummies		RE with Industry Dummies	
	Coef.	z	Coef.	z	Coef.	z
RDI	0.1928*	7.6	0.2312*	8.42	0.2472*	8.99
MOB	0.42***	1.9	0.8208*	2.89	0.7579*	2.68
AGE	0.0473*	4.76	0.0362*	3.42	0.0378*	3.59
SALE	0.00029*	2.78	0.00022***	1.87	0.00031*	2.6
Constant	-0.1046	-0.21	0.3384	0.64	-1.3941***	-2.18
Observations	176		176		176	
Log Likelihood	-2314.16		-2257.36		-2218.24	
Wald Chi2	88.13		193.9		928.38	
Prob > chi2	0		0		0	

Note: z records the ratios of the coefficient to the standard error.
The random effects follow a Gamma distribution.
The Wald Chi2 statistic is reported for the specification in each column.
Prob > chi2 reported is the p value of the test that coefficients are jointly zero.
† Industry dummies and year dummies were included in the estimation.
* significant at the 1% level for a 2 tailed t-test
** significant at the 5% level for a 2 tailed t-test
*** significant at the 10% level for a 2 tailed t-test

FIGURE 2.2. Annual Number of R&D Collaborations

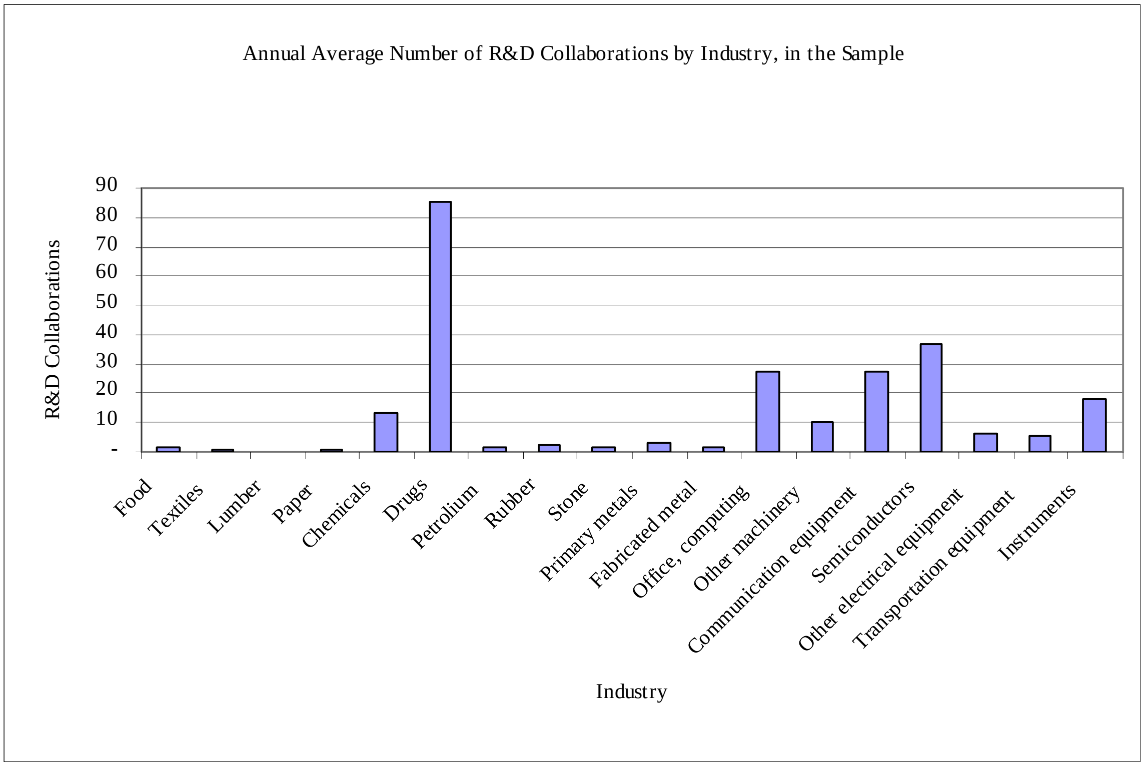
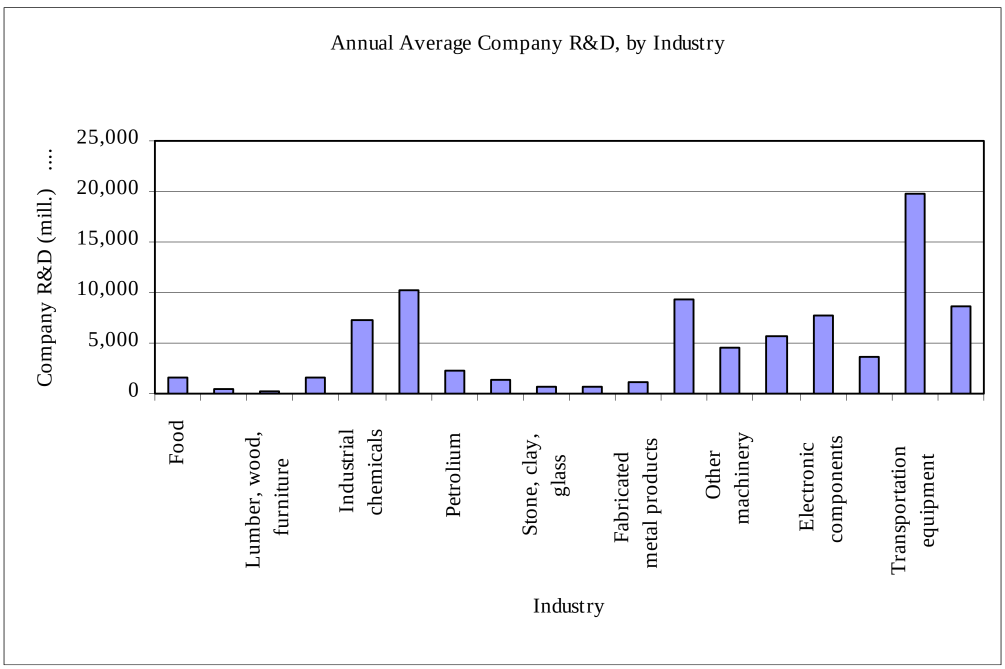


FIGURE 2.3. Annual Average Corporate R&D Spending



Chapter 3

Labor Mobility of Scientists and Engineers and the Pace of Innovation

3.1 Introduction

At least since Scotchmer and Green (1990) economists have accepted the idea that, as current research can build on the pool of existing technological knowledge, the pace of innovation depends critically on the amount of knowledge transferred among firms. There are many channels through which knowledge spreads.

One channel long recognized by economists as a potential mechanism of spreading technological knowledge is the labor mobility of scientists and research personnel from one firm to another. This idea goes back to 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 some industries, considerable movement of personnel from one firm to another, informal communications networks among engineers and scientists working at various firms, as well as professional meetings at which information is exchanged might allow the basic information concerning the nature and operation of an innovation to spread to the innovator's rivals and help them advance faster to the next generation of technology.

Recent evidence from the Bureau of Labor Statistics[1] suggests that the mobility of scientists and engineers is on the rise, especially among innovative firms. At the same

[1] BLS (2000), Labor Force Statistics from the Current Population Survey, at http://stats.bls.gov/cps_over.htm.

time, trends show that in all industries the technology cycle, as measured by the time lag between a current technology and its prior art, is on a decreasing path.[2] Earlier, technological innovation cycles were quite long, as in the case of water power, textiles and iron in the late 18th century, steam, rail and steel in the mid-19th century, and electricity and the internal combustion engine at the turn of the 20th century. Today, with semiconductors, fiber optics, genetics and software, the technological cycle has clearly shortened and continues to shorten.[3]

This essay investigates empirically the relation between knowledge dissemination through the labor mobility of research personnel and the pace of technological innovation.

The investigation employs a measure of the labor mobility of scientists and engineers constructed from the Current Population Survey, the March Supplements, along with an unbalanced panel of innovative firms across eight industries. As patents reference prior art, the paper uses patent citation data to construct a measure of the pace of innovation. For the overall sample, the results show that an increase in the annual measure of the labor mobility of scientists and engineers is significantly associated with a decrease in the measure of the pace of innovation.

