Technological Diffusion, the Diffusion of Skill and the Growth of Outsourcing in US manufacturing.

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Abstract.

What drives the observed rapid growth of outsourcing in US manufacturing? This article approaches this question in a novel way. It asks whether technological diffusion, as boosted by the shift in R&D performing industries from manufacturing to services and by an intensification of the input linkages between industries, is in part responsible for the growth of atypical work arrangements in the US. By relying on data on technological diffusion since the early 1970, this study provides robust evidence that the answer is yes. A ten percent increase in technological diffusion increases outsourcing by between 2.6 and 4.1 percent depending on the specification.

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1. Introduction.

The striking changes occurring in the internal organization of the firm since the early 1970s are well known. Tasks that were previously performed by workers directly hired by the firm are now increasingly done under contract with firms in the business service sector and through employment arrangements that involve temporary workers, outsourcing and sub-contracting. The causes of the spread of atypical employment arrangements are still to be identified, but the literature has focused on two main factors, namely the need to save on labor costs (the labor-cost saving hypothesis) and the product-market volatility hypothesis, the creation of dualistic labor markets in which the secondary component of the labor force is used as a buffer to protect the primary workers from the effect of product market volatility. According to the first argument the use of atypical employment arrangements is driven by the possibility of avoiding some of the high costs of employment. For instance, Autor (2003) finds that the introduction of legal obstacles to the application of the US employment-at-will doctrine from 1973 can explain 20 percent of the growth of employment outsourcing. Using BLS and CPS US data Abraham (1996) finds that although the possibility of avoiding high wage and fringe costs of employment may explain the use of temporary workers to fill low-skill jobs, other factors must be at work that explain the temporary employment of highly skilled workers. According to Abraham (1996) for high-skill work other explanations, such as special expertise possessed by the outside contractor and applicable to the hiring firm, must be appealed to. Segal and Sullivan (1997) and Kahn (2000) suggest that insofar tasks that require substantial investment in firm-specific skill are usually not well suited to the use of temporary workers, technological standardization is making firm-specific knowledge less important, thus shifting upward the demand for outsourced labor services. The hypothesis that technological diffusion and standardization may be behind the growth of outsourcing has been relatively overlooked by the literature and for this reason it needs to be investigated further.

The basic argument connecting technological diffusion to the spread of outsourcing runs as follows. Technological diffusion reduces the specificity of internal skill and induces convergence of firm-specific skill to general skill over time in a way theoretically explored by Silverberg, Dosi and Orsenigo (1988). This has
important implications for the internal organization of the firm. In reducing the distance between firm's specific skills, technological diffusion opens the possibility to apply firm-specific skill to other firms' needs. In other words, technology diffusion expands the market where technical skills are applicable and allow specialized workers to exploit economies of scale, leading to a predicted positive correlation between technology diffusion and the spread of outsourcing.

This study looks for empirical support to this argument. To better discriminate among the various explanations proposed for the spread of alternative employment arrangements, I use Robust and 2SLS regression analysis. As in Machin and Van Reneen (1998) starting from a simple restricted variable translog cost function for industry $i$ at time $t$ I derive empirical specifications in which the dependent variables is the wage-bill-share of purchased services, the real value of purchased services and the annual change in purchased services, respectively. Using a set of explanatory variables including proxies for technological diffusion, a measure of industry-specific output volatility and a measure of the relative cost of labor, I test alternative explanations to the use of outsourcing and its growth.

The main results can be summarized as follows. Consistently with the main hypothesis developed in this study, technological diffusion comes out as an important determinant of the growth of outsourcing in US manufacturing since the early 1970s. A 10 percent increase in technological diffusion (the sum of direct R&D and indirect R&D embodied in domestic intermediate and investment goods over industry output) accelerates outsourcing by 8 percent. Such a result is robust to changes in the measure of technological diffusion and in the choice of dependent variable. For instance, using a measure of technological diffusion that sums direct R&D to R&D embodied in domestic intermediate inputs I find that a 10 percent increase in technological diffusion increases the wage bill share of outsourced services by 2.6 percent, and the real value of outsourced services by 3.6-4.1 percent depending on the specification. Furthermore, although alternative explanations cannot be discarded at this stage, this study finds a much stronger support to the cost saving hypothesis than for the market volatility argument. Finally, these results are robust to changes in specifications that address the issue of the potential endogeneity of the technological variables.

The rest of the paper is organized as follows. Section two reports some stylized facts about the growth of
outsourcing and the extent of technological diffusion in the US economy. Drawing upon Silverberg, Dosi and Orsenigo (1988) it develops the theoretical link between technological diffusion and outsourcing. Section three introduces the data set and presents the empirical specifications. Section four reviews the empirical results and presents some robustness exercises. Section five concludes the paper.

2. The growth of outsourcing and its determinants.

It is well documented that the use of atypical employment arrangements, such as the ones involving temporary labor, subcontracting and contracting out, has been growing in both North America and Europe since the late 1960s (Abraham and Taylor, 1996; Appelbaum and Schettkat, 1990; Abraham, 1996, Blanchard et al. 1995, Bentolila and Dolado, 1994; Grubb and Wells, 1993; Segal and Sullivan, 1997). Table 1 below documents the growth of the cost share of purchased services (outsourcing) by manufacturing industries from 1949 to 1988, a period in which outsourcing grows from 5 percent to 12.8 percent.

Table 1. Cost share of outsourced services in the US manufacturing sector between 1949 and 1988.

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<tbody>
<tr>
<td>cost share</td>
<td>5.0</td>
<td>6.6</td>
<td>9.2</td>
<td>9.0</td>
<td>10.1</td>
<td>10.2</td>
<td>12.8</td>
</tr>
</tbody>
</table>


The literature has investigated the possibility that the spread of atypical employment arrangements allows employers to save on labor costs (Autor, 2003; Abraham and Taylor, 1996). Other studies have argued that market volatility requires flexibility that can be more easily provided by these types of employment arrangements (Abraham, 1996; Saint-Paul, 1996). Focusing on models of technological innovation and diffusion, Silverberg, Dosi and Orsenigo (1988) suggest that an overlooked factor in the attempt to explain the evolution of employment arrangements in the last few decades may be technology diffusion.

