Intra- and Inter-sectoral Knowledge Spillovers and TFP Growth Rates

Núria Quella*

Banco de México

February 2006

PRELIMINARY - Do Not Quote - Comments Welcome

*E-mail address: nquella@banxico.org.mx. I thank Jess Benhabib, Boyan Jovanovic, Theo Mamuneas, Ishaq Nadiri, and Sílvio Rendon for helpful comments and suggestions and Maury Gittleman, Dale Jorgenson, and Samuel Kortum for their valuable provision of data. I am also grateful to the participants in the Macroeconomics seminar at Banco de México and at the Instituto Tecnológico de Monterrey for useful suggestions. The usual disclaimer applies.

Abstract.- In this paper I estimate unobserved labor-generated knowledge spillovers within and among six large macroeconomic sectors covering the totality of the US civilian economy from 1948 to 1991. Unobserved spillovers are identified by observed TFP changes measured using Dale Jorgenson's quality-adjusted factor and product panel data. I construct a series of sectoral knowledge spillover matrices that show that changes in the magnitude and direction of spillovers are associated to the productivity slowdown in the US economy of the early seventies. These matrices also allow me to compute the gap between the market and the optimal allocation of labor among sectors. Moreover, I show that sectoral market wages do not capture the totality of spillovers and I measure the difference.

My measurement of spillovers shows that from 1948 to 1991 manufacturing generated knowledge for all sectors, being overall the main engine of growth. Using Samuel Kortum's data on patent production and use in the U.S. I find that sectoral labor generated knowledge flows coincide with the sectoral patterns of other, disembodied information flows.

I also find the productivity slowdown coincides with a change in the pattern of generation and diffusion of spillovers. In the mid seventies manufacturing initiates its decline as the engine of growth and trade starts to catch up as the main generator of knowledge spillovers to the economy; simultaneously, the relative weight of all intra-sectoral spillovers diminishes in favor of spillovers between sectors.

Finally, I find that the market allocates resources inefficiently, as spillovers are measured to be significant. More resources should go to the main spillover generating sector, that is, manufacturing, so that employment in this sector increases by 32%, and output by 8%; and wages increase in all sectors, except for services and mining.

Keywords: Knowledge spillovers; technology; productivity slowdown.
JEL Classification: D24, J24, O30, O40 .

1 Introduction

Although spillovers have always had an important role in economic theory and policy design, the empirical estimation of their magnitude and the extent of their contribution to productivity changes has not been as popular. Moreover, the amount of literature dedicated to *knowledge* spillovers is far inferior to the number of specialized studies dedicated to other kinds of externalities. The existing empirical work concentrates on R&D investment-generated spillovers and, more specifically, on the measurement of localized spillovers (Marshallian agglomeration economies), and on the difficulty in appropriating the benefits of one's own innovative activity. Also, most measurements of external economies refer to U.S. and European *manufacturing*.

In this paper I estimate labor-generated knowledge spillovers within and among large sectors; I also gauge wether the spillovers are related to observed productivity changes, and how they affect sectoral total factor productivity (TFP) growth rates. My approach introduces a twofold novelty: spillovers are generated by the quality of the *overall* human capital employed, and spillover estimates cover *all* sectors in the economy, not only the manufacturing industries. Here, knowledge spillovers in a particular industry are generated by the capacity of its employees at *all* stages and levels of the production process to learn from its own and from others' productive experience. In other words, employees *learn-by-doing* and recognize, adopt and adapt flows of knowledge originating elsewhere, be they blueprints, managerial techniques, new organizational designs or be they embodied in new capital equipment or intermediate goods.

The concept of labor-led knowledge spillovers feeds partly on the labor literature, and partly on studies of the learning process (Lieberman 1984). But, mostly, it feeds on the need to distinguish between substitution among different types of inputs (with different combinations of marginal productivity in their components) and growth in productivity. Often, what previous studies have called spillovers were really input quality improvements.[2] Once inputs are carefully measured, taking into account their heterogeneity and quality changes, the Total Factor Productivity (TFP) term will pick up the *costless* spillover effects.

In this paper I start from an index number approach in a production theoretic framework and go on to propose a static model, which is extendable to a dynamic setting. The estimation of spillovers proceeds in two stages: first, I compute sectoral TFP using a Tornqvist Index; in the second stage I recover the spillovers, identified by *observed* productivity changes, by a constrained least squares procedure. I use the data set of Ho & Jorgenson (1999) for the US civilian economy from 1948 through 1991 containing quality-adjusted factor and product sectoral panel data. I also compute the gap between the market and the optimal sectoral allocation of labor and its return rates.

I provide, first, a matrix of origin and destination of knowledge spillovers within and among six large macroeconomic sectors: Manufacturing, Mining, Construction, Services, Trade & Transportation, and Agriculture. Arguably, both the sectoral composition and the technological distribution of firms and industries are characteristics that define an economy. Both vary through time, and both determine the labor or human capital distribution within and across sectors. Therefore, the matrix of intra- and inter-sectoral knowledge spillovers is specific to each economy and period. Also, estimates are at their most robust when considered *ordinally*: it is their ranking and relative weights that are most decisive when assessing productivity gains and losses, not so much their absolute values.

Second, I examine how variations in the relative contribution of sector-specific and inter-sectoral spillovers to the total spillover change in reflection of the productivity slowdown of 1973. Third, I examine the transmission channel of knowledge spillovers: workers' mobility for embodied knowledge, and technology flows for dis-

[2] In reference to input quality improvement and the contribution of inputs to economic growth see Jorgenson, Gollop & Fraumeni (1987), Jorgenson, Ho & Fraumeni (1994), and Jorgenson & Stiroh (1994).

embodied knowledge. For the first, I compare the matrix of spillover estimations with a matrix of the economy's transitional labor flows and check whether both kind of flows show similarity in their variations by size and direction (origin and destination). For disembodied knowledge, I compare spillover flows with a matrix of patent expenditure by sector of origin and sector of use.

I find that labor generated knowledge flows coincide with the patterns of expenditure and use of patents and R&D, and that changes in spillovers are related to the 1973 productivity slowdown. During the whole 1948-1991 period Manufacturing was the leading knowledge generator, but the productivity slowdown coincides with a decline in intra-sectoral spillovers and the rise of Trade as the main generator of knowledge spillovers. I also find efficiency requires allocating more resources into the main spillover generating sector, Manufacturing, so that employment in this sector increases by 32%, and output by 8%; and wages in all sectors except Services and Mining increase.

The remainder of the paper is organized as follows. The first part of the next section describes a model with inter- and intra-industry knowledge spillovers generated by the labor force employed in each sector; the second part explains the estimation procedure to measure these spillovers, and the third part discusses the results for different levels of aggregation and subperiods. Section 3 compares these results with observed transmission channels of knowlege spillovers: worker flows and technology flows as measured by the production and the use of patents. Section 4 summarizes the main conclusions of this paper.

2 Model

This section presents a model where the production function incorporates knowledge externalities in labor. I show that the presence of spillovers leads to a difference between the competitive and the optimal solution in terms of labor's sectoral allocation and rates of return.

Consider an economy consisting of n sectors, each producing a differentiated final good Y_i with capital K_i, intermediate goods M_i, and labor L_i. The production function is characterized by sectoral knowledge spillovers in labor, that is,

$$Y_i = A_i K_i^{\beta_{iK}} M_i^{\beta_{iM}} L_i^{\beta_{iL}} \prod_{j=1}^{n} L_j^{\gamma_{ij}},\ i = 1, 2, \ldots, n.$$

The exogenous time-invariant scale factor A_i is here unrelated to the input variables and, hence, there is no endogenous growth derived from it.[3] The $L_j^{\gamma_{ij}}$ are sectoral spillovers, characterized by the *learning parameters* $\gamma_{ij} \geq 0$ that measure the extent to which sector i learns from sector j. If $i = j$, they are called sector-specific or intra-sectoral knowledge spillovers; if $i \neq j$, they are inter-sectoral knowledge spillovers.[4] Every sector i exhibits constant returns to scale $\beta_{iK} + \beta_{iM} + \beta_{iL} = 1$. Endowments are $K = \sum_{i=1}^{n} K_i$, $M = \sum_{i=1}^{n} M_i$, and $L = \sum_{i=1}^{n} L_i$. The consumer's utility function is $U(C_1, C_2, ..., C_n) = \prod_{i=1}^{n} C_i^{\alpha_i}$, where $\sum_{i=1}^{n} \alpha_i = 1$.

