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How Does the Border Affect Productivity? *Evidence from American and Canadian Manufacturing Industries*[*]

Robert Vigfusson[†]

Abstract

This study reports on how much productivity fluctuations are industry specific versus country specific. For the manufacturing industries in Canada and the United States, the correlation between cross-border pairings of the same industry are found to be more often highly correlated than previously thought. Furthermore, the study confirms earlier findings that the similarity of input use can help describe the comovement of productivity fluctuations across industries.

Keywords: productivity, comovement, border effects
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1 Introduction

A national border often appears to reduce the comovement between economic variables that are on opposite sides of the border. This reduction is called the border effect. This paper examines whether the border affects industry-level productivity fluctuations. Knowing whether the border effect extends to productivity fluctuations would be of interest for several reasons. Evidence either for or against a border effect would help us understand the true nature of these productivity fluctuations. Evidence that productivity fluctuations are industry-specific shocks that affect industries equally on either side of a national border would be evidence in favor of interpreting productivity fluctuations as being caused by changes in technology. Such a finding would, therefore, support using these industry-level measures to examine technology-driven explanations of economic fluctuations (as in Basu, Fernald, and Kimball. 2005). Evidence

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of a large country-specific factor would emphasize the need to gain greater understanding of the role of government, culture and other country-specific factors in determining industry-level productivity.[1]

The current paper describes a study of the productivity growth of manufacturing industries in Canada and the United States. Because these two countries are similar, one might expect to find no border effect.[2] Studies of both trade and prices, however, find border effects. McCallum (1995) and Helliwell(1996) find large border effects for trade. Recent work by Anderson and Van Wincoop (2003) suggests that the border effect is smaller than is reported by McCallum and Helliwell, but that the border still reduces trade 44 percent. Engel and Rogers (1996) find a border effect for Canada and the United States for prices. Furthermore, Costello (1993) studies the cross-country industry-level productivity correlations for some OECD (Organization for Economic Co-operation and Development) countries. In her study, none of the correlations between Canadian and American versions of the same industry are statistically significant. Because several pairs of American industries and several pairs of Canadian industries had significant correlations, Costello's finding of no significant cross border correlations can be interpreted as evidence of a considerable border effect.[3]

In this paper, the KLEMS data sets from Statistic Canada and the U.S. Bureau of Labor Statistics are used to measure productivity.[4] These data sets are what the respective statistical agencies use to measure multifactor productivity in the manufacturing industries. The acronym

[1] If productivity fluctuations do not depend on industry characteristics but rather are country-specific phenomena, would this finding be evidence against technology-driven models? If one could further identify that these productivity fluctuations are being driven by demand factors, then this additional finding would be evidence against technology-driven models. However, technology-driven models would be compatible with country-specific technological factors driving the business cycle.

[2] Although the countries are similar, Baldwin and Sabourin (1998) report survey evidence that Canadian and American firms differ on their views on technology adoption.

[3] Costello does not use the term *border effect*; however, I would describe her finding that "productivity growth is more correlated across industries within one country than across countries within one industry" (p. 207) as evidence of a border effect.

[4] One desirable extension of this research would be to compare industry-level productivity fluctuations across regions in the United States with each other and Canadian industries. Unfortunately, the data are not available to do such a comparison.

KLEMS stands for capital, labor, energy, materials, and business services. For each industry, the data set reports both an index of the amount used (the volume) and the nominal expenditure (the value) on any given input. The data set also reports the value and volume of each industry's gross output.

An important contribution of this study is that it uses information on intermediate inputs to construct productivity.[5] Other productivity studies, including Costello (1993), use data sets that lack information on intermediate inputs. Because productivity is measured as a residual, omitting any variables may result in an inaccurate measure.[6] In particular, Basu and Fernald (1995) argue that using data only on capital and labor to measure productivity can result in an inaccurate measure that overstates the degree of cross-industry comovement. Another advantage of the KLEMS data set is that because it has more industries, the study reports the correlations of ten additional industries beyond the five studied in Costello. The increased coverage of the KLEMS data set results in finding more positive correlations than are found for a data set restricted to Costello's original five.