The chapter is organized as follows. The next section presents a literature review, followed by section 3.3. which presents the main points of a theoretical model of labor mobility and incentives to innovate. Section 3.4. describes the data, while section 3.5. and 3.6. present the empirical strategy and the empirical results. Section 3.7. presents the conclusion.

---

[2] _______The New Innovators: Global Patenting Trends in Five Sectors, U.S. Department of Commerce, Office of Technology Policy, September 1998)

[3] The length of technology cycles has shortened from 40-30 years to figures today going between 15 years for slow moving technologies, such as shipbuilding, and under 5 years for fast moving technologies such as semiconductors.

3.2 Literature review

Most of the early economic literature on innovation and patenting, like Dasgupta and Stiglitz (1980), has assumed that the pace of innovation is determined only by each firm's rate of investment and by the number of firms that enter the patent race. Specifically, in a one-stage patent race model the expected time for discovery is generally decreasing in the number of firms under an appropriate stability condition. With a sequence of patent races for consecutively superior multiple discoveries, the expected time for each discovery would still be decreasing in the number of firms, if it is assumed that firms will patent patentable innovations.

Scotchmer and Green (1990) emphasize that, since current research can build on the previous technological knowledge disclosed, the pace of innovation depends critically on the amount of knowledge transferred among firms. In their paper, Scotchmer and Green focus in particular on the importance of disclosure requirements mandated by the patent laws in the technical advance, finding that the first-to-invent rule, applied in the U.S., discourages disclosure relative to first-to-file.[4]

Labor mobility has long been considered likely to be an important source of knowledge diffusion. Surveying one hundred founders of companies on the 1989 Inc. '500' list of the fastest growing companies in the U.S., Bhide (1994) finds that 71 percent 'replicated or modified an idea encountered through previous employment'.

A number of studies have examined the relevance of the labor mobility as a mechanism of knowledge diffusion. Levin, Klevoric, Nelson and Winter (1987), based on data derived from a survey of high-level R&D executives, finds that hiring R&D employees from innovative firms is a significant channel of learning about new processes and products. Almeida and Kogut (1999) investigates the relationship between the

[4] With first-to-invent, a first innovator does not need to patent in order to keep a claim on the market. If the competitor catches up and attempts to patent, the first innovator will successfully counter-patent, unlike in the first-to-file system where the counter-patent would be unsuccessful. There might be an advantage in not patenting initially, since no information is disclosed.

mobility of major patent holders and the localization of technological knowledge by looking at patent citations of important semiconductor innovations. They find that the engineers who hold major patents experience a high rate of inter-firm mobility in the semiconductor industry, and empirically show that the inter-firm mobility of engineers influences the local transfer of knowledge. A recent paper by Kim and Marschke (forthcoming) investigates the effect of labor mobility of scientists on the firm's patenting decision. They find evidence that scientists' turnover reduces the firm's R&D expenditures and does partially explain cross-industry patenting variation.

Evidence of this kind however does not shed any light on the impact of this channel of knowledge diffusion on the innovation process.

In her book, Saxenian (1994) 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 the Silicon Valley. However, Saxenian (1994) does not provide rigorous empirical evidence of the effect of the labor mobility on the innovative process.

Although it is well documented that in knowledge-driven industries employee mobility is often quite high despite each firm's interests in restricting this type of spillover, there is little theoretical literature addressing the mechanisms through which labor mobility actually occurs, and its effect on the innovation process.

A few papers specifically considered the labor mobility of workers and the incentives to innovate. Gersbach and Schmutzler (2001) investigates the conditions under which employee-generated spillovers arise endogenously when innovative firms compete in the market for human capital and in the product market. The paper provides some predictions about the determinants of labor mobility.[5] The results of the paper suggest that the incentives to innovate (i.e. expected additional profit for a firm from

[5] Qualified labor is more likely to move between firms when innovations are small, when products are differentiated, and so on.

innovation) are stronger for endogenous than for exogenous spillovers. However, this result cannot be extended to explain the effect of knowledge dissemination through labor mobility on the innovation pace.

Acemoglu (1997) shows that imperfect matching of skilled workers to firms can produce spillovers in human capital accumulation. Acemoglu (1997) assumes that the revenue for the innovative firm that hires a scientist for an innovation process is an increasing function of investments in general human capital and technology. Into this setting, Acemoglu (1997) adds a specific type of labor market friction: that some employment relationships are severed by random shocks after the human capital investments are made. In the reallocation of labor subsequent to these shocks, employees are randomly assigned to other employers with whom they must bargain for a share of the surplus created by prior investments in human capital and technology.

Although this model allows for labor mobility among innovative firms, the main focus is on the incentives of workers to invest in general training, given that they anticipate that part of their productivity gains created by training will be captured by their future employers. Regarding innovation, this essay argues that firms are more willing to innovate (adopt new technologies) when they expect the quality of the future workforce to be higher, that is, when workers invest more in their skills.

Lewis and Yao (2003) presents a dynamic contracting and matching model of the employment relationship between a firm and a worker (engineer) that provides an equilibrium explanation for high turnover. Incompleteness of the contracting relationship makes it optimal for firms to adopt open R&D environments as a recruitment inducement when labor is in relative short supply. Open R&D environments allow valued employees to depart to another firm. This model provides a framework for understanding how labor market mobility and innovation interact: facilitation of employee mobility increases dissemination of knowledge which feeds innovation and economic growth. This result allows for the empirical testing of the relation between the labor mobility and the pace of innovation.

To my knowledge, there is no direct empirical evidence in the literature of the effect of labor mobility on the innovative process.

This essay attempts to make a contribution to the literature by empirically testing the relation between knowledge diffusion through labor mobility of scientists and engineers and the pace of innovation.

3.3 Mobility and Innovation

This section presents the model from Lewis and Yao (2003) which, in a dynamic contracting and matching framework, explains the incentives of profit maximizing firms for permitting its employees to move from one company to another and to dissipate technological knowledge. Incompleteness of the contracting relationship makes it optimal for firms to adopt open R&D environments as a recruitment inducement when labor is in relative short supply. Such environments facilitate turnover and thus dissipation of technological knowledge, and foster innovation.

The result of the model allows for the empirical testing of the relation between the labor mobility and the pace of innovation in the empirical section of this essay.

3.3.1 General Setting

Before presenting the model, it is important to note a few key features that this model incorporates. The model makes two important assumptions about the firm-worker relationship. First, that R&D is inherently unpredictable and hard to measure. Unpredictability means that the research output of one firm may sometimes have a higher value use with another company. Also, the difficulty of measurement means that contracts for delivery and transfer of R&D will be incomplete. Second, labor mobility is protected by law and an R&D firm's intellectual property is partially bound in its workers. The embodiment of the intellectual property in employees means that departing workers will frequently take valuable knowledge to the new employer, in some cases effectively denying the original employer the returns to their investment. Firms moderate undesired worker separations by decreasing the "openness" of the research arrangement through restrictions on a employee's access to outside information and enforcement of legal sanctions of unauthorized use of intellectual property.

The general setting of the model involves a firm and an engineer that meet to produce a new product. During the innovation process, the engineer may learn whether his research is best commercialized by his current employer or another company. The employment contract is necessarily incomplete. The openness of the innovation process is governed by the firm's policy regulating the information exchange between employers outside the firm and the mobility afforded by the engineer in moving to another company. In equilibrium, market forces determine the openness of these arrangements as firms compete to hire engineers from a limited applicant pool.

3.3.2 The Model

The market consists of F firms and E engineers. Each firm hires one engineer to be part of an R&D process whose output will be commercialized by the firm. There is a continuum of firms and engineers. The size of the firm population is normalized to one. The size of the engineer population is P_E. Firms and engineers form matches. The equilibrium levels of unemployed engineers and inactive firms, denoted by $\rho_E P_E$ and ρ_F respectively[6], are determined by two conditions. One is that in each period, the number of employed engineers and active firms are equal. If each firm hires one engineer, then:

$$(1-\rho_F) = (1-\rho_E)P_E. \tag{3.1}$$

The second condition is that inactive firms and unemployed engineers seek new matches. Each period, the likelihood a vacant firm finds an unemployed engineer follows a Poisson process with success rate $\alpha\rho_E P_E$. The search efficiency parameter α measures a vacant firm's ability to identify prospective engineers. Assuming that the individual probability of successful matching is independent of the number of searching firms, the aggregate number of new matches each period is $\alpha(P_F)(\rho_E P_E)$. The lifetime of an existing job follows a Poisson process with a death rate of $\delta \in (0,1)$.