To explore this hypothesis I use a well-developed notion of technological diffusion, namely the one adopted by OECD (1996). Technology diffusion is the process where knowledge and technical expertise spread and are assimilated throughout the economy. A large theoretical and empirical literature has investigated the hypothesis that technology diffusion occurs by means of transactions of intermediate and capital inputs. In this framework, embodied technology diffusion is the introduction into production processes of
machinery, equipment and components that incorporate new technology. In advanced economies, much new technology is embodied in the capital goods that industries purchase to expand and improve production. For instance, the OECD documents that for the US the contribution of direct R&D in the economy-wide technology intensity (the sum of direct and embodied R&D) has been declining from 1972 to 1993 (OECD, 1996, p. 39). Services account for an increasing share of total business sector R&D expenditure. In recent years up to 40 percent of all R&D has been performed by the non-manufacturing sector, mainly by service firms (OECD, 1996, p.29 and graph 2.3).

Table 2 below shows that in the US the decline in R&D expenditure in high-technology industries, medium-technology industries and low technology industries has been partially offset by a rise in R&D performed by non-manufacturing industries. At the same time manufacturing industries continued to shift their input structure away from R&D intensive industries towards service industries (Wolff, 1997).

Table 2. Shares of total industry R&D performed by the manufacturing and the non-manufacturing sectors between 1965 and 1992.

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<tbody>
<tr>
<td>Manuf.</td>
<td>97.16</td>
<td>95.9</td>
<td>96.78</td>
<td>95.65</td>
<td>92.05</td>
<td>80.82</td>
<td>75.05</td>
</tr>
<tr>
<td>Non-manuf.</td>
<td>2.84</td>
<td>4.1</td>
<td>3.22</td>
<td>4.35</td>
<td>7.95</td>
<td>9.18</td>
<td>24.95</td>
</tr>
<tr>
<td>Industry R&amp;D</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Source: OECD, 1996.

Table 3 below illustrates the basic evidence, obtained from the data used in this study, that links the use of outsourced services in US 2-digit manufacturing industries to technological factors, primarily technological diffusion as induced by indirect R&D embodied in intermediate and investments goods.

Table 3. Average of annual purchased services, average of annual change in purchased services and average total R&D intensity in selected 2-digit manufacturing industries, 1972-1993.
Selected 2-digit manuf. industries  |  PS \((a)\)  | Change in PS | total R&D \((b)\) | indirect R&D \((c)\)
--- | --- | --- | --- | ---
Leather and leather products | 8.77 | -0.09 | 0.76 | 0.59
Lumber and wood products | 23.9 | 0.76 | 0.76 | 0.50
Apparel and other textile products | 34.2 | 1.24 | 0.76 | 0.59
Stone, clay and glass products | 23.6 | 0.53 | 1.81 | 0.54
Misc. manuf. industries | 30.8 | 0.78 | 2.22 | 0.77
Rubber and misc. plastic products | 43.1 | 2.35 | 2.40 | 1.15
Petroleum and coal products | 50.0 | 0.77 | 1.58 | 0.34
Instruments and related products | 73.6 | 2.94 | 8.22 | 1.13
Electronic and other electrical equip. | 121.2 | 5.49 | 11.7 | 0.71
Industrial machinery and equip. | 138.2 | 4.78 | 5.27 | 1.00
Chemicals and allied products | 187.2 | 7.30 | 4.66 | 0.48
Transportation equip. | 180.5 | 7.90 | 31.7 | 3.85

Source. KLEMS data and OECD R&D data. Note \((a)\): PS=Purchased services; \((b)\) total R&D is total R&D intensity, the sum of direct and indirect R&D on industry output; \((c)\) indirect R&D is indirect R&D intensity, the sum of indirect R&D embodied in domestically produced intermediate and investment products on industry output.

The positive sample correlation between outsourcing (and the change in outsourcing) and a measure of technological diffusion that Table 3 shows is the focus of this paper. Before turning to its empirical testing I explore the theoretical foundation of the technological diffusion hypothesis.

### 2.1 Technological diffusion and the diffusion of skill.

Anecdotal evidence suggests that specific capital is indeed relevant to explain the use of outsourcing. For instance Kahn (2000) study the productivity consequences of outsourcing and finds that whenever firm-specific skill and knowledge were needed for the jobs, managers were finding temporary workers inappropriate. Autor (2003) provides evidence that workers supplied by Temporary Help Supply firms work overwhelmingly in occupations that rely on general interchangeable skills. The hypothesis explored here is that technological diffusion, by inducing technological standardization and by making firm-specific knowledge less important, is among the determinants of the spread of outsourcing. To investigate this hypothesis more formally it is useful to refer to Silvelberg, Dosi and Orsenigo (1988), who analyze the process of adoption of a new technology by the generic \(i\)th firm, say technology \(\Omega_i\), in an economic environment where firms use a mature technology. Their model is explicitly evolutionary and represents the diffusion of a new technique under con-
dition of uncertainty, bounded rationality and endogeneity of market structure as a disequilibrium process. Uncertainty is crucial in their model as firms have to make guesses about when further improvements in efficiency and further technical progress will be achieved. While issues of the determinant of technology choice and technology development are central in Silverberg, Dosi and Orsenigo (1988) what is relevant here is that they formally analyze the impact of technological diffusion on the distance between internal (firm-specific) and external (general) skills. In their contribution firm-specific (internal) skill \( s_i \) evolves according to

\[
\frac{ds_i}{dt} = f(s_i, P(\Omega_i), CP(\Omega_i)) \text{ if } s_i > s_O
\]

where \( P(\Omega_i) \) is current production with the new technology \( \Omega_i \), \( CP(\Omega_i) \) is cumulated production with the new technology and \( s_O \) is the level of skill generally available in the industry even to those firms not yet producing on the new technology. (Internal) learning-by-using improves efficiency, a movement along the well-known learning or experience S-shaped curve.

As more and more firms adopt technology \( \Omega_i \), its diffusion affects the external skill \( s_O \) since it increases the stock of production knowledge “publicly” available to workers at the level of the entire economy. With technological diffusion the experience acquired by individual firms leaks out and becomes available to the rest of the industry. Thus public skill \( s_O \) evolves according to

\[
\frac{ds_O}{dt} = f(s_O, <s>)
\]

where \(<s> = \sum \lambda_i s_i\) is the average internal skill in the industry, \( \lambda_i \) is the market share of the i-th firm and \( s_i \) is the internal skill of the i-th firm. Figure 1 below reproduces the dynamics of firm-specific skill and general skill, respectively, as the new technology diffuses.