Each sector i receives total spillover $q_i = \sum_{j=1}^{n} \gamma_{ij}$ and emits total spillover $\Gamma_i = \sum_{j=1}^{n} \alpha_j \gamma_{ji}$. The economy-wide coefficient for each factor is $\beta_X = \sum_{j=1}^{n} \alpha_j \beta_{jX}$ and the economy-wide emission (and reception) of spillovers is $Q = \sum_{j=1}^{n} \alpha_j q_j = \sum_{i=1}^{n} \Gamma_i$.

Note that, whereas each sector i operates under the assumption of constant returns to the inputs it controls, social returns to its production function are $1 + q_i$ which, unless $q_i = 0$, means there are really sectoral and, hence, economy-wide increasing returns to scale.[5]

With this technology and these preferences I evaluate two possible arrangements next: a competitive market solution and the social planner's solution. If there is a

[3] A dynamic extension of this model would have A_i as a Hicksian neutral shift parameter: the scale factor A_i would vary over time as the productivity of inputs and/or the knowledge spillovers change. In this model A_i is the ratio of output to total factor input *plus* spillovers.

[4] The knowledge spillovers improve the marginal productivity of *all* inputs in the sector equally and costlessly.

[5] Note also that sectoral private returns to spillover-generating L_i are really $\beta_{iL} + \gamma_{ii}$ and social returns are $\beta_{iL} + \Gamma_i$.

wedge between the social and the private rates of return to spillover-generating labor, TFP estimates should reflect the externality. Otherwise, the effect of the knowledge spillover will be fully accounted for and disappear from the residual.

Market Solution

On the production side, representative firms ignore knowledge spillovers and thus maximize profits $P_i Y_i - w_K K_i - w_M M_i - w_L L_i$, choosing K_i, M_i, L_i by setting each input's marginal product equal to its return rate:

$$w_X = \beta_{iX} \frac{P_i Y_i}{X_i},\ X = \{K, M, L\}. \tag{1}$$

Assuming that all inputs are perfectly mobile across sectors *and* indifferent among them there is a unique competitive return rate for each input. Thus, using sector 1 as the numeraire, $P_1 = 1$:

$$P_i = \frac{\beta_{1X}}{\beta_{iX}} \frac{X_i}{X_1} \frac{Y_1}{Y_i}. \tag{2}$$

A competitive equilibrium is attained at zero profits for each sector: $P_i Y_i - w_K K_i - w_M M_i - w_L L_i = 0$, which implies that the value of total production equals the sum of the input values[6] or consumers' income: $\sum_{i=1}^{n} P_i Y_i = w_K K + w_M M + w_L L = y$.

On the demand side, the representative consumer chooses consumption goods $C_1, C_2, ...C_n$ to maximize her utility $U(C_1, C_2, ...C_n)$ subject to $y = \sum_{i=1}^{n} P_i C_i$. Consumers also ignore knowledge spillovers in deciding on their consumption. The first order condition, with $P_1 = 1$, yields

$$P_i = \frac{\alpha_i}{\alpha_1} \frac{C_1}{C_i}.$$

Setting supply equal to demand, $C_i = Y_i$ and combining this equation with Equation (2) yields $X_i = \frac{\alpha_i}{\alpha_1} \frac{\beta_{iX}}{\beta_{1X}} X_1$, which together with $X = \sum_{i=1}^{n} X_i$ implies that the market's

[6] This "product exhaustion" also implies that the value shares of all inputs sum to one.

sectoral allocation of inputs is

$$\frac{X_i^c}{X} = \frac{\alpha_i \beta_{iX}}{\beta_X},\ X = \{K, L, M\},$$

Hence, the market completely ignores the existence of labor spillovers: the competitive allocation of inputs, including labor, is determined exclusively by consumers' preferences and technology parameters.

Optimal Solution

The social planner, on the other hand, internalizes knowledge spillovers and chooses the L_i for each sector i that maximize the representative consumer's utility $U(Y_1, ..., Y_n)$ subject to $K = \sum_{i=1}^n K_i$, $M = \sum_{i=1}^n M_i$ and $L = \sum_{i=1}^n L_i$. The first order conditions for capital and intermediate goods are

$$\frac{\alpha_1 \beta_{1X}}{X_1} = \frac{\alpha_i \beta_{iX}}{X_i},$$

which imply

$$\frac{X_i^s}{X} = \alpha_i \frac{\beta_{iX}}{\beta_X},\ X = \{K, M\}.$$

Thus, the planner allocates capital and intermediate goods exactly as the market does. However, the first order condition for labor is

$$\frac{\alpha_1 \beta_{1L}}{L_1} + \sum_{j=1}^{n} \frac{\alpha_j \gamma_{j1}}{L_1} = \frac{\alpha_i \beta_{iL}}{L_i} + \sum_{j=1}^{n} \frac{\alpha_j \gamma_{ji}}{L_i},$$

which implies

$$\frac{L_i^s}{L} = \frac{\alpha_i \beta_{iL} + \Gamma_i}{\beta_L + Q}.$$

Thus the optimal allocation of labor depends on consumers' preferences, labor productivity, *and* knowledge spillovers.[7]

[7]The social planner will consider $\beta_{iL} + \gamma_{ii}$ as the labor coefficient for each sector i. A change in the intra-sectoral learning parameter γ_{ii} will cause TFP_i to increase, even if everything else remains

Proposition 1 *The planner allocates more labor than the market to sector i,* $L_i^s > L_i^c$*, iff* $\frac{\Gamma_i}{Q} > \frac{\alpha_i \beta_{iL}}{\beta_L}$. *The planner allocates less labor than the market to sector i,* $L_i^s < L_i^c$*, iff* $\frac{\Gamma_i}{Q} < \frac{\alpha_i \beta_{iL}}{\beta_L}$. *The planner allocates the same labor than the market to sector i,* $L_i^s = L_i^c$*, iff* $\frac{\Gamma_i}{Q} = \frac{\alpha_i \beta_{iL}}{\beta_L}$. *Proof:* $L_i^s \lesseqgtr L_i^c$ *if* $\frac{\alpha_i \beta_{iL} + \Gamma_i}{\beta_L + Q} \lesseqgtr \frac{\alpha_i \beta_{iL}}{\beta_L}$ *which is equivalent to* $\frac{\Gamma_i}{Q} \lesseqgtr \frac{\alpha_i \beta_{iL}}{\beta_L}$ ■

The planner's allocation of labor to sector i is larger (smaller, equal) than the market's only if sector i's relative emission of spillovers is larger (smaller, equal) than relative market allocation of labor in the sector.

When there are no inter-sectoral spillovers, that is, when $\gamma_{ij} = 0$, the planner's allocation becomes

$$\frac{L_i^s}{L} = \frac{\alpha_i \beta_{iL} \left(1 + \frac{\gamma_{ii}}{\beta_{iL}}\right)}{\sum_{j=1}^n \alpha_j \beta_{jL} \left(1 + \frac{\gamma_{jj}}{\beta_{jL}}\right)} = \frac{\alpha_i \left(\beta_{iL} + \gamma_{ii}\right)}{\sum_{j=1}^n \alpha_j \left(\beta_{jL} + \gamma_{jj}\right)}$$

Clearly, the planner allocates more labor to the sector with the largest intra-sectoral spillover. If relative learning parameters are equal across sectors ($\frac{\gamma_{ii}}{\beta_{iL}} = \frac{\gamma_{jj}}{\beta_{jL}}$), including when both are zero, there is no difference between the market and the planner's allocation of labor.

Figure **??** illustrates the market and the planner's labor allocation L_1 in a two-sector economy as a function of consumers' preferences α_1 when $\beta_{1L} = \beta_{2L} = \beta_L$ and $q_1 = q_2$. The solid black 45° line represents the market allocation; the six color lines represent the planner's allocation for different relative values of inter-sectoral learning parameters. When the line is red both sectors in the economy learn *equally* from one another ($\gamma_{12} = \gamma_{21} > 0$). When the line is yellow both sectors learn from one another, but sector 1 learns from 2 *more* than sector 2 from 1 ($\gamma_{12} > \gamma_{21} > 0$), and viceversa when the line is light blue ($0 < \gamma_{12} < \gamma_{21}$).