[6] $\rho_E \in (0,1)$ is the fraction of engineers not matched with a firm, while $\rho_F \in (0,1)$ is the fraction of firms not macthed with an engineer.

In equilibrium, jobs are created and destroyed at the same rate, such that:

$$\alpha(P_F)(\rho_E P_E) = (1 - \rho_F)\delta. \tag{3.2}$$

After the firm and the engineer meet, the engineer begins research. Research results are unpredictable and depend on the quality of the firm-engineer match.

After completing the research, the firm and the engineer learn about the innovation's commercial value. The value of commercialized research for application inside the firm is π^I. With probability $\lambda \in (0,1)$, π^I is high, equal to π_H, and with with probability $1-\lambda$ it is low, equal to π_L,where $\pi_H \succ \pi_L$. λ is the ex-ante probability of a good match.

Conditional on the match being poor, there is a probability $\mu \in (0,1)$ that the engineer learns the identity of the outside firms where his research skills could be applied more profitably. In this case, which occurs with probability $(1-\lambda)\mu$, the outside value of the research skills of the engineer, π^O, is high and equal to π_H. In all other instances the value of the outside commercialization is zero.

Once the research is complete, and π^I and $\pi^O$are known, the firm and the engineer decide where to commercialize and how to split the resulting surplus. The firm and the engineer will commercialize together, except when the outside commercialization value is high.

If the firm and the engineer stay together for commercialization, they generate a present value flow of joint surplus, $S(\pi^I)$, recursively defined by,

$$S(\pi^I) = \pi^I + B[(1-\delta)S(\pi^I) + \delta(V_E + V_F)], \tag{3.3}$$

where B is the discounting factor. The expected value of inside commercialization is the current period surplus, π^I, plus the discounted expected surplus in the following period, if the product survives (with probability $1-\delta$), plus the expected surplus, $V_E + V_F$, if the product dies and the parties become unemployed. V_i is the expected unemployment value for $i = E, F$.

If the parties separate, the firm retains possession of the intellectual properties. The separation yields the engineer the unemployment expected surplus V_E. The firm returns to the unemployed pool, yielding expected surplus of V_F. In addition, the firm receives some portion of the expected surplus, $\varepsilon\pi^I$, from commercializing the innovation without the assistance of the engineer. The portion of value $\varepsilon \geq 0$ that the firm captures increases with the degree to which the intellectual properties were codified before the engineer left, and on her legal rights to use the intellectual properties.

The parties' respective shares of the surplus denoted by $Y_j^I(\pi^I)$, for $j = E, F$, are,

$$Y_E^I(\pi^I) = \frac{S(\pi^I) + V_E - (V_F + \varepsilon\pi^I)]}{2}, \tag{3.4}$$

and

$$Y_F^I(\pi^I) = \frac{S(\pi^I) + (V_F + \varepsilon\pi^I) - V_E}{2}. \tag{3.5}$$

The employee may receive his share of surplus as a wage payment and/or as an ownership share of the company.

The innovation will be commercialized outside the firm when $\pi^O = \pi_H$ and the firm is unsuccessful in using the law to prevent the engineer from departing, spreading private information. Assume that non-compete clauses and intellectual property rights protect the firm by preventing the worker from leaving with probability $\gamma \in (0, 1)$.When the engineer cannot be prevented from leaving, the parties' respective share of surplus, denoted by $Y_j^O(\pi_H)$ for $j = E, F$ are:

$$Y_E^O(\pi_H) = S(\pi^O) - V_F, \tag{3.6}$$

and

$$Y_F^O(\pi_H) = V_F. \tag{3.7}$$

This sharing scheme assumes that the engineer gets all the surplus from its match with an outside firm.

Each party's expected surplus from a match, denoted by W_j for $j = E, F$ is

$$W_j = \sigma_H^I Y_j^I(\pi_H) + \sigma_L^I Y_j^I(\pi_L) + \sigma^O Y_j^O(\pi_H), \tag{3.8}$$

where $\sigma_H^I = \lambda$, $\sigma_L^I = (1-\lambda)(1-\mu(1-\gamma))$, and $\sigma^O = (1-\lambda)\mu(1-\gamma)$ are the probabilities that commercialization takes place inside the firm when $\pi^I = \pi_H$, $\pi^I = \pi_L$, and outside the firm, respectively. The expected surplus for each party is the probability weighted sum of surpluses arising when the innovation is commercialized inside and outside the firm.

When the firm and the engineer initially meet they negotiate an employment agreement which coupled with the underlying legal environment governs their subsequent interactions. Since research is unpredictable and difficult to specify, the contract is necessarily incomplete. However, the parties can commit to a set of contractile terms $\{P,\ \mu, \gamma\}$ that determines the rules for the employment relationship. P represents a non-negative direct payment from the firm to the engineer. P is a positive cash transfer like a wage. μ is the likelihood the engineer learns about a superior outside application for his research and research skills. Assume the firm commits to a certain μ through an information control policy regulating how the engineer acquires, shares and disseminates information with colleagues outside the firm. The lower and upper bound of μ, μ_L and μ_H respectively, depend on the industry environment in which research occurs. This policy is implemented through rules regarding the exchange of knowledge with outsiders, publication of research findings, and participation in industry workshops or standard-setting organizations and professional seminars. $\gamma \in (0, 1)$

is the likelihood that the engineer will be legally prevented from taking his innovation to another firm. λ is determined by the firm's enforcement of non-compete clauses and patent and trade secret rights.

The firm and the engineer negotiate their agreement, $\{P,\ \mu, \gamma\}$, employing the Nash bargaining solution. If they fail to reach an agreement, the firm and the engineer return to the unemployment pool and receive V_F and V_E, respectively. The equilibrium unemployment surpluses for the firm and the engineer are defined recursively by:

$$V_E = \alpha\rho_F(BW_E + P) + B(1 - \alpha\rho_F)V_E, \tag{3.9}$$

and

$$V_F = \alpha\rho_E P_E(BW_F - P) + B(1 - \alpha\rho_F P_E)V_F. \tag{3.10}$$

The expected surplus from being unemployed is the probability of securing a match multiplied by the expected surplus from a match, plus the probability of remaining unemployed next period multiplied by the discounted surplus from being unemployed.

Given the equilibrium values V_F and V_E, the firm selects the contract terms P and μ to maximize its net surplus, $BW_F - P$, subject to the constraint that the engineer must receive at least as much net surplus as the firm. Further, since the engineer is liquidity constrained, only positive payments from the firm to the engineer can be used.

$$\max\ BW_F - P\ over\ \{P,\, \mu\} \tag{3.11}$$

$$subject\ to\ BW_E + P - V_E \geq BW_F - PY_F - V_F, P \geq 0, \mu \in \{\mu_L, \mu_H\}$$

In an open contract arrangement the firm allows the worker to share research with colleagues outside the firm. An important implication of the analysis above is that firms and engineers have opposing preferences for contract openness.

Given the above, in equilibrium, the research agreements between the firm and the engineer will be second-best, open-constrained agreements, where the firm tries to restrict information flow and inhibit worker mobility.

An open-constrained agreement and market equilibria are defined as follows. Let $m = \{P_E, \alpha,\ \lambda,\ \varepsilon,\ \gamma, \delta\}$ describe the market environment. Then, given m, an open-constrained agreement consists of a probability of learning about an outside best application, $\mu(m) \in [\ \mu_L,\ \mu_H)$ which solves (11) subject to $P = 0$.

Definition 1: *An open-constrained equilibrium consists of a seven-tuple of values* $\{\mu(m), V_E(m), V_F(m),\ W_E(m), W_F(m), \rho_E(m), \rho_E(m)\}$ *satisfying conditions for efficient constrained agreements, the unemployment value equations (3.9) and (3.10), the match surplus equations (3.8), and the steady state employment and job creation conditions, (3.1) and (3.2).*

Lewis and Yao (2003) demonstrates existence and uniqueness of the open-constrained equilibrium. This open-constrained equilibrium can be interpreted as profit-maximizing firms allow for a certain degree of labor mobility of engineers, which increases the level of dissemination of private information among firms even when there are non-compete clauses and intellectual properties. As a conjecture, the dissemination of information through labor mobility contributes to the innovation process by shortening the lag to the next generation technology.