*Here figure 1.*

It shows that external skill, generally available in the economy, converges to firm-specific skill. Technology diffusion is the driving force behind such a process as it shortens the “distance” between firm-specific technology \( \Omega_i \) and economy-wide technology, say \( \Omega \). This process has interesting consequences for the firm’s internal organization. The next sections develop the implications of technological diffusion for the firm’s incentive to outsource.
2.2 Technological diffusion and outsourcing.

To analyze the effect of technological diffusion on the organization of the firm, I use Magnani (2003) theoretical framework in which $V_{it}^L$ and $V_{it}^O$ indicate the evaluation of an internal skilled worker and an external skilled worker, respectively, by the $i-th$ firm in time $t$. Internal skilled workers $L$ have long-term employment relationships with their employer, the features of which are the ones of internal labor markets. The steady state value $V_{it}^L$ the $i-th$ firm attributes to an internal skilled worker is thus derived in a multiperiod framework in which the firm deploys long-term employment arrangements to hire and train workers and maximizes the present discounted value of current and future profits obtained by employing internal skilled workers $L$ (see Magnani (2003) for details)

$$V_{it}^L = \frac{s_i(L; \Omega_i) - W}{r + q}$$  

(3)

where $\frac{\partial s_i(\cdot)}{\partial L} < 0$. Expression (3) states that the firm’s evaluation of internal skilled labor $V_{it}^L$ is a positive function of its productivity $s_i$. As in Silverberg, Dosi and Orsenigo (1988), internal skilled workers’ productivity derives from skill that is specific to technology $\Omega_i$. Furthermore, $V_{it}^L$ negatively depends on the internal skilled wage $W$, which is set in internal labor markets through bargaining between internal workers and the firm. Finally, the discount factor $(r + q)$ depends on the market interest rate $r$ and on the probability $q$ that the internal skilled worker terminates the employment relationship after being trained.

Conversely, the employment of external labor $O$ (outsourcing) involves market-mediated employment arrangements with individuals who are formally employed in a sector external to the firm. Consistently with Silverberg et al. (1988) result, technological diffusion shortens the distance between firm-specific skill and general skill (see Figure 1 above). This implies that the skill (productivity) of outsourced labor used in the $i-th$ firm is $s_O = s_O(|\Omega - \Omega_i|)$ and depends on the distance between economy-wide technology $\Omega$ and firm’s specific technology $\Omega_i$, $\frac{\partial s_O(\cdot)}{\partial |\Omega - \Omega_i|} < 0$. This simple assumption captures the idea that outsourced labor is employable in more than one firm/sector since it sells services that are more easily applicable to the wide economy the shorter the technological distance between firms’ specific technologies is.

We can express the firm’s evaluation of outsourced labor $V_{it}^O$ as the difference between the labor produc-
tivity of contracted out labor $s_O$ and its wage $w_t$

$$V_{it}^O = s_O(|\Omega - \Omega_i|) - w_t$$  \hfill (4)

where $w_t$ is set competitively, $s_O(\cdot) \geq w_t$.  

The firm’s employment decisions regarding internal labor $L^*$ and outside labor $O^*$ involves a comparison between the shadow value of internal labor $V_{it}^L$ and the short-term value of outsourced labor $V_{it}^O$

$$V_{it}^L \geq V_{it}^O \iff \frac{s_i(L; \Omega_i) - W}{r + q} \geq s_O(|\Omega - \Omega_i|) - w_t.$$  \hfill (5)

This simple framework allows us to formally relate the spread of alternative employment arrangements to technological diffusion as described in figure 1. Figure 2 shows the equilibrium level of employment of internal labor $L^*$ for given levels of the variables $-W, w, (r + q)$, and for a given level of technological distance $(|\Omega - \Omega_i|)$. It also shows that by shortening the distance between firm-specific technology $\Omega_i$ and general technology $\Omega$ as in Silverberg, Dosi and Orsenigo (1988), technology diffusion reduces the gap $(\frac{s_i(L; \Omega_i)}{r + q} - s_O(|\Omega - \Omega_i|))$ between internal skill and external (general) skill. This discussion leads to the following

**Proposition 1.** According to the technological diffusion argument at least for a set of specialized services, technological rather than labor markets imperatives are operative in inducing a spread of alternative employment arrangements (Abraham and Taylor, 1996; Abraham, 1996; Segal and Sullivan, 1997). In symbols

$$\frac{\partial O^*}{\partial (|\Omega - \Omega_i|)} < 0$$  \hfill (6)

In figure 2 the effect of technological diffusion is to shift upward the horizontal line which expresses the productivity of external labor $O$, $s_O(|\Omega - \Omega_i|)$ net of the wage differential $[w - W/(r+q)]$. As “average” technology prevailing in the economy $\Omega$ converges to the technology specific to firm $i \Omega_i$, technological diffusion induces a drop in the internal labor employment level from $L^*$ to $L^{**}$ and, for a given number of jobs, an

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1 While the condition $V_{it}^O = 0$ is compatible with perfectly competitive labor markets, $V_{it}^O = s_O(\cdot) - w_t$ can still be positive in imperfectly competitive labor markets in which the productivity of contracted out labor $s_O$ is enhanced by general training provided by a business service sector. In such a case a compression of wage profile that leads to $w_t < s_O$ prevents workers who are accumulating general human capital from quitting the firm that provides such training (Acemoglu and Pichke, 1999).

2 In Magnani (2003) both internal and external wages, $W$ and $w$, as well as the productivity of internal labor $s_i(\cdot)$ are endogenous variables, and they determine the dynamics of an economy from low use of outsourcing to high use of outsourcing following productivity shocks.
increase in the use of purchased labor services $O^\ast$.