The magenta and blue lines represent economies where *only* one sector learns from the other: when sector 1 is the one to learn the line is magenta ($\gamma_{12} > 0$, $\gamma_{21} = 0$);

unchanged, including the sectoral labor allocation and technology parameters.

when it is sector 2, the line is blue ($\gamma_{21} > 0$, $\gamma_{12} = 0$). When there are no inter-sectoral spillovers whatsoever, no sector learns from the other sector's productive experience ($\gamma_{12} = \gamma_{21} = 0$) and the line is green.

$\frac{L_1^s}{L} = \frac{\alpha_1(\beta_{iL}+\gamma_{11})+(1-\alpha_1)\gamma_{21}}{\beta_L+\alpha_1 q_1+(1-\alpha_1)q_2}$.

When $\alpha_1 = 0$ the market allocates no workers to sector 1, whereas the planner, as long as knowledge generated in sector 1 spills over to the *other* sector ($\gamma_{21} > 0$), will always assign some workers to sector 1, the more so the more the other sector learns from sector 1, regardless of consumers' preferences: $\frac{L_1^s}{L} = \frac{\gamma_{21}}{\beta_L+q_2} > 0$. At the other extreme, when $\alpha_1 = 1$, the market allocates all workers to sector 1, whereas the planner allocates some workers to sector 2, the more so the more sector 1 learns from the other sector (the larger γ_{12}), regardless of consumers' preferences: $\frac{L_1^s}{L} = \frac{\beta_L+\gamma_{11}}{\beta_L+q_1} < 1$.

Both the market and the planner respond to an increase in consumers' preferences for one good increasing the labor allocated to its production. However...

Social and Private Rates of Return to Labor

Return rates for capital and intermediate inputs for any sector i are the same for the market and the planner. From Equations (1) and (2) we know there is a unique competitive wage rate for all sectors: $w^c = \beta_{1L}\frac{Y_1^c}{L_1^c}$. Whereas, in the optimum, $w_1^s \neq w_2^s \neq ... \neq w_n^s$.[8]

The planner's equilibrium wage rate for sector i measures the productivity of labor employed in that sector expressed in physical units of output, that is, in real terms:

$$w_i^s = Y_{L_i}\frac{U_i}{U_1} = (\beta_{iL} + \gamma_{ii})\frac{Y_1^s}{L_i^s}\frac{\alpha_i}{\alpha_1}$$

where $Y_{L_i} = (\beta_{iL} + \gamma_{ii})\frac{Y_i^s}{L_i^s}$ is the marginal product of labor in sector i, and U_i is the marginal utility derived from the consumption of one extra unit of good i, with

[8] If sectoral planner wages were to be equal, the planner's equilibrium distribution of labor would be forced to disregard inter-sectoral spillovers.

$\frac{U_i}{U_1} = \frac{\alpha_i}{\alpha_1}\frac{Y_1^s}{Y_i^s}$.

In relation to the competitive wage rate:

$$\begin{aligned}\frac{w_i^s}{w^c} &= \left(1+\frac{\gamma_{ii}}{\beta_{iL}}\right)\frac{Y_1^s/Y_1^c}{L_i^s/L_i^c} \\ &= \left(1+\frac{\gamma_{ii}}{\beta_{iL}}\right)\left(\frac{L_1^s}{L_1^c}\right)^{\beta_{1L}}\prod_{j=1}^{n}\left(\frac{L_j^s}{L_j^c}\right)^{\gamma_{1j}}/\left(\frac{L_i^s}{L_i^c}\right),\end{aligned}$$

where $\frac{Y_1^s/Y_1^c}{L_i^s/L_i^c}$ is the optimal-to-market *average* product of labor ratio. Clearly, sectoral real productivity of labor depends on each sector's relative intra-sectoral spillover, $\frac{\gamma_{ii}}{\beta_{iL}}$, and on the distance between its relative spillover emission, $\frac{\Gamma_i}{Q}$, and its relative market labor allocation, $\frac{\alpha_i\beta_{iL}}{\beta_L}$, as per Proposition 1.

We can see that:

i. There is a constant *level* effect for all sectors, $\left(\frac{L_1^s}{L_1^c}\right)^{\beta_{1L}}$, that increases with the labor elasticity of output in the numeraire, and with the difference between the numeraire's relative emission of spillovers, $\frac{\Gamma_1}{Q}$, and relative market labor allocation, $\frac{\alpha_1\beta_{1L}}{\beta_L}$, as per Proposition 1. The larger (smaller) this level effect, *ceteris paribus*, the higher (lower) real productivity for all sectors is with the planner's allocation of labor. NOT TRUE.

ii. As long as sector i exhibits some degree of learning-by-doing (i.e. $\gamma_{ii} > 0$), productivity in real terms for sector i is larger with the planner's allocation of labor.

iii.

Without inter-sectoral spillovers competitive wages and, therefore, planner's wages are smaller for all sectors. Hence, the difference between the market and the planner's wage rates will be the same in relative terms as when $\gamma_{ij} > 0$, but in absolute terms it will be smaller. Relative sector productivity will not change either.

In an economy without spillovers, either sector-specific or inter-sectoral, there is no difference between the market's and the planner's distribution of labor. Market and social planner's wages are the same and so are relative sector productivities.*

The knowledge spillover measures also a wedge between the social and the private rates of return to labor, in other words, a market inefficiency.

3 Estimation Procedure

There has been some discussion in the literature as to how knowledge spills over from one industry to another, whether through intermediate goods (supplier-driven spillovers), customer linkages, or directly when productive processes are similar, even though products may be very different and the industries not transact with each other.[9] A matrix of estimated learning parameters ought to shed some light on this point.

In order to recover the learning parameters I will follow an estimation strategy that assumes constant returns to scale and perfect competition, and that stems directly from the relationship between rates of growth implied by the production function:

$$\dot{Y}_i = \beta_{iK}\dot{K}_i + \beta_{iM}\dot{M}_i + \beta_{iL}\dot{L}_i + \sum_{j=1}^{n}\gamma_{ij}\dot{L}_j$$

where $\dot{Y}$, $\dot{K}$, $\dot{M}$, and $\dot{L}$ are, respectively, the growth rates of the *index* quantities of output, physical capital, intermediate inputs, and labor inputs.

Stage 1: To perform the estimation of the learning parameters, I use the Tornqvist index of Total Factor Productivity (TFP), a discrete-time approximation to the Divisia index. TFP in each period is given by the difference between the growth rate of output and the growth rate of all inputs, each weighted by its average cost-share:

$$T\dot{F}P_i = \dot{Y}_i - \overline{S}_{iK}\dot{K}_i - \overline{S}_{iM}\dot{M}_i - \overline{S}_{iL}\dot{L}_i,$$

where $T\dot{F}P_i$ is the growth rate of TFP for sector i[10] and $\overline{S}_{iK}$, $\overline{S}_{iM}$, and $\overline{S}_{iL}$ are the average between-period shares of each input.[11] Given that under perfect competition

[9] Bernstein & Nadiri (1988) note that industries that "borrow" other industries' knowledge without transacting with them are usually industries where the rate of technological change is moderate to high.

[10] Approximated by the difference in the natural logarithms of current TFP and TFP in the previous period.

[11] Also calculated using index prices and index quantities.

output elasticities are equal to factor shares, $\beta_{iK} = \overline{S}_{iK}$, $\beta_{iM} = \overline{S}_{iM}$, and $\beta_{iL} = \overline{S}_{iL}$, we can rewrite it as:

$$T\dot{F}P_i = \sum_{j=1}^{n} \gamma_{ij} \dot{L}_j,$$

that is, the actual (observed) productivity growth equals the productivity growth predicted by the model's production function. The variation of the residual associated to sector i is the sum of each sector's variation in employment weighted by sector i's learning parameters (i.e. by what sector i learns from each sector, including itself). It measures the *costless* gains to sector i from the overall employment of skilled labor. Therefore, the residual is not a non-parametric method for estimating a fixed parameter of the production function, but the reflection of a process.