In the empirical section the relation between the increased information dissemination through the labor mobility of scientists and engineers and the pace of innovation will be tested empirically.

3.4 Data

To empirically examine the relation between the labor mobility of scientists and engineers and the pace of technological innovation, an unbalanced panel of 473 innovative firms across 8 industries, observed between 1989 and 1998, and a measure of the labor mobility of scientists and engineers are used. The dependent variable is a measure of the pace of innovation, while the explanatory variables are the firm's R&D investment and the measure of the labor mobility of scientists and engineers, among other variables.

The measure of the labor mobility of scientists and engineers (MOB) used in this essay is constructed from the Current Population Survey (CPS), the Annual March Supplements.[7] MOB is calculated as the rate of scientists and engineers[8] changing employers during the previous year of the survey, in each industry and year. The CPS March dataset has the advantage that mobility can be consistently defined in each year since 1989, and that the CPS data is based on a survey that represents a national population. The CPS March Supplements generate average annual records of 650 scientists and engineers for the industries in the sample. The average annual mobility rate for the entire sample is 8.4%, reflecting the turnover rate of scientists who changed employers at least once during the previous year of the survey. To account for the well accepted fact in the labor literature that inter-firm labor mobility is higher for younger workers who have fewer skills, a mean age of scientists and engineers (AGE) is calculated, by industry and year. The average mean age of the scientists in the sample is 34.

[7] The CPS March Supplements provide supplemental data on work experience, income, non-cash benefits, migration, employment status, occupation, and industry of persons 15 years old and older in addition to monthly labor force data.

[8] Defined by the following occupational categories, 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.

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. Note that the patent applicant has a legal duty to disclose any knowledge of the “prior art” contained in such patents or other published materials. Patent citations serve an important legal function as they delimit the scope of the property rights awarded by the patent. Thus, if one patent P_t cites a previous patent, say 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.[9]

This essay uses a measure of the pace of innovation based on patent citations. This measure captures the length of the technology cycle by identifying the time lag between prior art and the current generation of technology. It is calculated as the mean backward lag in citations, that is, the mean number of years between the grant year of the citing patent P_t and the grant year of the cited patents, P_{t-s}.[10]

Consider the following example. Patent P_t cites five previous patents, P^1_{t-17}, P^2_{t-15}, P^3_{t-15}, P^4_{t-14}, and P^5_{t-9},where the superscript identifies uniquely the patent, while the subscript gives the lag s in years between the grant year of patent P_t and the grant year of patent P^i_{t-s}. In this case the mean backward lag in citations is equal to $\frac{(17+15+15+14+9)}{5} = 14$ years.

If patents cite, on average, very ‘old’ patents in industry i, and relatively ‘new’ patents in industry j, it will be interpreted that industry j has a shorter technology

[9] For comprehensive reviews of the large literature utilizing the citation information, see Griliches (1990) and Lanjouw and Schankerman (1999).

[10] The backward lags are computed from the grant year of the citing patent to the grant year of the cited patent: the NBER/ Case Western Reserve University data set does not have the application year for patents granted prior to 1967, and hence it does not allow the computation of the lags from application to application years.

cycle length than industry i, or, in other words, that the innovation has a faster pace in industry j, relative to industry i.

The patent citation data set is available from the NBER/Case Western Reserve University data on all utility patents granted by the U.S. Patent Office matched with Compustat firm data.[11]

The full sample selected for this study contains firm level data for 473 firms in eight industries (Aerospace, Automotive, Biotech/Pharmaceuticals, Chemicals, Computers, Instruments, Semiconductors, and Telecommunications, as described in Table 3.1.), in an unbalanced panel, extending from 1989 to 1998. The data set contains information on the number of patents granted to a firm i, counted by the application year, ($PATENT\_COUNTS$) and the mean backward lag in citations for each patent granted to a firm i, year t ($BACK\_LAG$).[12]

Additional firm level data come from the annual Compustat data set, which was matched with the patent data. These firm level data include variables like 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, new variables are constructed, such as annual R&D intensity (RDI), capital intensity (K/L) and the Herfindahl Index ($HERF$).

In the full sample there are a few firms for which R&D expenditure data, along with information on the other characteristics of the firm taken from the Compustat database, are consistently missing for all years in which they are observed in the patent data set. After eliminating these firms from the panel, the working sample contains 378 firms in an unbalanced panel from 1989 to 1998.

Table 3.2. reports summary statistics of the mobility variable (MOB) and the

[11] For a full description of the data, see 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.

[12] 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 of firm i, year t.

measure of the pace of innovation ($BACK\_LAG$), along with the other variables used. Panel A of Table 3.2. shows the statistics of the full sample, while Panel B presents the statistics for the working sample.

In the full sample selected for this study the trends for the labor mobility of scientists and engineers (MOB) shows a clear upward trend bewteen 1989 and 1998, while the measure of the pace of innovation used here, $BACK\_LAG$, shows a downward trend, as presented in Figure 3.1.

As it is shown in Figure 3.2. the industry with the shortest lag between sequential generations of technologies is Semiconductors, with a mean $BACK\_LAG$ of 6.5 years, followed by telecommunications and computers, with 7.4 and 7.8 years respectively. The longest lag is recorded for Automotive and Aerospace, with 13 and 14.5 years, respectively. In terms of the labor mobility of scientists and engineers, as shown in Figure 3.3., the industry with the highest mobility is Semiconductors, with an annual turnover rate of 12%, while the lowest mobility measure is for Automotive, with a 5% annual turnover rate.

3.5 Empirical Strategy

In order to empirically identify the relation between the information dissemination generated by the labor mobility of scientists and engineers and the pace of innovation, this section starts with the consideration offered by the early economic literature on innovation and patenting, such as that presented in Dasgupta and Stiglitz (1980). This literature has assumed that the pace of innovation is determined by each firm's rate of investment and by the number of firms that enter the patent race.

As a starting point, the dependent variable is a measure of the pace of innovation, and the explanatory variables are the firm's R&D investment and a measure of firm concentration (the Herfindahl Index[13]).

Later literature, however, 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. The Lewis and Yao (2003) model shows that facilitation of employee mobility increases dissemination of knowledge which ultimately feeds innovation and economic growth.

A measure of the labor mobility of scientists and engineers is added to the regressors, resulting in the following estimation equation format:

$$BACK\_LAG_{it} = \alpha_i + \psi RD_{it} + \lambda HERF_{jt} + \gamma MOB_{jt} + \theta X_{it} + \varepsilon_{it},$$

where i denotes the firm, t denotes the year, $BACK\_LAG_{it}$ 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.

[13] The Herfindhal Index is constructed as a sum of the squared market shares of sales.

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. The reason for including these variables is because evidence suggests that larger firms are, on average, slightly quicker innovators, than smaller firms.[14] 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 results are presented in the following section.

[14]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.

3.6 Empirical Results

The pooled Ordinary Least Squares (OLS) results for the unbalanced panel of 378 firms, with a total of 2551 firm-year observations, are shown in Table 3.3. The dependent variable is $BACK\_LAG_{it}$, the firm's mean backward lag in citations received by all the patents successfully applied for by firm i, in year t. These 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 ten percent increase in the annual measure of the labor mobility of scientists and engineers is associated with a 1.8 years decrease in the lag between the grant year of a patent and the grant years of the cited patents. Given the size of the pool of scientists and engineers in the CPS March Supplements for the industries years considered in the sample, on average, a ten percent increase in the annual rate of scientists' turnover means an additional 65 scientists and engineers changing their employers. The elasticity calculated at the sample mean is -0.15.

The coefficient on research and development, $R\&D$, is negative and significant, as suggested in the theoretical literature. This coefficient indicates that an increase in the amount spent on $R\&D$ decreases the mean back lag in citations, which can be interpreted as an increase in the pace of innovation. The elasticity at the sample mean is -0.09. On average, an additional billion dollars in research and expenditure is associated with a reduction in the back lag of 4.2 years.

The coefficient on the number of firms in the industry, No_Firms, 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 any indication of the market structure. For this reason a Herfindahl index is used instead of the number of firms, 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, suggesting that the more concentrated the market, the shorter the lag between sequential generations of technological advancement is.