[here figure 2]

**Proposition 2.** An increase in the wage differential $(\frac{W}{r+q} - w)$ between the wage for long-term labor $W$ and the wage paid to outsourced labor $w$ induces a growth in the use of outsourced labor services

$$\frac{\partial O^\ast}{\partial (\frac{W}{r+q} - w)} > 0$$  \hspace{1cm} (7)

Inspection of the arbitrage condition (5) makes clear that an increase in the wage differential $(\frac{W}{r+q} - w)$ between the wage for long-term labor $W$ and the wage paid to outsourced labor also shifts the horizontal line in figure 2. This effect illustrates the labor cost saving hypothesis (e.g., Abraham, 1996), according to which a rise in the wage differential increases the propensity of firms to contract out to external workers.

**Proposition 3.** Outsourcing is more likely in industries in which firms face high product market volatility $(VARY)$, or

$$\frac{\partial O^\ast}{\partial VARY} > 0$$  \hspace{1cm} (8)

According to the market volatility argument (e.g., Segal and Sullivan, 1997) this is because overall labor costs are lower whenever employment arrangements are flexible as it is the case with outsourced labor (Autor, 2003).

Expressions (6), (7), (8) are the testable implications of the model sketched above. In the next section I present an empirical model for the spread of outsourcing in US manufacturing.


### 3.1 Data on outsourcing.

The focus of this empirical section is the assessment of the hypothesis that technological diffusion has had an impact on the use of market-mediated employment arrangements. As argued earlier, this term encompasses a variety of employment arrangements from outsourcing to temporary labor. In this study I follow Fixler and Siegel (1999) and concentrate on manufacturing industries outsourcing. Data on purchased services by man-
ufacturing industries are drawn from the US Bureau of Labor Statistics KLEMS dataset. Outsourced services fall into one of the following categories: Communication, Finance and Insurance, Real Estate and Rental, Personal and Repair Services, excluding autos, business services, auto repair and services, amusements, medical and education services, government enterprises. For the US Information Technology has historically been the most important input acquired (OECD, 1996). Labor and capital inputs, material and energy data are also drawn from the KLEMS dataset and transformed into real variables by using the KLEMS input prices. The KLEMS provides data on purchases services for the whole manufacturing and non-manufacturing sectors as well. The empirical specification uses an industry-level panel data set of 2-digit manufacturing industries (SIC 2039) for which outsourced services are known between 1949 and 1999.

3.2 The explanatory variables. Measures of technological innovation and diffusion.

Technology diffusion is the process where knowledge and technical expertise spread and are assimilated throughout the economy (OECD, 1996). As such it depends on both the direct \( R&D \) activities performed by an industry and on the indirect \( R&D \) that an industry imports from other industrial sectors of the economy. In the indirect component of industry \( R&D \), we can distinguish between embodied and disembodied technological diffusion. Disembodied technological diffusion involves the transmission of knowledge, technical expertise or technology in a way that does not imply the purchase of machinery and equipment incorporating new technology. Conversely embodied technology diffusion is the introduction into production processes of machinery, equipment and components that incorporate new technology.

Measures of direct \( R&D \) rely on data on Research and Development Expenditures by performer in constant dollars for the period 1953-92 (in millions of 1987 dollars) (direct \( R&D \)), which are part of the R&D Satellite account prepared by the US Bureau of Economic Analysis (BEA, 1994).\(^3\) The industry R&D measure refers to R&D activities conducted by (but not necessarily financed by) the business sector.

A measure of embodied technological diffusion must involve measurement of technology flows across industries and firms. Data on technological diffusion for the US manufacturing sector (the sum of direct

\(^3\) Most of the original source data were obtained from the Division of Science Resources Studies of the National Science Foundation.
and embodied R&D) have been made available by OECD researchers and refer to a small subset of years (1972, 1977, 1982, 1985, 1990, 1993). Here I consider technology flow indicators that focus on the R&D embodied in domestic products purchased by an industry. In other words, I overlook the international aspect of technological diffusion. Two major components of embodied R&D for each 2-digit SIC manufacturing industry are used in this study: (i) R&D embodied in domestically purchased intermediate inputs; (ii) R&D embodied in domestically purchased capital goods. OECD (1996) documents that information technology makes up the bulk of acquired technology in six of the ten OECD nations considered in that study between 1970 and 1993. For the US, Information Technology has historically been the most important technology acquired. Appendix I describes the formal definitions of R&D diffusion employed in OECD (1996).

3.3 The empirical specifications.

I start with a simple restricted variable translog cost function for industry $i$ at time $t$

$$C[\log W_{PS}, \log W_L, \log W_K, \log K, \log L, \log PSERV, \log Y, TEC_{DF}]_{it}$$

where

$W_X$ is the price of input $X$, $X = PS$ (purchased services), $L$ (hours of labor), $K$ (capital services), $Y$ is industry value added (production net of expenditure for materials and energy), and $TEC_{DF}$ is a measure of technological diffusion. From this cost function it is straightforward to derive a outsourced service wage-bill-share equation as in Machin and Van Reneen (1998)

$$SHARE_{it} = a_0 + a_1 \log(K_{it}) + a_2 \log(L_{it}) + a_3 \log(Y_{it}) + a_4 TEC_{DF_{it}} +$$

$$+ a_5 \log(W_{PS}/W_K)_{it} + a_6 \log(W_L/W_K)_{it} + a_7 VARY_{it} +$$

$$a_8 (trend_{it}) + \eta_{it}$$

(9)

where $SHARE$ is defined as the value of outsourced services over the wage bill (the sum of the value of labor services with the value of outsourced services)$^4$. In (9) $trend_{it}$ is a time variable (in logs) that captures the possibly non-linear relationship between time and outsourcing, while $VARY_{it}$ is a measure of industrial production volatility that aims to capture the effect of product market uncertainty on the use of outsourced services.

$^4$ The technology stock is assumed quasi-fixed as in Machin et al. (1998).
Following OECD (1996) I measure technological diffusion by means of total R&D intensity defined as total R&D, the sum of direct and embodied R&D, over industrial production. Thus $TEC\_DF_{it} = [(direct\ R&D + embodied\ R&D)_{it}/output_{it}]$. The embodied component of total R&D is measured differently depending on the specifications. Thus $TEC\_DF1_{it}$ is defined as $[(total\ R&D)_{it}/output_{it}]$, where the embodied component of $R&D_{it}$ is the sum of embodied $R&D$ in domestically purchased intermediate goods and embodied $R&D$ in domestically purchased investment goods. Conversely, in $TEC\_DF2_{it}$ the embodied component of $R&D_{it}$ is $R&D$ only embodied in intermediate goods domestically purchased by industry $i$ at time $t$. In both $TEC\_DF1_{it}$ and $TEC\_DF2_{it}$ R&D intensity is the average of R&D intensity over the period 1972-1993.