Another advantage of calculating productivity with data on intermediate inputs is that this method allows a reassessment of Conley and Dupor (2003), who study the industry-level comovement of productivity growth rates in the United States. Conley and Dupor construct their productivity series by using information on the changes of output, labor, and capital services (measured using electricity usage). Because U.S. data on material usage is not available at the quarterly frequency, Conley and Dupor can not use material usage data to construct their quarterly productivity series. Conley and Dupor's finding of a high degree of comovement could be subject to the criticisms of Basu and Fernald (1995). In particular, Basu and Fernald report that the earlier comovement results of Caballero and Lyons (1992) were highly dependent on constructing productivity without using data on material usage.

Conley and Dupor's comovement results are important because they provide an organizing principle for the observed empirical comovement patterns. In particular, Conley and Dupor

[5] Other papers, such as Basu, Fernald, and Kimball (1999), gave used intermediate inputs to construct productivity measures but have not looked for border effects.

[6] Appendix A provides details.

provide evidence that comovement between industries depends on the similarity of the inputs that each industry uses. (Although they have no quarterly data on intermediate input use, Conley and Dupor can classify industries by input use from the input-output tables. These benchmark input-output tables, however, are available only every five years.) Comovement has often been viewed as a defining characteristic of business cycles. Insights into comovement, therefore, should lead to a better understanding of business cycles. Confirmation of Conley and Dupor's results would emphasize the need for further investigation into how input usage leads to comovement. As one step in that investigation, I present a simple model that implies that comovement will depend on input usage.

The empirical evidence presented here confirms Conley and Dupor's results in two crucial ways. First, constructing the productivity series from data on material usage does not qualitatively change the observed comovement patterns in the United States. Second, the dependence on input similarity is not restricted to the United States. In Canada, comovement also depends on input similarity.

This study differs from others in the literature in that it reports results for three different productivity measures– labor productivity, multifactor productivity as reported by the national statistical agencies, and an estimated productivity series that controls for the possibility of non-constant returns to scale and varying unobserved utilization. Each measures has its relative advantages; but all three measures have similar results for productivity comovement.

In providing evidence concerning productivity comovement, this study uses instrumental variables to estimate returns-to-scale in production. These estimates are of independent interest and have been part of a large literature (e.g. Burnside, 1996). For the U.S. industries, statistical tests fail to reject the null hypothesis of constant-returns-to scale. For Canadian industries, statistical tests reject the null hypothesis of constant-returns in favor of increasing-returns to scale.

The rest of the paper has the following structure. Section 2 describes the data and some of the measurement issues in constructing productivity series. Section 3 reports correlations between industry pairs to provide evidence against earlier claims of a large border effect. Section 4 shows how, as in Conley and Dupor (2001), using information on input usage can concisely summarize the comovement patterns found in the data. Furthermore, this section shows that variation in input usage has a larger effect on correlations than does border separation. Section 5 offers conclusions and provides suggestions for future research.

2 How to Measure Productivity

Productivity measures how much output can be produced for a given amount of inputs. The standard approach is to linearize a production function and thereby express the growth in productivity dz as the growth in output dy minus the growth in inputs. Three measures of productivity are considered here. Beginning with the most general, output Y is produced by function with inputs: technology Z, capital services K, labor services L, and intermediate inputs (energy E, materials M, and business services S).

$$Y = F(K, L, E, M, S, Z)$$

Linearizing the production function results in the following equation that relates the growth rate in productivity dz as the difference between the growth rates of output dy and $d\chi$ the weighted sum of the growth rates of capital services dk, labor services dl, energy de, materials dm, and business services ds

$$\begin{aligned} dz &= dy - d\chi && (1) \\ d\chi &= \gamma_k dk + \gamma_l dl + \gamma_e de + \gamma_m dm + \gamma_s ds && (2) \end{aligned}$$

The output elasticities γ are calculated in several different ways. Statistics Canada and the BLS in calculating their productivity measure – multifactor productivity (MFP) – they assume that returns-to scale are constant and that the values of γ_j are the nominal expenditure on an input j as a share of the total nominal value of gross output, s_j resulting in the input growth rate being dx

$$dz^* = dy - dx \tag{3}$$

$$dx = s_k dk + s_l dl + s_e de + s_m dm + s_s ds \tag{4}$$

In the measurement of productivity, the inputs are referred to as capital services and labor services rather than capital and labor. This distinction emphasizes the need to differentiate between changes in output due to changes in inputs and changes in output due to better use of the same inputs. For example, a fixed amount of capital (a particular machine) can be run at a greater utilization rate and thereby provide additional capital services. Therefore, this paper controls for these fluctuations in utilization. In Burnside Eichenbaum and Rebelo (1993), Costello (1993), and Conley and Dupor (2003), changes in capital services are not measured with data on the measured capital stock but are rather approximated by changes in electricity consumption. Because dropping measured capital may be controversial, the approach taken here is based on the work of Basu, Fernald, and Kimball.[7] These authors have two goals – to relax the assumption of constant returns to scale and to correct for utilization. I attempt to meet these goals by estimating the following equation:

$$dz^* = dy - \mu dx + \xi de \tag{5}$$

The coefficients μ and ξ are estimated by an instrumental variables regression. The values of the shares, s_j, are the input shares. Changes in energy usage are used to approximate for changes in capital and labor utilization. The motivation for this approximation is the assumption that energy and input utilization can be varied simultaneously. Given this assumption, a cost-minimizing firm will increase both energy and utilization together to increase output.[8]

[7] Basu and Fernald (2000) discuss other approaches that one can use to approximate for changes in utilization. Their preferred approach, however, requires data on average hours worked per employee which is not available for the Canadian data. Average hours data are available for U.S. industries but not on a KLEMS-compatible basis.

[8] In more formal terms, using energy to approximate for utilization implies that, for empirically relevant values, the output expansion path is an upward sloping line. The assumption would be satisfied if output were

More-restricted measures are often constructed because of data limitations. An alternative approach is to ignore the data on capital usage and focus entirely on the amount of gross output produced using labor. Labor productivity is defined as

$$dz^l = dy - dl \tag{6}$$

The data set studied here is the KLEMS data set for Canada and the United States for 1960-97. Using this data set rather than other options has advantages. First, for any given industry, the statistical agencies construct output and inputs with a goal of being consistent. Other studies that have examined productivity often combine output data reported by one statistical agency with input data reported by another. For example, industrial production from the Federal Reserve is often matched with hours data from the BLS Current Employment Statistics survey. Differences in the industry definition between inputs and output may result in mismeasured productivity.[9] The KLEMS database is less at risk. An additional advantage of using the official KLEMS data sets from the two countries is that others have already studied the comparability of the two data sets. Eldridge and Sherwood (2001) found that the differences for the two data sets are minor and do not contribute substantially to any differences in average productivity growth.

The industries studied here are the two-digit Standard Industrial Classification (SIC) manufacturing industries. These industries can be divided into two groups: the durable goods industries and the nondurable goods industries. Table 1 lists each industry studied in this paper and its corresponding U.S. 1987 SIC code. The Canadian industries are mapped into their U.S. counterparts.

produced, for example, by a homothetic production function (such as Cobb-Douglas) using energy and utilization with constant costs of increasing either input. Basu, Fernald, and Kimball discuss more general restrictions.

[9] Choosing to combine different data sources is one of the many trade offs a researcher must make. For example, choosing to use the KLEMS data set implies that the researcher also chooses to work with annual data.

3 Empirical Results

The empirical results are presented in four parts. First, I describe the estimated coefficients of the production function that are used to construct the estimated productivity series. Second, I report pair-wise correlations for both the estimated productivity series and also the published labor and multifactor productivity series. The pair-wise correlations make clear that the border effect is smaller than had been previously reported. Third, I characterize the dependence of the observed productivity comovement on the similarity of input use. Fourth, I present results for hypothesis testing.

Two approaches are used to measures the dependence of comovement on input use. The first approach estimates a covariance matrix that depends on the input shares of capital, energy, labor, and materials. The second approach looks at material usage more carefully. In particular, the correlation between industries is assumed to depend on the similarity of more-detailed data on material usage. For this second approach, two sets of empirical results are reported. The first set of results is from linear regression of the sample correlation between industry pairs on the distance measure of input use similarity. The second set of results is based on the semi-parametric approach of Chen and Conley and, hence, is closer to the estimation strategies used in Conley and Dupor. Both approaches support the conclusion that the observed comovement is dependent on the similarity of input use. To strengthen these conclusions, several alternative hypotheses are tested. The hypothesis testing confirms that input use is a useful organizing tool. Further refinement, however, is needed.

3.1 Estimation-Based Productivity Series

To compute the correlations between American and Canadian productivity series, I need to estimate the most general production function and the resulting productivity series. As is done in Basu, Fernald, and Kimball and in Conley and Dupor, I characterize the industries as durable or nondurable industries. Using these categories, I then assume that the same set of coefficients applies for all industries from a given country. Therefore, only four sets of coefficients are estimated – Canadian durables, Canadian nondurables, American durables and

American nondurables.