$SALES$ and $EMPL$ are used as alternative controls for the size of the firm. The coefficients on $SALES$, as well as $EMPL$, are positive and significant, suggesting that there are possible 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 3.2 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 0.19 years. When running the pooled OLS for the industry aggregates, the results are similar in sign and significance.

The variables in the estimation may be trended, in which case the estimated effect of MOB on the measure of the pace of innovation could be spurious. A time trend, T, is used to test the sensitivity of the results to a time trend. As it is shown in Table 3.3, column 2, the coefficient on MOB is still significant. The coefficient on the capital-labor ratio, K/L, is not significant. The assumption made was that firms with a lower ratio might rely more on labor inputs in their innovation process, and thus, be more flexible in the innovation process. These firms will be considered faster innovators. One potential explanation is that this ratio includes all employees, not only those involved in research and development. The effect of AGE is also not significant. This variable is used as a control variable for MOB, since it has been shown in the labor literature that younger workers who have fewer skills were found to have higher inter-firm labor mobility.

Next, panel estimation techniques are used to better explore the panel format of the sample. As shown in Table 3.4., the fixed-effect (FE) model generates 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 (RE) 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 with the null hypothesis that the FE estimator is always consistent and the RE estimator is efficient, but inconsistent otherwise is employed. The null hypothesis is rejected with a p-value of 0.000, suggesting that the FE should be used over the RE model. However, as discussed above, the FE model doesn't provide a good fit.[15]

One reason for this might be the large number of dummy variables used for the individual firm effects (there are 378 firms in the panel) which might take away most of the variation in the sample.

An alternative specification is the between effects (BE) model, presented in Table 3.5. The BE estimates use the cross-sectional information reflected in changes between firms, while the FE estimators reflect the time-series or the within-firm information reflected in the changes within firms. The BE estimates for the labor mobility measure, MOB, are negative and significant, and are interpreted as follows. If two firms are exposed to levels of labor mobility of scientists and engineers that differ by 1%, the expected difference in the backward lag in citations for those firms is 0.56 years. At the sample mean, the elasticity is -0.46. This result has an additional interpretation in the context of the data set used in this essay, 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.

Heteroskedasticity (non-spherical disturbances) occurs often in panel data. To test for potential heteroskedasticity, a Breusch-Pagan/Cook-Weisberg test is employed. The test indicates at a 1% level of significance that the regression results are indeed heteroscedastic.[16]

---

[15] H_0: difference in FE and RE coefficients not systematic, H_1 ~H_0.
chi2(4) = (b-B)'[(Vb-VB)^(-1)](b-B)= 75.19
Prob>chi2 = 0.0000

[16] Ho: Constant variance
chi2(1) = 24.74
Prob > chi2 = 0.0000

To address this issue, a Generalized Least Squares (GLS) estimator for panel data is used.[17] The estimates are presented in Table 3.5. The sign of the coefficients is the same as in the pooled OLS regression. The significance level is slightly larger. Keeping the focus on the MOB coefficient, it indicates a negative relation between the labor mobility variable and the pace of innovation, as measured by the lag in backward citations.

In Table 3.6., column 3 presents the estimates from a panel GLS estimator with industry and year fixed effects. The sign of the MOB coefficient is negative, but not significant. The results generated by the FE model, and those from the GLS with heteroskedasticity-corrected standard errors with industry and year effects cannot be compared. However, it seems that the fixed effects are collinear with some of the explanatory variables, since the sign and the scale of the coefficients are not stable, once these fixed effects are used. To test this assumption, a partial correlation matrix is generated for all the right hand side variables, including the dummy variables. It does not appear that any of the explanatory variables are correlated with the industry and year dummies.

One potential way to further investigate the explanatory power of the labor mobility of scientists and engineers for the variation in the backward lag in citations in this panel is to expend the panel across a larger number of years. It appears that the fixed effects estimation consumes all the variation in the explanatory variables, making the coefficients insignificant and the model a poor fit. More years will increases the variation in the MOB variable. Note that this variable is constructed at the industry level, annually, and not at the firm level.

---

[17] A test for panel data heteroskedasticity was used as well, involving an iterated Generalized Least Squares (GLS) model that produces maximum likelihood estimates. Based on these estimates, a Likelihood Ratio (LR) test statistic can be calculated to compare the unrestricted model (GLS without heteroskedasticity corrections or Pooled OLS) and the restricted model (GLS with heteroskedasticity). The test is distributed Chi2. This test indicates heteroskedasticity as well, at a significance level of 1%.

3.7 Conclusions

This chapter presents some empirical evidence of the impact of knowledge dissemination generated through the labor mobility of workers on a measure of the pace of innovation. The test is provided by a model from Lewis and Yao (2003) who argues that, in equilibrium, profit-maximizing firms allow for a certain degree of labor mobility of engineers, and that mobility increases the level of dissemination of private information among firms even when there are non-compete clauses and intellectual property. This dissemination of information through labor mobility contributes to the innovation process by shortening the lag to the next generation technology.

Specifically, the paper provides an estimate of the impact the labor mobility of scientists and engineers on the mean lag between the grant year of patent applications submitted by firms each year, and the grant year of the patents they cite in their references. The justification for 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 is collected from the Current Population Survey March Supplements. The resulting data set is an unbalanced panel of 378 firms across eight industries, between 1989 and 1998.

Some of the results reported in the paper show a significant effect of the labor mobility of the pace of innovation used in the analysis. A pooled OLS coefficient shows that a ten percent increase in the annual measure of the labor mobility of scientists and engineers is associated with a 1.8 years decrease in the lag between the grant year of a patent and the grant years of the cited patents. Given the size of the pool of scientists and engineers in the CPS March Supplements for the industries considered and the years studied, on average, a ten percent increase in the annual rate of scientists' turnover means an additional 65 scientists and engineers changing their employer. The elasticity calculated at the sample mean is -0.15. If this is a result for the entire sample, the between panel estimator suggests specifically that firms in different industries, exposed to levels of labor mobility of scientists and engineers that differ by 1%, have an expected difference in the backward lag in citations of 0.56 years. At the sample mean, the elasticity is -0.46.

The fixed effects estimations for the individual firm effects appear to take away most of the variation in the sample, redering the coefficients insignificant and the model a poor fit. A potential way to further investigate the explanatory power of the labor mobility of scientists and engineers for the variation in the backward lag in citations in this panel is to expend the panel across a larger number of years.

Economists, managers and policy makers have always been concerned with issues related to innovation, potential spillovers and their impact on the incentives and capacity to innovate. The theoretical literature has shown increased interest in the recent years in offering a conceptual explanation of the growing mobility of the scientists and engineers. However, empirically, little is known about what generates the increased labor mobility of highly skilled workers. Also, 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 existing theory and to provide guidance for the better conceptual models that connect the labor mobility and the innovation process.

The results presented herein lead to some initial findings about the role of the labor mobility of research personnel on innovation and growth. This is only the beginning of the exploration of several potential venues of research. One way to further the analysis presented in this essay is to use not only references of prior art patents, but also science linkage, especially important for the health sector, which is building more on research reported in scientific journals.

A potential extension of this study is to address the localization of labor mobility and its relation to innovative firms concentrated in a geographical area. Ultimately, following the literature on the market value of innovation, one project of interest will be to test whether the market values faster innovators. Companies with shorter technology cycles relative to their competitors may be advancing faster from prior technology to current technology, which might positively affect the market valuation of their innovation.