An alternative specification where the dependent variable is simply real purchased services $PSERV$ (made real using the price deflator in the KLEMS) offers the advantage of showing more clearly the substitutability and complementarity relationships with other input (specifically hours of labor and capital).

$$\begin{align*}
(PSERV_{it}) &= b_1 \log(K_{it}) + b_2 \log(L_{it}) + b_3 \log(Y_{it}) + b_4 TEC\_DF_{it} \\
&\quad + b_5 \log(W_{PS}/W_K)_{it} + b_6 \log(W_L/W_K)_{it} + b_7 VARY_{it} + \\
&\quad b_8(trend_{it}) + \eta_{it}
\end{align*}$$

(10)

In order to sweep out possibly correlated industry-specific effects, I time difference equation (7) to estimate

$$\begin{align*}
\Delta(PSERV_{it}) &= c_1 \Delta \log(K_{it}) + c_2 \Delta \log(L_{it}) + c_3 \Delta \log(Y_{it}) + c_4 TEC\_DF_{it} \\
&\quad + c_5 \Delta \log(W_{PS}/W_K)_{it} + c_6 \Delta \log(W_L/W_K)_{it} + c_7 VARY_{it} + \\
&\quad c_8(trend_{it}) + \eta_{it}
\end{align*}$$

(11)

where $\eta_{it}$ assumes a RE specification.\(^5\)

\(^5\) Because the technological diffusion variable assumes either the initial value (1973 value) or it is an average of its values between 1973 and 1993), I cannot enter this variable in first differences. Also, since wage variables are likely to be highly endogenous I also estimate specifications (10) and (11) without the relative wage rates. The results (available upon request) are shown to be robust to the inclusion or exclusion of the industry-specific relative wage variables.
3.4 The testable implications of the model.

In all specifications (9), (10) and (11) I estimate in this study the coefficient of the technological diffusion measure $TEC\_DF$ is expected to have a statistical significant and positive impact on industry outsourcing (see Proposition 1 in section 2). The main alternative hypotheses concerning the determinants of outsourcing in US manufacturing industries are (i) that it represents a strategy used by firms to save on labor costs (see Proposition 2) and (ii) that it is a way to shelter firm-hired labor from economy-wide volatility (see Proposition 3). According to the cost saving hypothesis, the relative prices of purchases services $\log(W_{PS}/W_K)$ should have a negative impact on outsourcing, while the cost of formal labor $\log(W_L/W_K)$ should be positively correlated with the dependent variable.

In line with the second alternative hypothesis a measure of economy-wide output volatility $VARY_t$ at year $t$

$$VARY_t = \frac{1}{12} \sum_{i=1}^{12} (q_{i,t} - q_{i-1,t})^2$$

(12)

the simple average of the squared deviations of monthly industrial production for month $i$ from its previous level, should positively impact on purchased services.

3.5 Potential endogeneity of R&D.

The assumption of exogenous R&D is notoriously problematic. For example, if the price of purchases services increase over time, firms may have an incentive to substitute away from these specialized inputs, developing in site alternatives, which may require R&D activities to fit the prevailing technology into the firm-specific organization. To address this potential problem I estimate specifications (13), (14) and (15) below by means of two-stages-least squares (2SLS)

$$SHARE_{it} = a_0^{IV} + a_1^{IV} \log(K_{it}) + a_2^{IV} \log(L_{it}) + a_3^{IV} \log(Y_{it}) +$$

$$+ a_4^{IV} TEC\_DF(IV)_{it} + a_5^{IV} \log(W_{PS}/W_K)_{it} +$$

$$+ a_6^{IV} \log(W_L/W_K)_{it} + a_7^{IV} VARY_t + a_8^{IV}(trend)_{it} + \eta_{it}$$

(13)

$$PSERV_{it} = b_0^{IV} + b_1^{IV} \log(K_{it}) + b_2^{IV} \log(L_{it}) + b_3^{IV} \log(Y_{it}) +$$

(13)
\[ \Delta PSERV_{it} = c_0^{IV} + c_1^{IV} \Delta \log(K_{it}) + c_2^{IV} \Delta \log(L_{it}) + c_3^{IV} \Delta \log(Y_{it}) + c_4^{IV} TEC_{DF}(IV)_{it} + c_5^{IV} \Delta \log(W_{PS}/W_{K})_{it} + c_6^{IV} \Delta \log(W_L/W_K)_{it} + c_7^{IV} VARY_{it} + c_8^{IV} (trend)_{it} + \eta_{it} \]

where \( TEC_{DF}(IV)_{it} \) is the result of the first stage estimation (Instrumental Variables estimation). As in Machin and Van Reneen (1998) who instrument R&D variables in a study of changes in skill structure in OECD manufacturing industries, \( TEC_{DF} \) is here instrumented by means of a set of variables comprising industry dummy variables and government-funded business enterprise R&D (US Bureau of Economic Analysis). The results obtained with specifications (9)-(11) are robust to inclusion and exclusion of industry dummy variables in the main equation.

4. The empirical results.

The empirical results obtained by estimating equations (9)-(11) are organized in table 4. Since the Hausman test does not reject the hypothesis of no systematic difference between random effect and fixed effect specification, I report the random effect (RE) empirical results obtained with robust GLS estimation. In table 4 the technological diffusion variable, which is measured by \( TEC_{DF1} \) and \( TEC_{DF2} \) depending on the specification, is consistently statistically significant at the 5 percent level at least. The R&D measures where indirect R&D is embodied in domestic intermediate inputs \( (TEC_{DF2}) \) has a significantly larger coefficient in all specifications. The difference in the size of the coefficients suggests that the nature of the (input) linkage between 2-digit manufacturing industries and the service sector is important in explaining outsourcing. Nonetheless, technological diffusion consistently appears to be an important determinant of the decision to employ outsourced services. A 10 percent increase in technological diffusion as measured by \( TEC_{DF2} \) increases the wage-bill share of outsourcing \( (SHARE) \) by 2.6 percent. A similar computation illustrates that a 10 percent increase in \( TEC_{DF2} \) increases the real value of purchased services \( (PSERV) \) by 4.1
percent and accelerates outsourcing by 8 percent in the specification with $\Delta PSERV$ as a dependent variable. These results are consistent with the implication of the model outlined in section 2 and further discussed in the previous section according to which technological standardization and diffusion have gone hand in hand with the growing provision of outside services to the manufacturing sector. Interestingly, when technological diffusion is proxied by means of expenditures in R&D performed in non-manufacturing sectors this variable assumes an expected positive coefficient and it is statistically significant at the 5 percent level. These results are available upon request.