Stage 2: Recover the learning parameters minimizing the distance between predicted and observed TFP growth, subject to values of the sum q_i determined *ex-ante* and to a non-negativity constraint. For each period t ($\bar{t} \geq n$ guarantees a unique solution) I use annual growth rates computed from the five-year central moving averages of observed annual data. This eliminates or, at least, moderates the unwanted short-term effects of business cycles on the model's productivity estimates (Bartelsman, Caballero & Lyons 1994), that will *not* reflect changes in the rate of utilization of inputs. The problem is then to choose parameters $\gamma_{i1}, \gamma_{i2}, ..., \gamma_{in}$, for each sector $i = 1, 2, ..., n$, to

$$\min \sum_{t=1}^{\bar{t}} \left[T\dot{F}P_{it} - \sum_{j=1}^{n} \gamma_{ij} \dot{L}_{jt} \right]^2,$$

subject to

$$q_i = \sum_{j=1}^{n} \gamma_{ij} \text{ and } \gamma_{ij} \geq 0, \forall i, j.$$

4 Data

The panel data set used in the estimation is an update on Dale W. Jorgenson's original sectoral input-output database for the 1948-1979 period, also described in Jorgenson & Stiroh (2000), Jorgenson (1990), and Jorgenson et al. (1987). It covers the whole of the U.S. civilian economy[12] and consists of annual observations on the value and the price of output and quality-adjusted inputs for 35 industries at roughly the 2-digit Standard Industrial Classification (SIC) level from 1948 to 1991.

By using a data set that disentangles the quantity and quality effects of inputs, I ensure that the estimated TFP term will only capture the effects of costless spillovers, not of embodied technical change. For the same reason, estimates of knowledge spillovers are free from the upward aggregation bias associated with internal shifts in the composition of the inputs,[13] and computed TFP growth becomes a lot smaller (Jorgenson & Griliches 1967). In general, the use of quality-adjusted data allows us to distinguish between factor augmentation and TFP growth, which can then be safely attributed to factor augmentation (Jorgenson et al. 1994). In particular, accounting for the quality of the labor force is important as the majority of previous studies were not able to distinguish between marginal productivity (i.e. quality) improvements and spillovers proper.[14]

The sectoral TFP indexes measure the value-added output per combined unit of capital (K), labor (L), energy (E), and materials (M) in private business. The use of value added is more advantageous than gross output measures because industrial value added always sums up to total value added (GDP), independently of the degree of vertical and horizontal integration and of the proportion of intermediate goods used in

[12] Gross of capital depreciation and including the government sector and the flow of services from consumer durables.

[13] E.g. the compositional bias due to a shift from long-lived equipment in the capital stock, or the bias due to the shift toward a more educated workforce with higher marginal product.

[14] According to Jorgenson & Stiroh (1994) and Jorgenson et al. (1994) about ten percent of the growth of the US economy in between 1947 and 1989 is due to increases in labor quality, which is the *source* of the spillover, but not the spillover itself.

production.[15] Intermediate inputs (energy plus materials) are treated symmetrically to capital and labor, thus taking into account substitution possibilities among *all* inputs.[16]

The labor series in the data correspond to hours worked adjusted for changes in their composition by age, sex, education, employment class, and occupation. Growth in labor input reflects the increase in labor hours, as well as changes in the composition of hours worked as firms substitute among heterogeneous types of labor. Growth in labor quality is defined as the difference between the growth in labor input and hours worked.

Capital stocks are estimated applying the perpetual inventory method on investment data from the Bureau of Economic Analysis. Capital stocks are then aggregated using rental prices as weights (Jorgenson & Griliches 1967). The price estimates incorporate differences in asset prices, service lives and depreciation rates, and the tax treatment of capital incomes.[17] The growth in capital quality is the difference between growth in capital services and capital stock; as with the labor input, this represents substitution towards assets with higher marginal products.[18]

Grouping of Industries into Sectors

After eliminating government enterprises, the remaining 34 industries have been aggregated into six larger sectors to use in the estimation. This six-sector economy follows the division drawn by Long & Plosser (1983) when analyzing real business cycles: Manufacturing (M), Mining (N), Construction (C), Services (S), Trade &

[15] Aggregate value-added is immune to the kind of aggregation bias that occurs when sectoral share-weights change with the reallocation of GDP among sectors with different TFP levels and growth rates, creating a path dependence problem for the aggregate productivity index.

[16] Conceptually, TFP derived this way is closest to the producers' approach. Moreover, value added will not change wether outsourcing takes place.

[17] Note that it is not necessary to assume constant returns to scale as long as we use an independent measure of the return to capital to construct the share-weights in the estimates of sectoral TFP (Hulten 1973, 2000), as is the case here.

[18] The shift toward IT, for example, increases the quality of capital, since computers, software, and communications equipment have relatively high marginal products.

Transportation (T), and Agriculture (A). The industrial composition of each sector can be seen in Apendix A.

Aggregation of industries into a smaller number of sectors generates, on the one hand, an increase in the heterogeneity of the labor input (by *type* and *level* of knowledge) and, on the other, an increase in the magnitude of sectoral spillovers q_i, as more sources of spillovers "pile up" in a given sector.[19]

Magnitude and Ranking of Sectoral Spillovers

Finally, the estimation requires an acceptable range for the value of knowledge spillovers received by each sector q_i. This range is set by empirical results in previous literature, where differences arise from assumptions regarding inputs or from the level of aggregation used. They are summarized as follows:

Authors	Implied q_i
Hall (1988, 1990), Domowitz, Hubbard & Petersen (1988), Caballero & Lyons (1992), Baxter & King (1991)	0.40 - 0.60
Morrison (1993), Bartelsman, Caballero & Lyons (1991, 1994)	0.12 - 0.30

The earliest estimates imply that q_i lies somewhere in between 0.4 and 0.6. However, these methodologies ignore the share of intermediate goods and, hence, produce estimates that are too large.[20] Clearly, intermediates themselves are produced with markups or externalities and under increasing returns that pile up in aggregation. The authors in the second group use aggregated gross output measures weighted to reflect the immediate suppliers or customers of the industry and obtain lower estimates. The large aggregation levels at which both groups work must also be taken into account.

The acceptable range for our q_i ought to be, then, closer to the second group's

[19] A sector's spillovers will reflect the combined effect of spillovers within the individual industries and the induced effects on those industries of intermediate inputs produced themselves with spillovers. Basu & Fernald (1997) suggest most estimates of returns to scale suffer an upward aggregation bias whether the estimation uses gross or value-added output data.

[20] See Basu & Fernald (1995, 1997) for criticism to these earlier estimates.

estimates but start at a lower level, given that the model will be estimated for a six-sector economy. Once the *range* of the sectoral spillovers has been delimited, sectors are ranked *ordinally* according to their learning potential, proxied by the proportion of labor employed in their R&D section,[21] and assigned a corresponding level of q_i:

Ranking	Sector		q_i
1	Manufacturing	M	0.30
2	Services	S	0.25
3	Mining	N	0.20
4	Trade & Transportation	T	0.15
5	Construction	C	0.10
6	Agriculture	A	0.05

The interested reader can see Apendix B for a more thorough description of the data and method used in the ranking.

5 Results: A Matrix of Knowledge Flows

The estimated results for the learning parameters, expressed as percentages of the total sectoral spillover q_i, are reported in Table 1, in the form of a matrix of intra- and inter-sectoral spillovers flowing from sectors of origin j to sectors of destination i. The solid line encapsulates sectors into the three larger divisions of the economy: the primary sector (agriculture), industry or the secondary sector (manufacturing, mining, construction), and the tertiary sector (trade & transportation, services).

The findings in this table can be summarized as follows:

i. All sectors receive spillovers from, at least, one other sector in the economy, although not all sectors generate spillovers back into the economy.

ii. Most flows occur *between* industry and the tertiary sector, industry being the most dynamic both internally and externally (that is, industry generates and receives most flows). In particular, manufacturing and trade & transportation are the only sectors to learn from each other.

[21] Mansfield, Romeo, Schwartz, Teece, Wagner & Brach (1982) argue that producing "inventions" is not the only objective of R&D: firms use R&D as a device to *recruit* and *train* people who eventually will move on to general management. Also, R&D not only transfers research findings, but often includes activities that are essentially technical service for parts of the firm (or even for customers or suppliers).

iii. Manufacturing is the one and only sector to learn from itself. Moreover, manufacturing learns more from its own productive experience than from any other single sector or from the rest of the economy as a whole.

iv. From the outflow perspective, manufacturing and trade & transportation are the main source of spillovers in the economy. Services and agriculture, on the other hand, do not contribute at all to the generation of knowledge, neither internally nor externally.

v. From the inflow perspective, mining, construction, and trade & transportation are completely dependent on one single sector for the totality of their spillover. For both construction and trade & transportation this unique source is manufacturing.