Table 3.1. Definition of Industry Variables

Industry Name	**SIC code**
Chemicals	28(except for 283)
Biotech/Pharma	283
Computers	357
Telecommunications	366
Semiconductors	3674
Automotive	371
Aerospace	372, 376
Instruments	382, 384, 385

FIGURE 3.1. Trends in the Labor Mobility of Scientists and Engineers and the Pace of Innovation

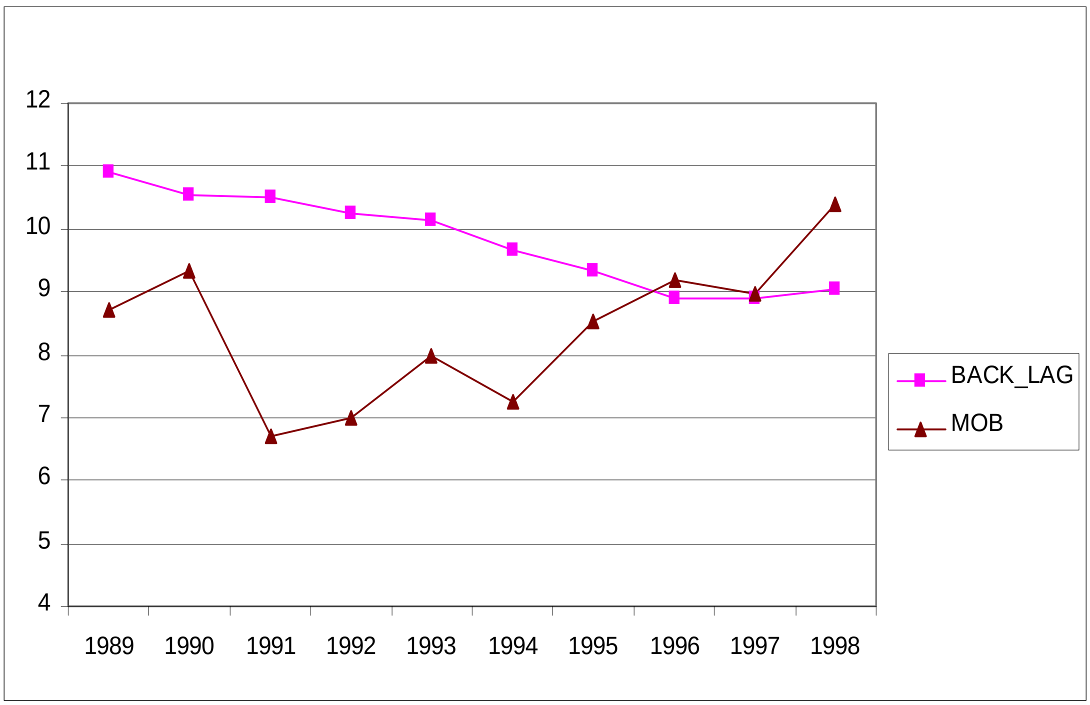


FIGURE 3.2. The Mean Backward Citation Lag, Averages by Industry

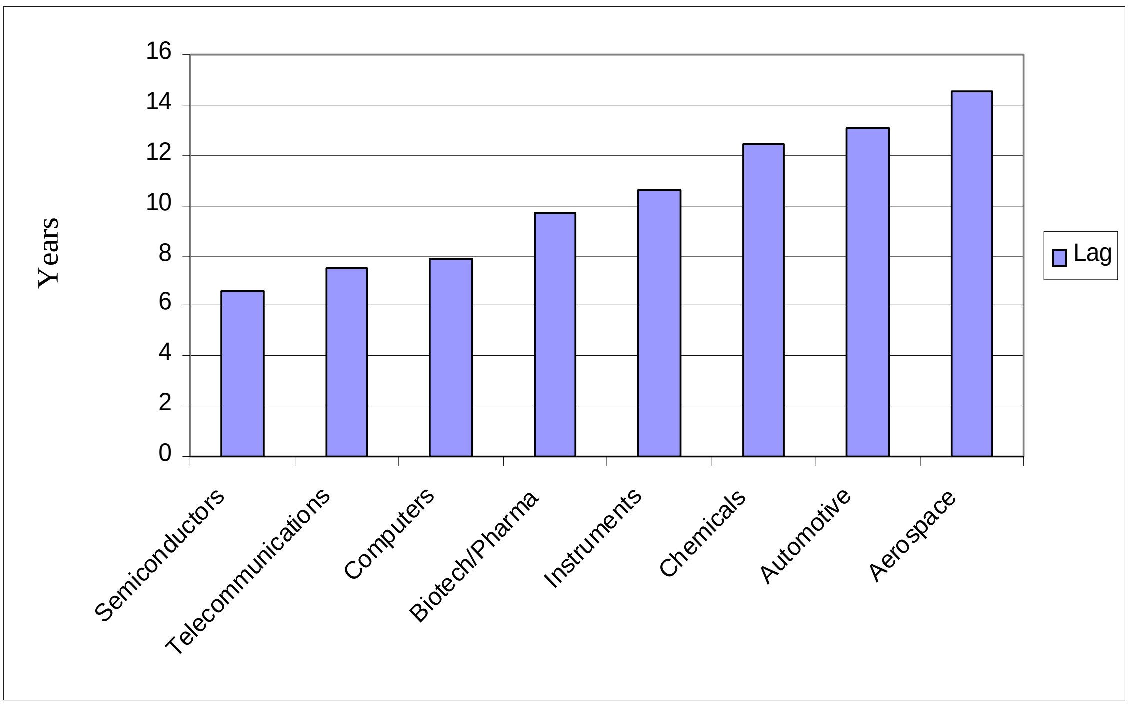


FIGURE 3.3. The Labor Mobility of Scientists and Engineers, Averages by Industry

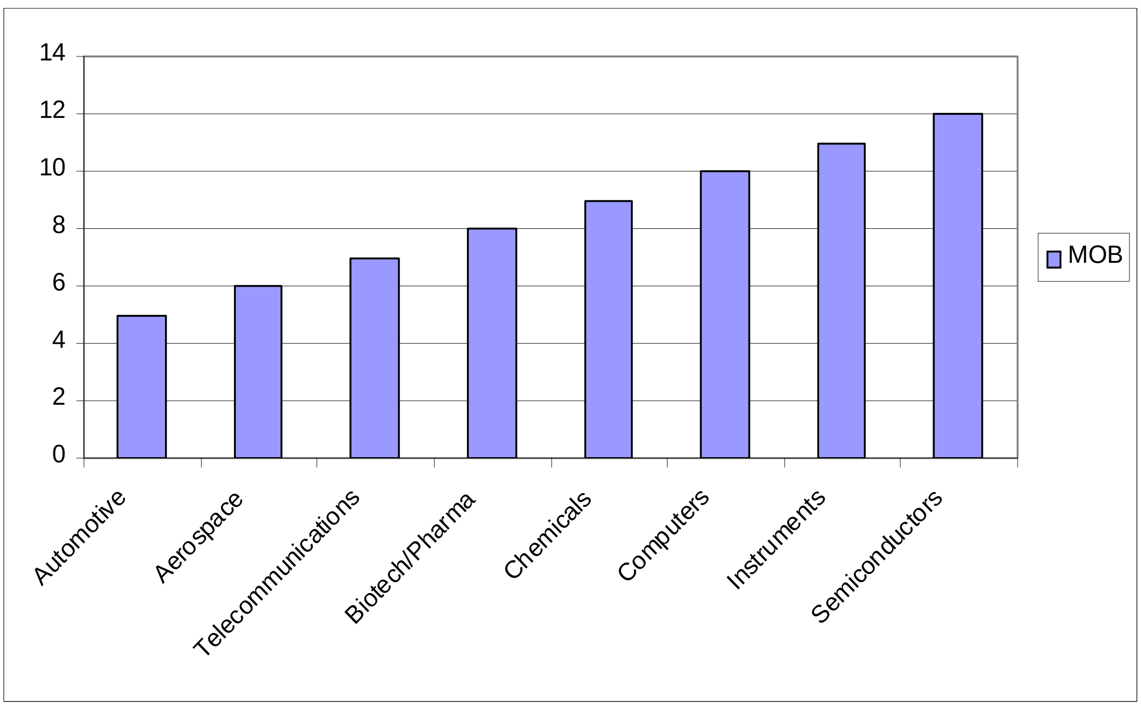


TABLE 3.2. Summary Statistics

Summary Statistics

Variables	Panel A Full Sample Mean	Std. Dev	Min	Max	Panel B Working Sample Mean	Std. Dev	Min	Max
MOB	0.0883	0.0388747	0	0.1854839	0.0891528	0.0388244	0	0.1854839
BACK_LAG	11.27382	5.547857	1	52.6	11.02473	5.395982	1	52.6
R&D	236.92	726.3	0.048	9483.2	238.69	729.23	0.0488	9483.21
SALES	4034.25	14462.83	0	179535.6	4154.34	14779.8	0	179535.6
EMPL	17.18401	56.08865	0.006	775.1	17.62247	57.13078	0.006	775.1
K/L	60.64	61.59	0	964.25	58.4	50.42	0	558.16
AGE	34.19197	4.815717	23	48.2	34.23241	4.78145	23	48.2
HERF	.1681	.129	.072	.645	.1720	.131	.072	.657
No. of Firms	473 firms (3241 firm-year observations)				371 firms (2551 firm-year observations)			