For industry j the productivity series is the residual from the following regression.

$$\triangle \ln y_j = \mu \Delta x_j + \xi \triangle \ln e_j + z_j \tag{7}$$

where Δx is defined as

$$\Delta x_j = s_k \triangle \ln k + s_l \triangle \ln l_j + s_e \triangle \ln e_j + s_m \triangle \ln m_j + s_s \triangle \ln s_j$$

The productivity series is defined as z. The observable variables in the equation are output y, capital k, labor l, energy e, materials m, and services, s. Fluctuations in utilization rates are approximated by changes in energy usage.[10]

The values of the observed inputs may depend on the value of the productivity shock. Therefore, a consistent estimate of equation 5 requires using instrumental variables. For both countries, the estimation process uses five instrumental variables to estimate the four coefficients. For the American industries, the instruments are the current and lagged values of the changes in the log of real U.S. defense expenditure and the current and lagged values of the changes in the log of the IMF spot oil price.[11] An additional instrument is the current value of a monetary policy shock taken from the vector autoregression estimated in Christiano Eichenbaum and Evans (1999).[12] For Canada, the instruments include current and lagged changes in the oil price and the U.S. monetary policy shock. An additional instrument is the current change of non-oil commodity prices. That the Canadian economy responds to commodity price fluctuations is well established. For example, Amano and van Norden (1995) report on the

[10] Some might be concerned that energy usage may reflect weather fluctuations. Because the energy usage data are on a national basis, geographic diversification should limit dependence on weather. In addition, because the data are annual, seasonal fluctuations should be smoothed.

[11] These instruments are common used in the literature including by Basu Fernald and Kimball (2005).

[12] In the Christiano Eichenbaum and Evans paper, the sample period is only from 1964 to 1995. I extend the sample back to 1959 and forward to 1997 to match the span of the KLEMS data. The shocks do result in similar impulse responses. Because of data revisions, the shocks identified here, however, are not identical to the shocks they identify. The correlation between their monetary policy shocks and the ones used here is 0.62.

strong relationship between the Canadian exchange rate and commodity prices. Because the productivity fluctuations may be correlated across industries, the equations for all the industries in a particular country are estimated jointly by using three-stage least squares (two-step general method of moments GMM). The weighting matrix is constructed by using the standard sample covariance matrix. Standard asymptotic confidence intervals are also reported.[13]

Table 2 reports the estimated coefficients. The coefficients do vary between durables and nondurables and between Canada and the United States. For the United States, the return-to-scale estimates are sightly below one, an indication of decreasing returns to scale. However, as indicated by the confidence intervals, one would fail to reject the null hypothesis of constant returns to scale. In Canada, the estimated coefficients are consistent with both kinds of industries having increasing returns to scale, but only the estimate for the Nondurable industries is statistically significant. Furthermore, as discussed in appendix B, an alternative statistical test, one valid under the hypothesis of weak instruments, would fail to reject constant returns to scale even for the Canadian nondurable industries.

For the United States, economists have found different estimates of the relative size of the returns-to-scale in the durable and non-durable goods industries. Basu, Fernald, and Kimball (2005) found that nondurables have lower returns to scale than durables, but Conley and Dupor found the opposite result. Given the wide confidence intervals of the two estimates, the results reported here are insufficient evidence to decide the issue.

The utilization coefficient estimates are always positive, a finding consistent with the theory that energy and utilization move together and that increased utilization leads to higher measured productivity. The estimates, however, are imprecisely estimated. In both Canada and the United States, estimates of the utilization coefficient are larger for the durable goods industries than for the nondurable goods industries. This result suggests a response to the more-cyclical demand for durable goods than for nondurable goods.

[13] Appendix B discusses the possibility of weak instruments and how it might affect the inference concerning the size of the border effect.

3.2 Pair-wise Correlations

This section reports the sample correlations between industry pairs across borders and also for different industries within a country. These correlations are reported for several different productivity measures– labor productivity, the multifactor productivity measures reported by the BLS and Statistics Canada, and the estimated productivity series. In all cases, the measures are constructed by using the BLS and Statistics Canada KLEMS data sets.