I have performed a series of robustness checks on the estimates of the learning parameters, such as setting all sectoral spillovers to the same value ($q_i = q \ \forall i$) and going through the whole range (fully constrained case); dividing the whole period in two equal-length independent sub-periods; increasing the level of aggregation from six to three sectors and estimating for all values of q; imposing q_i ex-ante but allowing the individual learning parameters to acquire positive, negative or zero values; and lifting all restrictions on both q_i and the learning parameters. For the last two checks I obtain some negative parameters, although signs do not maintain any sort of consistency.

As for the value of the objective function, it is always larger for the fully constrained case, which is the only case for which each and every parameter estimation falls within the range of credibility consistent with previous empirical studies. It is also the case that exhibits the most stable parameter estimates for all values of $q_i \ \forall i$.

Observed Transmission Channels

In this section, I compare the matrix of estimated knowledge flows with, successively, a matrix of worker flows and a matrix of technology flows. Any industry employing skilled labor ought to benefit from labor-generated spillovers. When knowledge is embodied in workers, it is measured as an input and weans off productivity measures: skills, experience and training "travel" with workers moving within and among sectors.

When knowledge is considered in its disembodied form, however, it can be treated either as an input (expenditure on R&D, patents bought) or an output (patents produced), it can be transferred with technology flows within and among industries, and proxied by measures of production *and* use of patents.[22]

Labor Flows

To examine whether embodied knowledge flows are the main source of spillovers I compare the matrix in Table 1 with the equivalent matrix of average worker flows in Table 3. To construct the transitional labor flow matrix I use a dataset created by Maury Gittleman, of the Bureau of Labor Statistics, that consists of March to March matches of the Current Population Survey (CPS) from 1968 to 1992. The interested reader can see Apendix C for a more detailed description of data and procedure.

Overwhelmingly, most of the turnover occurs within the same sector, for all sectors. Most sectors receive negligible inflows from manufacturing, services or trade, and the remaining sectors generate even smaller outflows.

Technology Flows

Table 4 reports technology flows measured as the expenditure in R&D and patent production (origin) and the use of patents. It is constructed using data collected by Scherer (1984) on companies' expenditures on R&D for the fiscal year 1974. Clearly, Manufacturing is the main generator of technology inflows for all sectors, followed at a respectable distance by Construction & Services, that generate a small contribution to all sectors. No other sectors generate a important outflows.[23]

Comparison

The matrix of relative learning parameter estimates is more similar to technology

[22]Embodied technology flows embodied in capital or intermediate goods are already picked up by input quality changes and will *not* affect measures of TFP.

[23]I use Kortum (1995) data set on the number of U.S. and total patents applied for in the U.S. from 1957 to 1983, which uses the same 35-sector industrial classification, to update Table 4. Assuming changes through time in the ranking of sectors of origin are mirrored by equivalent changes in sectors of use, the updated matrix of technology flows looks very much like Table 4.

flows than worker flows. While sectoral labor transitions proxy flows of embodied knowledge and occur mostly *within* sectors, information contained in patents and R&D is disembodied knowledge and travels mostly *between* sectors. As with the estimated matrix of knowledge flows in Table 1, manufacturing and the tertiary sector in Table 4 are the net sources of knowledge in the economy. This would drive us to conclude that labor generated knowledge spills over mostly through disembodied technology flows.

6 The Productivity Slowdown of the Early Seventies and the Shift in Spillovers

The matrix of knowledge spillovers in Table 1 helps us interpret the TFP residual; but does it contribute to explain the productivity slowdown of the early seventies? Was the productivity slowdown associated with any change in the creation or the absorption of knowledge?

The slowdown has been attributed to a large number of competing reasons. Explanations range from the reduction in real company financed R&D (Scherer 1984) to the incorrect measurement of output (especially in services). According to a different view (Greenwood & Yorukoglu 1997, Kortum 1997, Bessen 2002, Comin 2002), the productivity slowdown saw the underlying rate of technological change speed up. Alternatively, the slowdown has been explained as a consequence of the stagnation of the growth in the quality of human capital (Jorgenson et al. 1987, 1994).

In this model, fluctuations in total factor productivity of sector i can be attributed to any combination of the following: a slowdown in the growth rate of L_i; a decline in the spillover $\prod_{j=1}^{n} L_j^{\gamma_{ij}}$, and, hence, to a decline in L_j for $j \neq i$ or to smaller learning parameters γ_{ij}. I check wether data support any of this possibilities and I find that correlation between TFP_i and L_i is........................ Correlation between TFP_i and L_j is .... To see whether there has been a change in the creation or absorption of knowledge within and among sectors I split data into a pre-73 and a post-73 period, and do an independent estimation of the set of learning parameters for each. The resulting matrices are presented in Tables 5 and 6.

After 1973,

i. Within sector knowledge transfers disappear for all sectors but for Trade & Transportation.

ii. Industry becomes completely dependent on Trade & Transportation, now the main generator of knowledge spillovers to the economy.

iii. Manufacturing and, to a lesser extent, Construction and Services, cease generating knowledge for the rest of the economy.

iv. Only Services benefit from knowledge generated by Manufacturing.

7 Is the market efficient?

Clearly, the market does not allocate labor among sectors in an optimal way; the wedge between the social and the private rates of return to labor, the spillover generating input, is reflected in the sectoral residuals via the knowledge spillovers (i.e. the learning parameters). This market inefficiency is reflected in Table 8 for the whole period and in Tables 9 and 10 for the pre- and post-73 periods, respectively. These figures are not to be taken literally, but as an indication of the directionality and relative magnitude of market inefficiencies.

It is important to note that in this model only the market's allocation of labor can be improved upon, whereas the competitive allocation of capital and intermediates, the inputs that do not generate spillovers, is already optimal.

According to the model's estimates for the whole period, it would be optimal to increase the number of workers the market allocates to manufacturing by 32%, raising this sector's output by 8%. Except for Mining -where employment would increase by 12%- and Services -where it would remain practically unchanged- it would be optimal for all other sectors to shed workers. Thus, Manufacturing's share of total employment would go from 30% to 40%; wages in all sectors, except for Mining and Services, would increase by, at least, 18%, with workers in Manufacturing perceiving wages 37% above market; and production economy wide increasing by 1%.

If this model's results seem a bit excessive, they can be compared to those obtained by Bernstein (1988) by estimating spillovers of R&D capital (physical & human) and their private and social rates of return for seven Canadian two-digit SIC industries from 1978 through 1981. He finds that intra- and inter-sectoral spillovers affect production costs and the structure of production. He also finds that spillovers create a wedge between the private and the social rates of return to the spillover-generating input. Table **??** shows that his results and my estimations coincide broadly. He uses industries at a more desaggregate level, which puts the value of his spillovers below 0.2. The ratio of the social to private rates of return is substantially higher for the Canadian industries because a larger propensity to invest in R&D capital unambiguously leads to high intra-industry spillovers, which account for most of the differential between the social and private rates of return. Whereas in the paper investing in (employing) high-quality human capital does lead to larger intra-sectoral spillovers, *but* their upward impact on the social rate is dampened by the simultaneous downward pressure of higher cost-weighted shares of labor β_L.

8 Conclusions

In this paper, I perform a two-stage measurement of spillovers, which shows that from 1948 to 1991 the Manufacturing sector generated knowledge for all sectors, being the main engine of growth. I find that labor generated knowledge flows coincide with the patterns of other information flows, as patents and R&D, which are flows of disembodied knowledge.

I also find the productivity slowdown coincides with a change in the pattern of generation and diffusion of spillovers. After 1973 Manufacturing stops being the engine of growth and Trade takes over as the main generator of knowledge spillovers to the economy; intra-sectoral spillovers diminish.

The market allocates resources inefficiently, as spillovers are measured to be significant. More resources should go to the main spillover generating sector, that is, manufacturing, so that employment in this sector increases by 32%, and output by 8%; and wages in all sectors, excep for Services and Mining.

Further research will extend static model to a dynamic, Olley-Pakes type setup, account for investment in human capital in the estimation of the production function.