Notes:

a. MOB = the share of scientists and engineers who changed their employers, by year and 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 [in million $ 2000]

d. Sales = annual sales at firm level [in million $ 2000]

e.EMPL = employment [in thousands]

f. RDI = R&D / Sales

g. K/L = plant and equipments [in million $ 2000]/ Employment [in thousands]

h. PAT/RD = patent counts/ R&D

i. AGE = average age of scientists and engineers, by industry and year

j. HERF= the Herfidahl Index, sum of squared market shares based on sales

Table 3.3. Pooled Ordinary Least Squares Results

Pooled OLS Estimations

Dependent Variable: BACK_LAG	[1]	[2]	[3]	[4]	[5]
RD	-0.0042*	-0.0026*	-0.00041*	-0.0043*	-0.0042*
	(-9.45)	(-7.72)	(-9.56)	(-9.72)	(-9.41)
MOB	-0.1889*	-0.1927*	-0.1962*	-0.1836*	-0.2107*
	(-6.78)	(-6.87)	(-6.95)	(-6.72)	(-7.28)
No_Firms	0.0112***	0.0143**	0.014**		
	(1.87)	(2.37)	(2.25)		
SALES	0.00019*		0.0002*	0.0002*	0.00019*
	(9.02)		(9.12)	(9.19)	(8.91)
T			0.0648***		
			(1.64)		
HERF				-1.486***	-1.869**
				(-1.85)	(-2.25)
EMPL		0.0319*			
		(7.21)			
K/L					-.001
					(-0.49)
AGE					.001
					(0.08)
Constant	12.434*	12.238*	12.055*	13.108*	13.46*
	(38.11)	(37.11)	(30.15)	(41.21)	(15.95)
F-test	37.03	29.47	30.18	37.01	26.15
P Value	0.000	0.000	0.000	0.000	0.000
No. of Obs.	2551	2551	2551	2551	2551

Note: (t-stat)

* significant at the 1% level for a 2 tailed t-test

** significant at the 5% level for a 2 tailed t-test

*** significant at the 10% level for a 2 tailed t-test

Table 3.4. Fixed Effects and Random Effects Estimation Results

FE and RE Estimations

Dependent Variable: BACK_LAG		
	[re]	[fe]
RD	-0.0011**	-0.00004
	(-2.20)	(-0.08)
MOB	-0.021	0.4972
	(-0.97)	(0.54)
SALES	0.00005***	-0.00002
	(1.83)	(-0.54)
HERF	-.0713	-0.8063
	(-0.05)	(-0.27)
Constant	11.333*	11.233*
	(29.16)	(21.34)
Chi2	6.12	0.23
P value	0.1905	0.9220
No. of Obs.	2551	2551

Note: (z-stat)

* significant at the 1% level for a 2 tailed t-test

** significant at the 5% level for a 2 tailed t-test

*** significant at the 10% level for a 2 tailed t-test

TABLE 3.5. Generalized Least Squares and Between Effects Results

GLS and BE Estimations

Dependent Variable: BACK_LAG		
	[be]	[gls]
RD	-0.0064*	-0.0036*
	(-4.81)	(-23.61)
MOB	-0.5694*	-0.17*
	(-5.52)	(-14.04)
SALES	0.0002*	0.0001*
	(4.41)	(21.09)
HERF	-3.568*	-3.084*
	(-2.11)	(-7.75)
Constant	17.086*	13.181*
	(15.60)	(121.18)
Chi2	13.79	960.04
P value	0.000	0.000
No. of Obs.	371	2551

Note: (z-stat)

* significant at the 1% level for a 2 tailed t-test

** significant at the 5% level for a 2 tailed t-test

*** significant at the 10% level for a 2 tailed t-test

Table 3.6. Generalized Least Squares with Dummy Variables Results

GLS with Dummies

Dependent Variable: BACK_LAG			
	(1)	(2)	(3)
RD	-0.0008*	-0.0035*	-0.0006*
	(-6.58)	(-22.13)	(-5.27)
MOB	0.0971	-0.15937*	-0.223
	(0.11)	(-11.41)	(-0.68)
SALES	0.00001***	0.0001*	0.000006
	(1.92)	(20.19)	(1.03)
HERF	-0.0788	-1.731*	2.662***
	(-0.06)	(-4.74)	(1.69)
Constant	12.902*	12.512*	12.713*
	(72.45)	(86.91)	(55.81)
Chi2	5311.11	783.63	5301.78
P value	0.000	0.000	0.000
No. of Obs.	2551	2551	2551

Note: (z-stat)

* significant at the 1% level for a 2 tailed t-test

** significant at the 5% level for a 2 tailed t-test

*** significant at the 10% level for a 2 tailed t-test

(1) is a GLS with industry dummies

(2) is a GLS with year dummies

(3) is a GLS with industry and year dummies

References

[1] Acemoglu, D., 1996. A Microfundation for Social Increasing Returns to Human Capital, Quarterly Journal of Economics, Vol. 111, 779-804

[2] Acemoglu, D., 1997. Training and Innovation in an Imperfect Labour Market, The Review of Economic Studies, Vol. 64 (3), 445-464

[3] Acemoglu, Daron, 2002. Technical Change, Inequality and the Labor Market, Journal of Economic Literature, Vol. XL, 7-72

[4] Allen, S. G., 2001. Technology and the Wage Structure, Journal of Labor Economics, Vol. 19 (2), 440-483

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

[6] Amir, R., 2000. Modeling Imperfectly Appropriable R&D via Spillovers, International Journal of Industrial Organization, 18, 1013-1032

[7] Anand, B. N., Khanna, T, 2000. Do Firms Learn to Create Value? The Case of Alliances. Strategic Management Journal, 21, 295-315

[8] 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

[9] Aurora, A., Gambarella, A., 1990. Complementarity and External Linkages: the Strategies of the Large Firms in Biotechnology, Journal of Industrial Economics, Vol. 38, 361-379

[10] Autor, D.H., Levy, F., Murnane, R., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration, Quarterly Journal of Economics, Vol. 118 (4), 1279-133

[11] Bar-Gill, O., Parchomovsky, G., 2004. Intellectual Property Law and the Boundary of the Firm, Discussion Paper No. 40- 2004, Harvard Law School

[12] Bartel, A. P., Sicherman, N., 1999. Technological Changes and Wages: An Interindustry Analysis, The Journal of Political Economy, Vol. 107 (2), 285-325

[13] Becker, G., 1971. The Economics of Discrimination, The University of Chicago Press

[14] Berman, E., Bound, J., and Machin, S., 1998. Implications of non-neutral Technological Change: International Evidence, Quarterly Journal of Economics, Vol. 113 (4), 1245-80

[15] Berman, E., Bound, J., and Z. Griliches, 1994. Change in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures, Quarterly Journal of Economics, Vol. 109, 367-397

[16] Bernstein, J., 2001. Wage Inequality Poised to Grow in 2002, QWES Wage Supplement, Quarterly Wage and Employment Series, The Economic Policy Institute, Washington, D.C.

[17] Bessen, J. Patent Thickets: Strategic Patenting of Complex Technologies, Working Paper, http://www.researchoninnovation.org/online.htm#thicket

[18] Bhide, A., 1994. How Entrepreneurs Craft Strategies that Work, Harvard Business Review, Vol. 72, 150-161

[19] Blau, Francine D. and Kahn, Lawrence M., 1994. Rising Wage Inequality and the U.S. Gender Gap, American Economic Review, Vol. 84 (2), 23-28.

[20] Blau, Francine D. and Kahn, Lawrence M., 1997. Swimming upstream: trends in the gender wage differentials in the 1980s, Journal of Labor Economics, Vol. 15 (1), 1-42

[21] Blau, Francine D. and Kahn, Lawrence M., 2000. Gender Differences in Pay, Journal of Economic Perspectives, Vol. 14 (4), 75-99

[22] Borjas, G. J., Ramey, V., 1995. Foreign Competition, Market Power and Wage Inequality, Quarterly Journal of Economics, Vol. 110, 1075-1110

[23] Bound, J., Johnson, G. , 1992. Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations, American Economic Review, Vol. 82 (30), 371-392

[24] Bresnahan, T., 1997. Computerization and Wage Dispersion: An Analytical Reinterpretation, working paper, presented at the BNER Summer Institute, August 4.