Studying sample correlations is analogous to Costello (1993).[14] For Canada and the United States, Costello does not find any statistically significant correlations between an American industry and its Canadian counter-part (own-industry correlation). Costello, however, does report a number of significant correlations for industries that are located in the same country.

Table 3 reports the correlation between the U.S. and Canadian versions of the same industry. This table directly addresses Costello's finding of no statistically significant cross-border own-industry correlations. Of the fifteen industries studied here, labor productivity correlations are statistically significant for nine industries, multifactor correlations are significant for twelve industries, and the estimated productivity series has statistically significant correlations for ten industries. The large percentage of statistically significant correlations suggests that the border effect is less important than Costello claims. A major reason for the different results is the industries studied. The five industries that Costello studies are some of the least likely to have significant cross-border correlations. For the results reported here, both food and textiles are never statistically significant. For all three measures, the chemicals industry is statistically significant. Both primary metals and fabricated metals have statistically significant correlations for the MFP measure. For the estimated productivity series, the fabricated metals industry does have a statistically significant correlation, whereas the primary metals industry does not. Overall, these results suggest that Costello's conclusion of a large border effect is highly dependent on the industries that she studied. Studying a greater number of industries reverses her conclusion and allows us to conclude that the border effect is smaller than previously claimed.

[14] Although the sample period is longer than Costello's, using the shorter sample is not responsible for the results.

3.2.1 Further Diagnostics

Table 4 reports further diagnostics of the productivity series. For each industry, the table reports the standard deviation of the MFP measure and the ratio of that measure to two others – the labor productivity series and the estimated productivity series. One of the standard explanations for mismeasured productivity growth is labor hoarding, in which workers vary their effort over the business cycle. If labor hoarding were a serious issue at the annual frequency, then the labor productivity series would have a much higher standard deviation than the MFP measure. If the estimation procedure actually corrects for the roles of market power and the changes in utilization, then the estimated productivity series should have a much lower standard deviation than the multifactor productivity series.[15]

As reported in Table 4, labor productivity often has a much larger standard deviation than does the MFP. A larger standard deviation is suggestive of a labor hoarding hypothesis. Labor hoarding is most likely to occur in industries with highly skilled workers that are difficult to replace. In both countries, the two industries with the largest ratios are apparel and transportation equipment. That the industry that produces airplanes and automobiles is a high skill industry seems sensible. The high ratio for apparel is perhaps more puzzling because it contradicts conventional stereotypes.

For Canada, the estimated productivity series has, on average, a much lower standard deviation than the MFP measure. The lower value further suggests that the estimation process did correct for the role of utilization. In particular, the standard deviation for the durable goods industries is much lower. It is commonly thought that durable goods industries would be the categories most likely to have large time-varying utilization rates.

Table 4 also reports the ratio of the variance of U.S. industries with their Canadian counterpart. There is evidence of heterogeneity. Some Canadian industries are more volatile than their

[15] The claim may be false if utilization changes and technology changes were negatively correlated. Many macroeconomic models would have a positive correlation. Of course, counter examples do exist. For example, suppose that an increase in utilization results in a greater depreciation rate for capital. In a model with investment adjustment costs, utilization and technology could then be negatively correlated. A reduction in utilization would be way to avoid the investment adjustment costs and to preserve capital for the next period.

American counterparts and some are less volatile. Further work studying this heterogeneity would be useful.

4 Input Usage and Comovement

Conley and Dupor find that input usage helps describe productivity comovement among U.S. industries. Using different data sources and a variety of estimation strategies, I further explore how much input-usage explains productivity comovement. My basic finding is that input usage matters. Furthermore, by examining simultaneously both the border effect and input usage, I am able to characterize the size of the border effect. In particular, industries that are separated by a border and use similar inputs are, on average, more highly correlated than industries that are located in the same country but use dissimilar inputs.