This paper has estimated a model of labor generated knowledge spillovers. The main purpose has been to establish the basic facts about the diffusion of knowledge across industrial sectors. A finding of this paper is that the productivity slowdown in the early seventies in the US is associated with the decline of spillovers within industrial sectors in favor of spillovers between sectors. Although workers' turnover happens within each sector, disembodied knowledge circulates increasingly between sectors. This change parallels the uprising of the tertiary sector as the main generator and supplier of knowledge in the economy. A matter of future research is to explain this puzzling evidence, namely, why the productivity slowdown is associated with the integration of industrial sectors with each other.

Appendix

A Industry Classification

Jorgenson	SIC (1987)	6-sector Economy
1 Agriculture, fisheries and forestry	01,02,07,08,09	A
2 Metal mining	10	N
3 Coal mining	12	N
4 Oil and gas extraction	13	N
5 Non-metallic mining	14	N
6 Construction	15,16,17	C
7 Food and kindred products	20	M
8 Tobacco	21	M
9 Textile mill products	22 less 225	M
10 Apparel	23,225	M
11 Lumber and wood	24 less 2451	M
12 Furniture and fixtures	25	M
13 Paper and allied	26	M
14 Printing, publishing and allied	27	M
15 Chemicals	28 less 282	M
16 Petroleum and coal products	29	M
17 Rubber and misc plastics	30,282	M
18 Leather	31	M
19 Stone, clay, glass	32	M
20 Primary metal	33	M
21 Fabricated metal	34 less 348	M
22 Machinery, non-electical	35	M
23 Electrical machinery	36	M
24 Motor vehicles	371	M
25 Transportation equipment & ordnance	348,2451,37 less 371	M
26 Instruments	38	M
27 Miscellaneous manufacturing	39	M
28 Transportation	40 to 47 less 43	T
29 Communications	48	S
30 Electric utilities	491	S
31 Gas utilities	492	S
32 Trade (retail and wholesale)	50 to 59	T
33 Finance, insurance, and real estate (FIRE)	60 to 67	S
34 Services	70 to 89	S
35 Government enterprises	91 to 99, plus 43	-

B Ranking of Sectoral Spillovers q_i

The data I use to rank the paper's six sectors by their capability to learn was constructed by Hadlock, Hecker & Gannon (1991). Their data on R&D employment is derived from the Bureau of Labor Statistics Occupational Employment Statistics (OES) program, which provides current occupational employment data on salary and wage workers by industry.[24] The data was collected in 1987, 1988, and 1989 for three-digit SIC industries. These industries are classified as high-tech if their proportion of R&D employment is at least equal to the average proportion for all industries. Then the high-tech industries are divided into two groups: R&D-intensive and R&D-moderate. An industry is R&D-intensive if its proportion of R&D employment is at least fifty percent higher than the average proportion for all industries surveyed. All other industries are R&D-moderate. All high-tech industries also show an above average annual pay level, the more so the higher the proportion of R&D employment in the industry.

This classification results in thirty R&D-intensive and ten R&D-moderate industries. Of the R&D-intensive industries, twenty-four are manufacturing industries, and of the remaining six, five are services industries and one corresponds to mining (crude petroleum and natural gas operations).[25] All ten R&D-moderate industries are in manufacturing.

C Construction of the Transitional Labor Flow Matrix

The Current Population Survey (CPS) contains information on the longest job held the previous year for all matches in between 1967 and 1991, except for 1970-71, 1971-72, 1975-76, and 1984-85 due to technical reasons.

The industry of employment in the first and in the second year of each match is recoded to fall into one of the six sectors of interest: A, C, M, N, S, T, plus U (for Unemployment). Transitional labor flow matrices are then constructed for the whole 1967-1992 period, and for the 1967-1974, 1974-1979, 1979-1984, and 1985-1991 subperiods.

Only individuals that are white, male, aged 25 to 44 in the first year of the match, with 12 or more years of schooling and have worked full-time year-round in both years of the match have been included in the sample. The average frequencies per transition have been constructed using absolute frequencies and the relative weights of each transition with respect to the total number of observations per period or subperiod. That is:

$$W_n = \frac{L_{t+k,t+k+1}}{L_{t,\tau+1}},$$

and

$$f_{ij} = \Sigma_{n=t}^{\tau} f_{ij}(n) W_n,$$

where $i, j = A, C, M, N, S, T$, and t and τ are, respectively, the first and the last "previous year" of every match or transition pair of years in a period. Therefore, $\Sigma_{n=t}^{\tau} W_n = 1$ for each period that spans from year t (previous year) to year $\tau + 1$ (current year).

[24] Only manufacturing industries and selected non-manufacturing industries are surveyed for R&D employment, defined as the number of workers that spend the *majority* of their time in R&D, as determined by their employer.

[25] The industry ranking according to percentage of R&D employment responds to what one would expect: in manufacturing, the top industries correspond to chemical manufacturing, missiles, space vehicles and parts, petroleum refining, computer and office equipment, and instruments (search and navigation, measuring and control devices, medical instruments and supplies, photographic equipment). The service R&D-intensive industries are research and testing, computer and data-processing, and then engineering and architectural services, miscellaneous, and management and public relations services.

D Construction of the Technology Flow Matrix

The paper uses Scherer (1984) data on companies' expenditures on R&D for the fiscal year 1974 to construct a matrix of disembodied technology flows. The time span of the patent sample is the ten-month period from June 1976 through March 1977, because in the US. the average total lag between the invention (moment of R&D expenditure) and the issuance of a patent is assumed to be 28 months (9 months between the conception of an invention and the application for a patent, and 19 months between the application for a patent and its issue). The midpoint in the sample's ten-month period is lagged exactly 28 months from June 30, 1974.

The sample comprises 15,112 patents or, roughly, 61 percent of all patents issued during the sample period to US. industrial corporations. Following a verified and corrected version of the Federal Trade Commission's Line of Business surveys, each patent is classified first by industry of origin, where the R&D expenditures have been recorded. Then these expenditures are carried over or transmitted to the industry(ies) of use via a fairly complicated algorithm. I aggregate Scherer's (41×53) matrix into a (7×6) version in Table 4.

References

Bartelsman, E., Caballero, R. & Lyons, R. (1991), Short and Long Run Externalities. NBER Working Paper No. 3810.

Bartelsman, E., Caballero, R. & Lyons, R. (1994), 'Customer- and Supplier-Driven Externalities', *American Economic Review* **84**, 1075–1084.

Basu, S. & Fernald, J. (1995), 'Are Apparent Productive Spillovers a Figment of Specification Error?', *Journal of Monetary Economics* **36**(8), 165–188.

Basu, S. & Fernald, J. (1997), 'Returns to Scale in U.S. Production: Estimates and Implications', *Journal of Political Economy* **105**(2), 249–283.

Baxter, M. & King, R. (1991), Productive Externalities and Business Cycles. Federal Reserve Bank of Minneapolis, Institute for Empirical Macroeconomics, Discussion Paper No. 53.

Bernstein, J. (1988), 'Costs of Production, Intra- and Interindustry R&D Spillovers: Canadian Evidence', *Canadian Journal of Economics* **2**, 324–347.

Bernstein, J. & Nadiri, I. (1988), 'Interindustry R&D Spillovers, Rates of Return, and Production in High-Tech Industries', *American Economic Review* **78**(2), 429–434.

Bessen, J. (2002), 'Technology Adoption Costs and Productivity Growth: The Transition to Information Technology', *Review of Economic Dynamics* **5**(2), 443–469.

Caballero, R. & Lyons, R. (1992), 'External Effects in U.S. Procyclical Productivity', *Journal of Monetary Economics* **29**(2), 209–225.

Comin, D. (2002), 'Comments on James Bessen's "Technology Adoption Costs and Productivity Growth: The Transition to Information Technology"', *Review of Economic Dynamics* **5**(2), 470–476.

Domowitz, I., Hubbard, R. & Petersen, J. (1988), 'Market Structure and Cyclical Fluctuations in U.S. Manufacturing', *Review of Economics and Statistics* **70**, 55–66.

Greenwood, J. & Yorukoglu, M. (1997), '1974', *Carnegie-Rochester Conference Series on Public Policy* **46**, 49–95.

Hadlock, P., Hecker, D. & Gannon, J. (1991), 'High Technology Employment: Another View', *Monthly Labor Review* **7**, 26–30.