[25] Caloghirou, Y., Ioannides, S. and N. S. Vonortas, 2003. Research joint ventures: A critical survey of theoretical and empirical literature, Journal of Economic Surveys, Vol. 17, 541-570

[26] Card, D., DiNardo, J. E., 2002. Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, Journal of Labor Economics, Vol. 20 (4), 733-783

[27] Cassiman, B., Veugelers, R., 2002. R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium, American Economic Review, 92, 1169-1184

[28] Cohen, W. M., Levinthal, D.A., 1989. Innovating and Learning: The Two Faces of R&D, The Economic Journal, 99 (397), 569-96

[29] Dasgupta, P., Stiglitz, J., 1980. Uncertainty, Industrial Structure, and the Speed of R&D. Bell Journal of Economics, Vol. 11 (1), 1-28

[30] D'Aspremont, C., Jacquemin, A., 1988. Cooperative and Non-cooperative R&D in Duopoly with Spillovers, American Economic Review, 78, 1133-37

[31] DeBondt, R., 1997. Spillovers and Innovative Activities. International Journal of Industrial Organization, 15, 1-29

[32] Galor, O., Weil, D. N., 1996. The Gender Gap, Fertility and Growth, American Economic Review, Vol. 86 (3), 374-387

[33] Geroski, P. A., 1995. Do Spillovers Undermine the Incentive to Innovate?, in Economic Approaches to Innovation, edited by Dowrick, S., Edwar Elgar, Aldershot, UK

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

[35] Goldin, C., 1989. Life-Cycle Labor Force Participation of Married Women: Historical Evidence and Implications, Journal of Labor Economics, Vol. 7, 20-47

[36] Greene W. H. , 2000. Econometric Analysis, Prentice Hall, 4th Edition

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

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

[39] Hagedoorn, J., Link, A. N., Vonortas, N. S., 2000. Research Partnerships, Research Policy, April, Vol. 29, 567-586

[40] 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.

[41] Hernan, R., Martin, P, Siotis, G., 1999. An Empirical Evaluation of the Determinants of Research Joint Venture Formation, prepared for the project "Science and Technology Policies Towards Research Joint Ventures", Project SOE1-CT97-1075, TSRE, European Commission, DG XII

[42] Hicks, J., 1932. The Theory of Wages, 1st Edition, London, Macmillan & Co.

[43] Jaffe, A. B., Trajtenberg, M. and Henderson, R., 1993. Geographic Knowledge Spillovers as Evidenced by Patent Citations. Quaterly Journal of Economics, 108 (3), 577-98

[44] Juhn, C. Murphy, K. M., Pierce, B., 1993. Wage Inequality and the Rise in Return to Skill" Journal of Political Economy, Vol. 101, 410-442

[45] Kamien, M. I., Muller, E., Zang, I., 1992. Research Joint Ventures and R&D Cartels, American Economic Review, 82 (5), 1293-1306

[46] Kamien, M. I., Zang, I., 2000. Meet Me Halfway: Research Joint Ventures and Absortive Capacity, International Journal of Industrial Organization, Vol. 18, 995-1012

[47] Katz, M. L., 1986. An Analysis of Cooperative Research and Development, The RAND Journal of Economics, 17 (4), 527-43

[48] Katz, L.F., Murphy, K.M., 1992. Changes in Relative Wages, 1963-1987: Supply and Demand Factors, Quarterly Journal of Economics, Vol. 107, 35-78

[49] Katz, L. F., Autor, D. H., 1999. Changes in the Wage Structure and Earnings Inequality, in the Handbook of Labor Economics, Vol. 3A, Ashenfelter, O. C. and Card, D., (Eds), North-Holland

[50] Kim, J., Marschke, G., 2004. Labor Mobility of Scientists, Technological Diffusion, and the Firm's Patenting Decision, The RAND Journal of Economics, forthcoming

[51] Kogut, B., 1991. Joint Ventures and the Option to Expend and Acquire, Management Science, Vol. 37, 19-33

[52] Lanjouw, J. O. and Schankerman, M., 2004. Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators, The Economic Journal, 114, 441-465

[53] 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

[54] Levin, R. C., Reiss, R., 1988. Cost Reducing and Demand Creating R&D with Spillovers, The RAND Journal of Economics, 19, 538-556

[55] Lewis, T. R., Yao, D. A., 2003. Innovation, Knowledge Flow, and Worker Mobility Working paper

[56] Motta, M., Ronde, T., 2002. Trade Secret Laws, Labor Mobility, and Innovations, European University Institute, Florence, Working Paper

[57] Oaxaca, R. L., 1973. Male-Female Wage Differentials in Urban Labor Markets, International Economic Review, October, Vol. 14 (3) 693-709

[58] Oaxaca, R. L., Ransom, M.R., 1994. On Discrimination and the Decomposition of Wage Differentials, Journal of Econometrics, Vol. 61 (1), 5-21

[59] O'Neill, J., Polachek, S. ,1993. Why the Gender Gap in Wages Narrowed in the 1980s, Journal of Labor Economics, Vol. 11 (1), 205-228

[60] Pakes, A., Nitzan, S., 1983. Optimum Contracts for Research Personnel, Research Employment, and the Establishment of 'Rival' Enterprises, Journal of Labor Economics, Vol. 1, 345-365

[61] Piga, C. A., Vivarelli, M., 2004. Internal and External R&D: A Sample Selection Approach, Oxford Bulletin of Economics and Statistics, Vol. 66 (4), 457-482

[62] Rosenkopf, L. and Almeida, P. 2003. Overcoming Local Search through Alliances and Mobility. Management Science 49, 751-766

[63] Sampson, R. C., 2003. R&D Alliances & Firm Performance: The Impact of Technological Diversity and Alliance Organization on Innovation, Working Paper, NYU-Stern School of Business

[64] Sanders, M., Baster Weel, 2000. Skill-Biased Technological Change: Theoretical Concepts, Empirical Problems and a Survey of the Evidence, Working Paper, University of Maastricht

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

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

[67] Stephan, P., 1996. The Economics of Science, Journal of Economic Literature, Vol. 34 (3), 1199-1235

[68] Thompson, P., Fox Kean, M., 2005. Patent Citations and the Geography of Knowledge Spillovers: A Reassessment, American Economic Review, 95 (1), 450-460

[69] Vedpuriswar, A. V., Chowdhary, N., Ghori, A.S.K., 2002. A Strategic Approach to Managing Technology Risks, The Icfaian Journal of Management Research, Vol. 1, (1)

[70] Veugelers, R., 1998. Collaboration in R&D: An Assessment of Theoretical and Empirical Findings. Economist. 146, 419-443

[71] Veugelers, R., DeBondt, R., 1992. Co-operative Innovative Activities, in C. Antonelli (Ed.) The Economics of Information Networks, Noth-Holland, Amsterdam

[72] Windmeijer, F., 2000. Moment Conditions for Fixed Effects Count Models with Endogenous Regressors, Economics Letters, 68 (1), 21-24

[73] Windmeijer, F., 2002. ExpEnd, A Gauss Programme for Non-linear GMM Estimation of Exponential Models with Endogenous Regressors for cross-section and Panel Data, The Institute for Fiscal Studies, Deptartment of Economics, UCL, Cemmap working paper CWP14/02

[74] _______1998, The New Innovators: Global Patenting Trends in Five Sectors, U.S. Department of Commerce, Office of Technology Policy, September

[75] ___ 1999 , Closing the Gap Between Men's and Women's Wages, in Economic Snapshots, Economic Policy Institute, Washington D.C.

[76] ___ 2002, CPS Labor Extracts 1979-2001, prepared by Daniel Feenberg and Jean Roth for NBER, http://www.nber.org/data/morg.html

[77] ___ CPS Design and Methodology, Technical Paper 63RV, Current Population Survey, U.S. Department Of Labor, Bureau of Labor Statistics and U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau, http://www.bls.census.gov/cps/tp/tp63.htm.

[78] _________ Strategic Research Partnerships: Proceedings from NSF Workshop (NSF 01-336)