4.1 Economic Modeling

Conley and Dupor present an econometric model in which the covariance between industries is a function of the similarity of input usage. However, they do not explicitly model why input usage might matter.[16] In this section, I present a production function where productivity growth depends on input usage because of input-specific productivity growth. The model is the following: Industry j in country A produces output Y_j by combining inputs x_{ji} in the following production function:

$$Y_j^A = \theta_A \theta_j \prod_{i=1}^{N} (x_{ji} v_i)^{\gamma_{ji}} ,$$

where θ_A is an aggregate productivity term, θ_j is an industry-specific productivity term, and v_i is an input-specific productivity term. For intuition, the reader could think of θ_A as gains due to national infrastructure; θ_j from industry-specific production improvements that are not readily transferable to other industries, such as the steel industry finding an improved way to make steel; and v_i as a general technology that makes better use of a particular input i. Examples of input-

[16] The closest model is Dupor (1996), in which productivity comovement depends on where industries sell their output. The evidence in Conley and Dupor, however, is more supportive of productivity comovement depending on where industries buy their inputs.

specific improvements include vintage capital, human capital, labor-augmenting technological progress, or even something as simple as fewer defects per box of metal fasteners.[17] The log of each of these productivity terms is assumed to be a random walk with the disturbances having a constant variance and being independent of each other. Suppressing time subscripts for notational simplicity, these assumptions can be expressed as:

$$\begin{aligned}
\Delta \ln v_i &= u_i \\
\Delta \ln \theta_j &= \varepsilon_j \\
\Delta \ln \theta_A &= \varepsilon_A,
\end{aligned}$$

where $[u_i, \varepsilon_j, \varepsilon_A]$ are independent both across time and each other with variances $\left\{\sigma_{vi}^2, \sigma_{\theta j}^2, \sigma_A^2\right\}$. The change in the log of industry-level productivity, Δz_j^A, would be the following

$$\Delta z_j^A = \Delta \ln \theta_A + \Delta \ln \theta_j + \sum \gamma_{ji} \Delta \ln v_i$$

Hence, the covariance between any two industries in the same country can be written as follows:

$$\begin{aligned}
E\Delta z_j^A \Delta z_k^A &= E\left(\Delta \ln \theta_A\right)^2 + E\left(\Delta \ln \theta_j \Delta \ln \theta_k\right)^2 + \sum \left(\gamma_{ji}\gamma_{ki}\right) E\left(\Delta \ln v_i\right)^2 \\
&= \sigma_A^2 + \sum \left(\gamma_{ji}\gamma_{ki}\right) \sigma_{vi}^2 \quad \text{if } j \neq k \\
&= \sigma_A^2 + \sigma_{\theta j}^2 + \sum \left(\gamma_{ji}\right)^2 \sigma_{vi}^2 \text{ if } j = k
\end{aligned}$$

[17] Although the BLS does account for changes in skill composition for private business labor productivity, the BLS does not correct for changes in skill composition at the industry-level. (BLS Handbook of Methods, 1997).

An industry that reduces the fraction of defective output would have a measured increase in productivity only if the defective output had not been previously counted as output. Furthermore, if improved inspections reduced the amount of output sold but not produced, then measured productivity would actually fall. In such a case, a lower rate of defective inputs would then show up as an improvement in productivity for the using industry.

Cross-border pairs, with one industry in Country A and one in Country B, are similar – except that they do not share a common aggregate term.

$$\begin{aligned}
E\Delta z_j^A \Delta z_k^B &= 0 + E\left(\Delta \ln \theta_j \Delta \ln \theta_k\right)^2 + \sum \left(\gamma_{ji}\gamma_{ki}\right) E\left(\Delta \ln v_i\right)^2 \\
&= 0 + \sum \left(\gamma_{ji}\gamma_{ki}\right) \sigma_{vi}^2 \quad \text{if } j \neq k \\
&= 0 + \sigma_{\theta j}^2 + \sum \left(\gamma_{ji}\right)^2 \sigma_{vi}^2 \text{ if } j = k
\end{aligned}$$

Assuming perfect competition, constant-returns-to-scale, and industry-level cost minimization, the above Cobb-Douglas production function implies that γ_{ji} equals the industry's expenditure share, s_{ji}. If all the individual input-productivity terms (σ_{vi}^2) have the same variance (σ_v^2), the resulting covariance function would be the following:

$$\begin{aligned}
E\Delta z_j \Delta z_k &= \sigma_A^2 + \sigma_v^2 \sum s_{ji} s_{ki} \quad \text{if } j \neq k \\
&= \sigma_A^2 + \sigma_{\theta j}^2 + \sigma_v^2 \sum \left(s_{ji}\right)^2 \text{ if } j = k
\end{aligned}$$

Therefore, the covariance between two industries is larger for those industries that have more similar input shares because more similar shares implies a larger value for the product of input shares $\sum s_{ji} s_{ki}$.

4.2 Variance Decomposition

In the above model, common movements in productivity are due to both national factors and input usage. This section reports estimates of the model and measures the importance of these contributions.