Hall, R. (1988), 'The Relation Between Price and Marginal Cost in the U.S. Industry', *Journal of Political Economy* **96**, 921–948.

Hall, R. (1990), Invariance Properties of Solow's Productivity Residual, *in* P. Diamond, ed., 'Growth, Productivity, Unemployment', MIT Press, Cambridge.

Ho, M. S. & Jorgenson, D. W. (1999), The Quality of the U.S. Workforce, 1948-95. Harvard University, mimeo.

Hulten, C. R. (1973), 'Divisia Index Numbers', *Econometrica* **41**, 1017–1025.

Hulten, C. R. (2000), 'Total Factor Productivity: A Short Biography', *NBER Working Paper No.* **7471**.

Jorgenson, D. W. (1990), Productivity and Economic Growth, *in* Ernst R. Berndt & Jack E. Triplett, eds, 'Fifty Years of Economic Measurement: The Jubilee Conference on Research in Income and Wealth', University of Chicago Press, Chicago, IL.

Jorgenson, D. W., Gollop, F. & Fraumeni, B. (1987), *Productivity and U.S. Economic Growth*, Harvard University Press, Cambridge, MA.

Jorgenson, D. W. & Griliches, Z. (1967), 'The Explanation of Productivity Change', *Review of Economic Studies* **34**, 249–280.

Jorgenson, D. W., Ho, M. & Fraumeni, B. (1994), The Quality of the U.S. Workforce, 1948-90. Cambridge, NBER Summer Institute on Productivity.

Jorgenson, D. W. & Stiroh, K. J. (1994), Investment in Computers and U.S. Economic Growth. Harvard University, Institute of Economic Research, Discussion Paper No. 1707.

Jorgenson, D. W. & Stiroh, K. J. (2000), 'Raising the Speed Limit: U.S. Economic Growth in the Information Age', *Brookings Papers on Economic Activity* **1**, 125–211.

Kortum, S. (1995), Data on Canadian and U.S. Patent Application, 1957-1983.

Kortum, S. (1997), '1974, A Comment', *Carnegie-Rochester Conference Series on Public Policy* **46**, 97–105.

Lieberman, M. (1984), 'The Learning Curve and Pricing in the Chemical Processing Industries', *Rand Journal of Economics* **15**, 213–228.

Long, J. & Plosser, C. (1983), 'Real Business Cycles', *Journal of Political Economy* **91**(1), 39–69.

Mansfield, E., Romeo, A., Schwartz, M., Teece, D., Wagner, S. & Brach, P. (1982), *Technology Transfer, Productivity, and Economic Policy*, Norton, New York.

Morrison, C. (1993), 'Productive and Financial Performance in the U.S. Manufacturing Industries: An Integrated Structural Approach', *Southern Economic Journal* **60**(2), 376–392.

Scherer, F. (1984), Using Linked Patent and R&D Data to Measure Interindustry Technology Flows, *in* Z. Griliches, ed., 'R&D, Patents, and Productivity', University of Chicago Press.

Table 1: Knowledge Spillovers, 1948-1991

Sector of Destination (i)[a]	**Sector of Origin (j)** M	N	C	S	T	A	**Spillover** q_i
M (Manufacturing)	**0.55**	0	0	0	0.45	0	0.30
N (Mining)	0	**0**	0	0	1.00	0	0.20
C (Construction)	1.00	0	**0**	0	0	0	0.10
S (Services)	0	0.30	0	**0**	0.70	0	0.25
T (Trade & Transp.)	1.00	0	0	0	**0**	0	0.15
A (Agriculture)	0	0	1.00	0	0	**0**	0.05

a All entries are percentages over sectoral spillover q_i.

Sector of Destination (i)[a]	**Sector of Origin (j)**[a] M	N	C	S	T	A	**Spillover** q_i
M (Manufacturing)	**0.39**	0	0.33	0.27	0	0	0.30
N (Mining)	1.00	**0**	0	0	0	0	0.20
C (Construction)	0.49	0	**0.51**	0	0	0	0.10
S (Services)	0	0	0	**0**	1.00	0	0.25
T (Trade&Transp.)	0	0	1.00	0	**0**	0	0.15
A (Agriculture)	0	0	0	1.00	0	**0**	0.05

a All entries are percentages over total sectoral spillover q_i.

Table 2: Bernstein's R&D Capital-generated Knowledge Spillovers for Canada, 1978-1981bernstein

Sector of Destination (i)	**Knowledge Spillovers** Intra-sec. γ_{ii}/q_i	Inter-sec. $\sum \gamma_{ij}/q_i$	Total q_i	**Social to Private Rates of Return**[a] $\omega_i^s/\omega^c = 1 + q_i/\omega^c$
Chemical Products	0.84	0.16	0.148	2.27
Electrical Products	0.84	0.16	0.141	2.22
Aircraft & Parts	0.81	0.19	0.114	1.98
Pulp & Paper	0.81	0.19	0.088	1.76
Metal Fabricating	0.75	0.25	0.086	1.74
Food & Beverage	0.77	0.23	0.084	1.72
Non-electrical Machinery	0.71	0.29	0.077	1.66

a $\omega^c = 0.1162$ for all industries.

Table 3: Labor Turnover: Average Worker Flows, 1967-1991

Sector of Inflow (i)	Sector of Outflow (j) M	N	C	S	T	A	U	Total Inflow
M (Manufacturing)	**0.89**	0	0.01	0.04	0.05	0	0	0.30
N (Mining)	0.09	**0.81**	0.02	0.04	0.04	0	0	0.01
C (Construction)	0.05	0	**0.81**	0.10	0.04	0	0	0.05
S (Services)	0.03	0	0.01	**0.92**	0.03	0	0	0.40
T (Trade&Transp.)	0.07	0	0.01	0.06	**0.85**	0	0	0.21
A (Agriculture)	0.04	0	0.01	0.07	0.06	**0.81**	0	0.01
U (Unemployment)	0	0	0	0.51	0	0	**0.49**	0.00
Total Outflow	0.30	0.01	0.06	0.40	0.20	0.01	0.00	

Table 4: Technology Flows: Production and Use of Patents, 1974

Sector of Use (i)	Sector of Origin (j)[a] M	N	C & Serv.	Trade & FIRE	Trans.& P.Util.	A	Total Used
M (Manufacturing)	**0.93**	**0**	0.01	0	0	0	0.36
N (Mining)	0.69	**0.29**	0	0	0	0	0.01
C (Construction)	0.99	0	**0**	0	0	0	0.02
S (Services)	0.94	0	**0.02**	**0**	**0**	0	0.25
T (Trade&Transp.)	0.94	0	0	**0**	**0**	0	0.10
A (Agriculture)	0.94	0	0	0	0	**0.06**	0.03
Final Consumption	0.96	0	0	0	0	0.04	0.23
Total Origin	0.96	0	0.02	0	0	0.01	100π

a. Scherer's classification for sectors of origin does not exactly correspond to our classification. Mining as a sector of origin excludes petroleum and natural gas extraction, activities with a large R&D component. Construction & Services (including R&D); Trade, Finance & Real Estate (Trade & FIRE); Transportation & Public Utilities in the origin correspond, as a whole, to the sum of Services and Trade & Transportation of our sectors of use.

Table 5: Pre-1973 Knowledge Spillovers

Sector of Destination (i)[a]	**Sector of Origin (j)**[a] M	N	C	S	T	A	**Spillover** q_i
M (Manufacturing)	**0**	0	0	0	1.00	0	0.30
N (Mining)	0	**0**	0	0	1.00	0	0.20
C (Construction)	0	0	**0**	0	1.00	0	0.10
S (Services)	0.67	0.33	0	**0**	0	0	0.25
T (Trade&Transp.)	0	0	0	0	**1.00**	0	0.15
A (Agriculture)	0	0	1.00	0	0	**0**	0.05

a All entries are percentages over total sectoral spillover q_i.