Table 4 shows that labor inputs are positively correlated with outsourcing and with its annual change, $PSERV$ and $\Delta PSERV$ respectively, but they are negatively correlated with the wage-bill share of outsourced services ($SHARE$). Note that the facts that labor inputs and outsourced services move in the same directions in terms of level but in opposite directions in terms of wage-bill share are not totally inconsistent. However these results do not allow to assess unambiguously the nature of the substitutability/complementarity relationship between internal labor and outsourced services. On the contrary, capital inputs are consistently positively correlated with outsourcing in all specification, a result that offers further support to the hypothesis of a link between use of market-mediated employment arrangements and technology. Another interesting results involve the impact of the industry-specific value on the decision to outsourced services. While industries with high valued added appear to employ less outsourced services than other industries, industry value added is positively correlated with the annual change in outsourced services, a result that suggests a process of convergence in the use of outsourced services.

What can the RE results say about the relative importance of the technological standardization hypothesis versus alternative explanations for the growth of alternative employment arrangements? In table 4 the direct price effect is consistently negative and statistically significant at the 5 percent level at least. A increase in the relative price of purchased services induces a shift away from such input. Interestingly, purchased services are a substitute of firm-hired labor as shown by the positive sign of the coefficient of the relative price of labor $\log(W_L/W_K)$, which is highly statistically significant in all specifications in table 4. These results cast support to the hypothesis that market-mediated employment arrangements are part of the firms’
strategies to reduce labor costs as illustrated in the model of section two and as discussed in Abraham (1996). These results are consistent with the ones illustrated in a few contributions on the growth of market mediated employment arrangements. Grubb and Wells (1993) and Blanchard et al. (1995) for Europe, and Segal and Sullivan (1997) and Abraham (1996), Abraham and Taylor (1996) and Laird and Williams (1996) for the US, empirically explore the reasons why the temporary services industries has grown so fast starting from the first oil shock. High hiring costs and insiders’ wages and the availability of a reserve-army of relatively young and educated workers in the outside labor market are among the driving forces behind the rapid growth of market-mediated employment arrangements in Europe (Grubb and Wells, 1993; Blanchard et al., 1995).

Conversely, the hypothesis that output volatility has required firms to shelter the permanent labor force from the risk of unemployment comes out as unfounded. The output volatility measure \( VARY \) is either statistically significant but wrongly signed or non-statistically significant. Survey data recently collected in the United States suggest that the availability of high quality temporary labor services, and lower cost of flexibility may have driven the trend towards increasing use of alternative employment arrangements, particularly in times of general product market volatility. However, contrary to the hypothesis discussed in the previous sections, these results indicate the existence of a negative correlation between purchased services and economy-wide output volatility. The result for \( VARY \) contrasts with the one obtained by Laird and Williams (1996), in which product market volatility resulted non statistically significant in a regression analysis for Temporary Help Supply Employment. Obviously future research will need to focus more specifically on the impact of uncertainty and market volatility on the input requirements and employment strategies adopted by firms. In what follows I check the robustness of these results to changes in the technological diffusion measures (table 5) and to changes in the assumptions underlying the exogeneity of the total R&D measures (table 6).

### 4.1 Robustness exercises.

In the first robustness exercise I measure technology diffusion by means of the initial (1973) value of \( TEC_{DF1} \) and \( TEC_{DF2} \). Because industrial R&D intensity tends to be persistent over time, the way the technological
variables is entered in equations (9)-(11) is expected to make little difference to the results. Table 5 summarizes these results and shows that all results discussed above are robust to changes in the measurement of technological diffusion. Equations (9)-(11) have been estimated by including dummy variables for the 2-digit manufacturing industry among the right-hand side variables, but the results are robust to their exclusion. Furthermore, the inclusion of business cycle indicators do not make any difference to the coefficients of the main variables as illustrated in tables 4 and 5.

To address the potential endogeneity of R&D measures, I estimate equations (13)-(15) by means of 2SLS. I carefully choose the set of instrumental variables by following Machin and Van Reneen (1998). In particular I use government funded business enterprise R&D as an instrument for R&D diffusion. If government behavior can be taken as exogenous, it will be uncorrelated with the error terms in these specifications. As government funded R&D varies across industries, I combine government funded R&D with industry dummy variables in the 2SLS procedure. Compared with the models where R&D is assumed exogenous in tables 4 and 5, the IV estimates of table 6 are very close. In table 6, the IV coefficients of the labor variables ($\log(L)$ and $\log(W_L/W_K)$) increase slightly in size, while the coefficients of the capital variable and $\log(W_{PS}/W_K)$ decrease. The industry value added is positively correlated with the yearly change in purchased services but it is non statistically significant in the other specifications of the dependent variable. The overall trust of the results remains very robust.

5. Conclusions.

This paper addresses the question of what has determined the growth of market-mediated employment arrangements in the past few decades. The term market-mediated employment arrangements has come to identify a complex set of employment situations such as contracting out and subcontracting, temporary labor and outsourcing. In this paper I empirically explore an overlooked factor that may have determined this phenomenon, namely technological diffusion. This last hypothesis argues that since technological diffusion shortens the technological distance between firm-specific technology and the technology generally available in the market, the firm may have a lower incentive to invest in firm-specific human capital through training and
long-term contracts. The availability of readily available skills from the general market and the trust that
these skills can be applied to a rapidly diffusing technology make the firm more keen to use outsourcing and
market-mediated employment arrangements in general.