The above model can be rewritten as follows. Take the observed productivity growth rates Δz_{it} for the n U.S. industries and n Canadian industries and stack these into a vector, Z_t. For this model, when there are two countries and k inputs, the process for these growth rates can be written as follows

$$Z_t = \hat{1} \left[\begin{array}{cc} \varepsilon_t^a & \varepsilon_t^c \end{array} \right] + S_t v_t + u_t$$

where S_t is the observed $(n+n)$ by k matrix of input shares, ε_t^a and ε_t^c are two unobserved country-specific shocks, v_t is the k element vector of unobserved shocks and u_t is a $(n+n)$ element vector of unobserved and uncorrelated shocks (note that k is smaller than $n+n$) and where $\hat{1}$ is the matrix

$$\hat{1} = \begin{pmatrix} 1_{n\times 1} & 0_{n\times 1} \\ 0_{n\times 1} & 1_{n\times 1} \end{pmatrix}$$

where $1_{n\times 1}$ is an n-by-one vector of ones and $0_{n\times 1}$ is an n-by-one vector of zeros. This specification is used to estimate how much of the observed variance of Z_t is due to the country-specific shocks, ε_t^a and ε_t^c, and how much is due to the combined effects of the input-specific shocks u_t. This model is estimated by using maximum likelihood where the likelihood is defined as

$$\begin{aligned} L\left(\Phi, \Upsilon\right) &= \sum_{t=1}^{T} \ln\left((2\pi)^{-n/2} \left|\Omega_t^{-1}\right|^{1/2} \exp\left[-\frac{1}{2} Z_t' \Omega_t^{-1} Z_t' \right] \right) \\ \Omega_t &= \begin{bmatrix} \hat{1} & S_t \end{bmatrix} \Phi \begin{bmatrix} \hat{1} & S_t \end{bmatrix}' + \Upsilon \end{aligned}$$

where Φ and Υ are diagonal matrices. In this section the input-usage S_t is measured using the time-varying input shares for capital, labor, energy, and materials from the KLEMS database. The results of this estimation are reported in Table 5. Both the aggregate shocks and the input-specific shocks make important contributions to the variance of Z_t. However, for both countries and all three measures, the input-specific shocks are more important than the aggregate shocks.

4.3 Correlation Functions Based On Input Usage

This section reports estimates of comovement similar to Conley and Dupor. Unlike the previous section, these results are for correlations rather than covariances. These results are reported for correlation rather than covariance for four reasons. First, covariances are discussed in Section 4.2. Second, correlations are more readily interpretable than covariances. Third, the previous literature in this field (Costello and Conley and Dupor) worked with correlations. Finally, using correlations can result in a more parsimonious model. As is reported in Table 4, the standard deviation of the productivity growth rates varies across industries. Because economy-wide shocks are being used to explain comovement, variations in the standard deviation may cause a problem for the estimation. In particular, the variance of economy-wide shocks is limited by the size of the smallest industry-level productivity growth rate.[18] For all four reasons specified here, the following sections will report results for correlations rather than covariances.

4.4 Econometric Spatial Model

In estimating the covariance between industries, Conley and Dupor assume that the covariance between any two industries can be written as a function c() of input share:

$$E\Delta z_j \Delta z_k = c\left(s_{ji}, s_{ki}\right).$$

Furthermore, they assume that all of the information in the input shares s_{ji} and s_{ki} can be expressed in terms of a measure of economic distance, defined as the Euclidean distance:

$$d_{jk} = \sqrt{\sum \left(s_{ji} - s_{ki}\right)^2}.$$

This specification implies that each industry has a location that is described by the vector s_j that describes its input shares $\{s_{ji}\}_{i=1}^{N}$. The covariance between two industries then depends on the distance d_{jk} between these industries' locations; so $c(d)$ can be estimated with a spatial

[18] An example may help illustrate this point. Suppose that one wants to explain the time series for all of the different industries $\{\Delta z_{it}\}_{i=1}^{n}$ using a single aggregate shock x_t and industry-specific shocks u_{it}. In particular, consider the following time series.

$$\Delta z_{it} = x_t + u_{it}.$$

The variance of Δz_{it} can be written as the following:

$$\mathrm{VAR}\left(\Delta z_{it}\right) = \mathrm{VAR}\left(x_t\right) + \mathrm{VAR}\left(u_{it}\right) + 2\mathrm{COV}\left(x_t, u_{it}\right)$$