Table 6: Post-1973 Knowledge Spillovers

Table 7: Market and Optimal Solutions

Sector	α_i	β_{Li}	γ_{ii}/q_i	q_i	L_i^s/L	L_i^c/L	L_i^s/L_i^c	Y_i^s/Y_i^c	w_i^s/w^c
M	0.41	0.25	0.55	0.30	0.40	0.30	1.32	1.08	1.37
N	0.03	0.23	0	0.20	0.02	0.02	1.12	0.98	0.95
C	0.08	0.37	0	0.10	0.07	0.09	0.76	0.93	1.40
S	0.24	0.39	0	0.25	0.27	0.28	0.99	0.96	1.10
T	0.18	0.51	0	0.15	0.21	0.27	0.78	0.92	1.40
A	0.05	0.27	0	0.05	0.03	0.04	0.71	0.90	1.50

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	q_i	K_i/K	M_i/M	L_i^s/L	L_i^c/L	L_i^s/L
M (Manufacturing)	0.41	0.25	0.09	0.65	0.55	0.30	0.25	0.53	0.40	0.30	1.3
N (Mining)	0.03	0.23	0.36	0.41	0.00	0.20	0.06	0.02	0.02	0.02	1.1
C (Construction)	0.08	0.37	0.08	0.55	0.00	0.10	0.04	0.09	0.07	0.09	0.7
S (Services)	0.24	0.39	0.26	0.34	0.00	0.25	0.42	0.17	0.27	0.28	0.9
T (Trade & Transp.)	0.18	0.51	0.15	0.34	0.00	0.15	0.18	0.12	0.21	0.27	0.7
A (Agriculture)	0.05	0.27	0.15	0.58	0.00	0.05	0.05	0.06	0.03	0.04	0.7

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	q_i	K_i/K	M_i/M	L_i^s/L	L_i^c/L	L_i^s/L
M (Manufacturing)	0.44	0.26	0.10	0.64	0.39	0.30	0.28	0.56	0.42	0.33	1.3
N (Mining)	0.02	0.24	0.36	0.40	0.00	0.20	0.06	0.02	0.02	0.02	1.1
C (Construction)	0.09	0.36	0.07	0.57	0.51	0.10	0.04	0.10	0.07	0.09	0.7
S (Services)	0.21	0.39	0.29	0.32	0.00	0.25	0.38	0.13	0.23	0.23	1.0
T (Trade & Transp.)	0.19	0.54	0.16	0.30	0.00	0.15	0.19	0.11	0.22	0.29	0.7
A (Agriculture)	0.06	0.29	0.14	0.57	0.00	0.05	0.05	0.07	0.04	0.05	0.7

Table 8: Market and Optimal Solutions, 1947-1991

Table 9: Pre-1973 Market and Optimal Solutions

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	q_i	K_i/K	M_i/M	L_i^s/L	L_i^c/L	L_i^s/L
M (Manufacturing)	0.38	0.24	0.09	0.67	0.00	0.30	0.23	0.49	0.36	0.27	1.33
N (Mining)	0.03	0.22	0.36	0.42	0.00	0.20	0.07	0.02	0.02	0.02	1.14
C (Construction)	0.08	0.39	0.08	0.53	0.00	0.10	0.04	0.08	0.07	0.09	0.73
S (Services)	0.30	0.39	0.23	0.38	0.00	0.25	0.46	0.22	0.34	0.35	0.97
T (Trade & Transp.)	0.18	0.47	0.13	0.39	1.00	0.15	0.16	0.14	0.19	0.25	0.79
A (Agriculture)	0.04	0.24	0.17	0.59	0.00	0.05	0.04	0.05	0.02	0.03	0.72

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	γ_{ii}	$\gamma_i - \gamma_{ii}$	γ_i	q_i	K_i/K	M_i/M
A (Agriculture)	0.05	0.27	0.15	0.58	0.00	0.00	0.00	0.00	0.05	0.05	0.06
N (Mining)	0.03	0.23	0.36	0.41	0.00	0.00	0.02	0.02	0.20	0.06	0.02
C (Construction)	0.08	0.37	0.08	0.55	0.00	0.00	0.00	0.00	0.10	0.04	0.09
M (Manufacturing)	0.41	0.25	0.09	0.65	0.55	0.17	-0.06	0.10	0.30	0.25	0.53
T (Transportation)	0.18	0.51	0.15	0.34	0.00	0.00	0.10	0.10	0.15	0.18	0.12
S (Services)	0.24	0.39	0.26	0.34	0.00	0.00	0.00	0.00	0.25	0.42	0.17
Economy-wide pars)	1.00	0.34	0.15	0.50	0.30	0.07	0.16	0.23	0.23	1.00	1.00

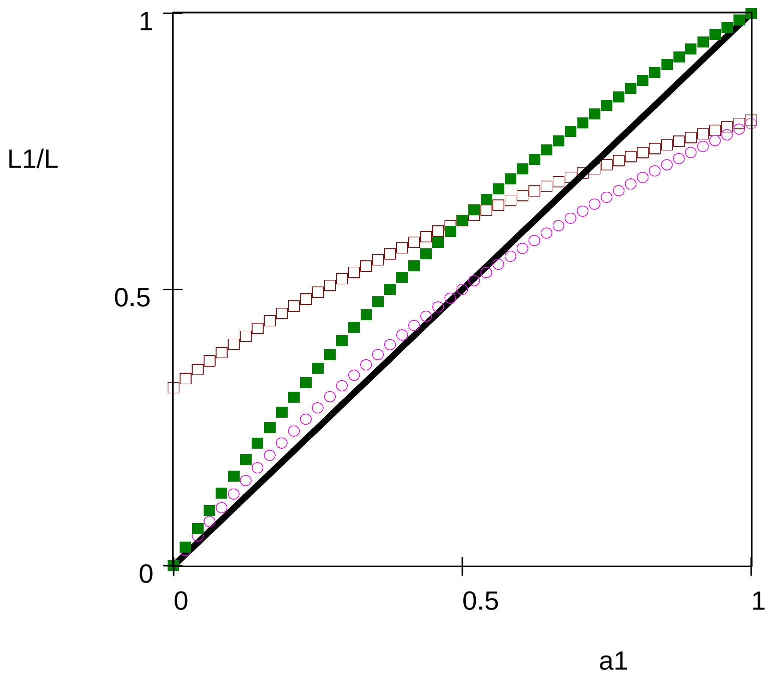
Table 10: Post-73 Market and Optimal Solutions

Table 11: Market and Optimal Solutions, 1947-91

Table 12: Pre-73 Market and Optimal Solutions

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	γ_{ii}	$\gamma_i - \gamma_{ii}$	γ_i	q_i	K_i/K	M_i/M
A (Agriculture)	0.06	0.29	0.14	0.57	0.00	0.00	0.00	0.00	0.05	0.05	0.07
N (Mining)	0.02	0.24	0.36	0.40	0.00	0.00	0.00	0.00	0.20	0.06	0.02
C (Construction)	0.09	0.36	0.07	0.57	0.51	0.05	0.02	0.08	0.10	0.04	0.10
M (Manufacturing)	0.44	0.26	0.10	0.64	0.39	0.12	-0.06	0.06	0.30	0.28	0.56
T (Transportation)	0.19	0.54	0.16	0.30	0.00	0.00	0.05	0.05	0.15	0.19	0.11
S (Services)	0.21	0.39	0.29	0.32	0.00	0.00	0.04	0.04	0.25	0.38	0.13
Economy-wide pars)	1.00	0.35	0.16	0.50	0.25	0.06	0.17	0.23	0.23	1.00	1.00

Sector	α_i	β_{Li}	β_{Ki}	β_{Mi}	γ_{ii}/q_i	γ_{ii}	$\gamma_i - \gamma_{ii}$	γ_i	q_i	K_i/K	M_i/M
A (Agriculture)	0.04	0.24	0.17	0.59	0.00	0.00	0.00	0.00	0.05	0.04	0.05
N (Mining)	0.03	0.22	0.36	0.42	0.00	0.00	0.02	0.02	0.20	0.07	0.02
C (Construction)	0.08	0.39	0.08	0.53	0.00	0.00	0.00	0.00	0.10	0.04	0.08
M (Manufacturing)	0.38	0.24	0.09	0.67	0.00	0.00	0.05	0.05	0.30	0.23	0.49
T (Transportation)	0.18	0.47	0.13	0.39	1.00	0.15	0.00	0.15	0.15	0.16	0.14
S (Services)	0.30	0.39	0.23	0.38	0.00	0.00	0.00	0.00	0.25	0.46	0.22
Economy-wide pars)	1.00	0.34	0.15	0.51	0.12	0.03	0.20	0.23	0.23	1.00	1.00



Market and Optimal Allocation of Labor ($n = 2$, $\beta_{1L} = \beta_{2L}$ and $q_1 > q_2$)