By focusing on manufacturing industries’ service outsourcing as measured by the US Bureau of Labor
Statistics I have explored the various hypotheses discussed in the literature, namely the cost saving hypoth-
esis, the market volatility hypothesis and the technological standardization hypothesis. According to the
technological diffusion hypothesis outsourcing becomes relevant to the firm when equivalent services can
be purchased outside of the firm, a condition that, I argue, strictly depends on the “distance” between firm-
specific technology and technology available in the rest of the economy.

To empirically test these hypotheses, I follow OECD methodology to define technological diffusion as
total R&D intensity, where total R&D is computed as the sum of direct R&D expenditure and R&D embodied
in input linkages between industries. Technological closeness is directly affected by technological diffusion,
a process which reflects both the spreading of R&D activities in industries other than the one considered and
the extend of the intensification of input linkages between industries.

This paper reports robust evidence that technological diffusion is an important explanation to the growth
of outsourcing in US manufacturing industries. A 10 percent increase in technological diffusion as measured
by \((TECDF2)\) increases the wage-bill share of outsourcing by 2.6 percent in the specification for the wage-
bill share of outsourced services. A similar computation illustrates that a 10 percent increase in \((TECDF2)\)
increases the real value of outsourced services by 4.1 percent and accelerates outsourcing by 8 percent. These
results are consistent with the view expressed by Abraham and Taylor (1996) according to which in the US
the nature of technological progress and diffusion and the existence of economies of scale in the provision of
specialized skills may have driven the race towards subcontracting and contracting out.

Alternative hypotheses such as the labor costs saving argument and the idea that market volatility requires
strategies to shelter permanent workers from work instability cannot be discarded at this stage. However, this
study finds a much stronger support for the cost saving hypothesis than it does for the market volatility
argument. Future research aims to apply a similar methodology to test the robustness of the technological
standardization argument to alternative measures of market-mediated employment arrangements.

**Appendix I.**

The methodology used rests on two basic assumptions. R&D expenditures are a proxy for technology and interindustry transactions are the carriers of technology across industries (OECD, 1996). Thus technology flows from one industry to another when industry originating the R&D sells products (intermediate or capital goods) embodying its R&D to other industries to be used as inputs in their production processes. Equating demand and supply for output $X$

$$X = A^d X + F^d \Rightarrow X = (I - A^d)^{-1} F^d \tag{16}$$

where $X$ is the vector of gross outputs, $A^d$ is the matrix of domestic input-output coefficients, $F^d$ is the final demand vector for domestic outputs. The matrix $(I - A^d)^{-1}$ indicates how much the output of industry $i$ would need to increase in order to satisfy a one-unit increase in the final demand of industry $j$. Call this matrix $B = (I - A^d)^{-1}$ the square matrix of interindustry technical coefficients at time $t$. The total domestic R&D embodiment per unit of final demand for industry $j$ can then be defined as the $j$th column sum of the matrix $B$

$$r_{fj} = \sum_{i=1}^{n} r_i b_{ij} \tag{17}$$

$j = 1, 2, ...n,$ and $r_i = R_i/X_i$ is the direct R&D intensity per unit of output of industry $i$. Using the elements of matrix $B$ the R&D embodied in the final demand for industry $j$ can be obtained by pre-multiplying the direct R&D intensity $r_i$ as follows

$$R&D_{DINT_j} = \sum_{i=1}^{n} r_i b_{ij} F_j \tag{18}$$

The calculation of total R&D embodiment in one unit of gross output of industry $j$ is quite similar as it is calculated from the matrix $B$.

For R&D embodiment in capital goods

$$R&D_{CAP_j} = \sum_{i=1}^{n} r_i \left( \sum_{k=1}^{n} b_{ik} I_{kj}^d \right) \tag{19}$$

where $I_{kj}^d$ is industry $j$’s investment expenditure for the i-th product embodied in capital input $k$ and $\left( \sum_{k=1}^{n} b_{ik} I_{kj}^d \right)$ is the total input requirement of product $i$ in investment goods $I_1, I_2, ... I_n$ by industry $j$.  

Table 4.

Random effect regressions of the wage-bill share of service outsourcing ($SHARE$), purchased services ($PSERV$) and the yearly change in purchased services ($\Delta PSERV$) on total R&D intensity, labor costs and macroeconomic volatility ($VARY$). Robust GLS estimation with standard errors in parentheses.

<table>
<thead>
<tr>
<th>Selected expl. variables</th>
<th>$SHARE$</th>
<th>$SHARE$</th>
<th>$PSERV$</th>
<th>$PSERV$</th>
<th>$\Delta PSERV$</th>
<th>$\Delta PSERV$</th>
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<td>(a)</td>
<td>(b)</td>
<td>(a)</td>
<td>(b)</td>
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<td>21.86***</td>
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<td>30.61***</td>
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<td>(1.19)</td>
<td>(2.99)</td>
<td>(2.99)</td>
</tr>
<tr>
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<td>0.03***</td>
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<td>39.83***</td>
<td>4.86</td>
<td>4.86</td>
</tr>
<tr>
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<td>(1.17)</td>
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<td>(3.17)</td>
</tr>
<tr>
<td>log(Value Added)</td>
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<td>-2.74***</td>
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<td>11.48***</td>
</tr>
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<td>(0.51)</td>
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<td>(1.96)</td>
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<td>0.009**</td>
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<td>67.58***</td>
<td>20.64***</td>
<td>20.64***</td>
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<td>(1.63)</td>
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<td>(2.63)</td>
</tr>
<tr>
<td>log($W_{ps}/W_K$)</td>
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<td>-0.007**</td>
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<td>-65.52***</td>
<td>-20.36***</td>
<td>-20.36***</td>
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<tr>
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<td>(1.70)</td>
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<td>(2.77)</td>
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<td>-1047***</td>
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<td>122.9</td>
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<td>(182)</td>
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<tr>
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<td>(86.63)</td>
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<td>-2448</td>
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<td>72199***</td>
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Notes: (a) RE specification where total (direct plus indirect) R&D intensity is the average over the period 1973-1993 ($TEC_{DF1}$).

(b) RE specification where total (direct plus embodied in domestic intermediate goods) R&D intensity is the average over the period 1973-1993 ($TEC_{DF2}$).

(c) (Sectoral) R&D intensity is R&D expenditure over total (sectoral) output.

(d) Annual measure of output variability of output is measured by sectoral squared monthly differences in shipments, by 2-digit industries ($VARY$).
Table 5.

Robustness exercise I: estimation results with alternative measures of technological diffusion (see notes for details). Random effect regressions of the wage-bill share of service outsourcing (SHARE), purchased services (PSERV) and the yearly change in purchased services (ΔPSERV) on total R&D intensity, labor costs and macroeconomic volatility (VARY). Robust GLS estimation with standard errors in parentheses.

<table>
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<tr>
<th>Selected expl. variables</th>
<th>SHARE (a)</th>
<th>SHARE (b)</th>
<th>PSERV (a)</th>
<th>PSERV (b)</th>
<th>ΔPSERV (a)</th>
<th>ΔPSERV (b)</th>
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<td>0.009**</td>
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<td>-0.007**</td>
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<tr>
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<td>-1047***</td>
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<tr>
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</table>

Notes: (a) RE specification where total (direct plus indirect) R&D intensity assumes the initial (1973) value (TEC_DF1.0).
(b) RE specification where total (direct plus embodied in domestic intermediate goods) R&D intensity assumes the initial (1973) value (TEC_DF2.0).
(c) (Sectoral) R&D intensity is R&D expenditure over total (sectoral) output.
(d) Annual measure of output variability of output is measured by sectoral squared monthly differences in shipments, by 2-digit industries (VARY).
Table 6.

Robustness exercise II: Potential endogeneity of technological diffusion. Instrumental variable regressions of the wage-bill share of service outsourcing (SHARE), purchased services (PSERV) and the yearly change in purchased services (ΔPSERV) on total R&D intensity, labor costs and macroeconomic volatility (VARY). Standard errors are in parentheses.

<table>
<thead>
<tr>
<th>Selected expl. var.</th>
<th>SHARE (a)</th>
<th>SHARE (b)</th>
<th>PSERV (a)</th>
<th>PSERV (b)</th>
<th>ΔPSERV (a)</th>
<th>ΔPSERV (b)</th>
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<tbody>
<tr>
<td>log(L)</td>
<td>-0.08***</td>
<td>-0.08***</td>
<td>31.39**</td>
<td>31.39**</td>
<td>37.5***</td>
<td>37.5***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(10.15)</td>
<td>(10.15)</td>
<td>(8.06)</td>
<td>(8.06)</td>
</tr>
<tr>
<td>log(K)</td>
<td>0.04**</td>
<td>0.04**</td>
<td>33.66***</td>
<td>33.66***</td>
<td>7.92</td>
<td>7.92</td>
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<tr>
<td></td>
<td>(0.01)</td>
<td>(0.009)</td>
<td>(8.24)</td>
<td>(8.24)</td>
<td>(10.8)</td>
<td>(10.8)</td>
</tr>
<tr>
<td>log(Value Added)</td>
<td>-0.008</td>
<td>-0.008</td>
<td>-3.76</td>
<td>-3.76</td>
<td>28.5***</td>
<td>28.5***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(5.40)</td>
<td>(5.40)</td>
<td>(6.08)</td>
<td>(6.08)</td>
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<tr>
<td>log(W_L/W_K)</td>
<td>0.01</td>
<td>0.01</td>
<td>72.35***</td>
<td>72.35***</td>
<td>14.09*</td>
<td>14.09*</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(10.6)</td>
<td>(10.6)</td>
<td>(7.7)</td>
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</tr>
<tr>
<td>log(W_Ps/W_K)</td>
<td>-0.005</td>
<td>-0.005</td>
<td>-62.94***</td>
<td>-62.94***</td>
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</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(11.2)</td>
<td>(11.2)</td>
<td>(7.9)</td>
<td>(7.9)</td>
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<tr>
<td>total R&amp;D inten. (c)</td>
<td>0.003***</td>
<td>0.03***</td>
<td>2.10***</td>
<td>22.23***</td>
<td>0.22***</td>
<td>2.32**</td>
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<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(5.5)</td>
<td>(5.5)</td>
<td>(0.07)</td>
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<td>output volatility (d)</td>
<td>-1.48**</td>
<td>-1.48**</td>
<td>-16.06***</td>
<td>-16.06***</td>
<td>179.2</td>
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<td></td>
<td>(0.64)</td>
<td>(0.64)</td>
<td>(4.0)</td>
<td>(4.0)</td>
<td>(146.6)</td>
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<td>time trend</td>
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<td>0.002***</td>
<td>0.29</td>
<td>0.29</td>
<td>0.11***</td>
<td>0.11***</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.30)</td>
<td>(0.30)</td>
<td>(0.02)</td>
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<tr>
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<td>-2.85**</td>
<td>-784.5</td>
<td>-794.9</td>
<td>-217.8***</td>
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<td></td>
<td>(0.96)</td>
<td>(0.96)</td>
<td>(601.1)</td>
<td>(599.8)</td>
<td>(43.9)</td>
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<td>R²</td>
<td>0.84</td>
<td>0.84</td>
<td>0.87</td>
<td>0.87</td>
<td>0.18</td>
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<td>F-test</td>
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<td>$F_{695}^{24}$</td>
<td>$F_{695}^{24}$</td>
<td>$F_{695}^{24}$</td>
<td>$F_{695}^{24}$</td>
<td>$F_{695}^{24}$</td>
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<tr>
<td></td>
<td>=161.2***</td>
<td>=161.2***</td>
<td>=196***</td>
<td>=196***</td>
<td>=7.6***</td>
<td>=7.6***</td>
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<tr>
<td>Observations</td>
<td>720</td>
<td>720</td>
<td>720</td>
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Notes: (a) RE specification where total (direct plus indirect) R&D intensity is the average over the period 1973-1993 (TEC_DF1).
(b) RE specification where total (direct plus embodied in domestic intermediate goods) R&D intensity is the average over the period 1973-1993 (TEC_DF2).
(c) (Sectoral) R&D intensity is R&D expenditure over total (sectoral) output.
(d) Annual measure of output variability of output is measured by sectoral squared monthly differences in shipments, by 2-digit industries (VARY).
References.


Figure 1. Technological diffusion and the convergence of internal and external skill over time (Silverberg et al. 1988).
Figure 2. The effect of technological diffusion on the optimal employment levels of internal skilled labour and outsourcing.