However, with the assumption that x_t is uncorrelated with u_{it}, the variance of x_t cannot be larger than the value of $\min \{\mathrm{VAR} y_{it}\}_{i=1}^{n}$. Working with correlations eliminates this constraint. An alternative model would be

$$y_{it} = \alpha_i x_t + u_{it}$$

where α_i is an industry-specific shift term. This term would relax the constraint on the $\mathrm{VAR}(x_t)$. The relaxed constraint would, however, come at the cost of many more coefficients to estimate.

estimator:

$$E\Delta z_j \Delta z_k = c\left(d_{jk}\right).$$

Note, that this distance is an economic distance not a geographic distance.[19]

Although Conley and Dupor use a non-parametric kernel regression to estimate $c\left(\right)$, I estimate $c\left(\right)$ two other ways: a linear regression and the semi-parametric estimator from Chen and Conley (2001). This semi-parametric estimator has the property that, with sign restrictions on the coefficients, the resulting covariance matrix will be positive definite.[20] The Conley and Dupor's non-parametric estimator does not necessarily result in a valid covariance matrix. A positive definite covariance matrix is a requirement for the hypothesis tests reported below.

4.4.1 Input-Output Tables

Before describing the regressions, this section discusses additional data on input usages. In Section 4.2, I measure input usage by the input shares from the KLEMS database. This measure, however, does not differentiate between different kinds of materials. The Input-Output *use* table has more-detailed information on input usage, namely how much of various kinds of materials and labor an industry uses in production. Table 6 reports the U.S. Input-Output table. To reduce the dimension of the space, the Input-Output use table is condensed into a table with eighteen rows – fifteen rows for the manufacturing industries studied here, one row for petroleum, one row for labor, and one for all other industries.[21] Likewise, the aggregated table has fifteen columns representing each industry's use of the inputs. Each element of this table is divided by its associated column sum to make a matrix S of input shares. The element s_{ij} denotes the share of industry j's inputs that come from industry i. Input-similarity between

[19] Geographic distance is not applicable here because the KLEMS data measure productivity for industries, not plants. So there is only one time series for the U.S. auto industry, although automobile production in the United States takes place in many different states.

[20] See Appendix C for more details.

[21] The Input-output *use* table measures what inputs each industry uses. The *make* table measures what inputs each industry produces. Given my interest in inputs, just looking at the *use* table seems reasonable. If instead, I were interested in upstream links between industries, then one would want to combine information from both the use and make tables.

industries j and k, d_{jk} is defined as the Euclidean distance between the two industries' input shares.

Figure 1 reports the distribution of the distance-based measures of input similarity. The distribution has a mass at zero because the distance between an industry and itself is zero. About eighty percent of the distribution is located between 0.25 and 0.6. The number of zero distances is smaller for the cross-border distances because the Canadian and U.S. industries have different input requirements.

4.4.2 Estimation by Linear Regression

The following regression explores the relationship between input-similarity and the correlation between industries:

$$\rho\left(\Delta z_i, \Delta z_j\right) = \beta_0 + \beta_1 d_{ij} + \beta_2 d_{ij}^2 + u_{ij}$$

where $\rho\left(\Delta z_i, \Delta z_j\right)$ is the correlation between productivity growth in industry i and industry j. The distances d_{ij} are based on the input shares in 1992. Table 7 reports coefficients and the R^2 of the regression for each possible set of pairings (i.e. a regression for all Canadian pairs, another for all American pairs, and another for cross-border pairs). The table also reports the F-test of the distance coefficients both being equal to zero. For both countries, input similarity helps explain the pattern of productivity correlations. In particular, the F-test rejects the hypothesis that input similarity does not help. As can be seen by the R^2 statistics, the input-usage information is useful, but a great deal of unexplained variation remains. Whether the unexplained variation comes from omitted explanatory variables or mismeasured productivity growth is an open question. From Figure 2, the decline in correlation as a function of input-similarity is somewhat greater for the U.S. estimates than for the Canadian estimates. The evidence for cross border pairs depending on input-similarity is strongest for the estimated productivity series.

To investigate further the cross-border effects, consider the following direct test of the border effect for all pairs, both within each country and across countries:

$$\rho\left(\Delta z_i, \Delta z_j\right) = \beta_0 + \beta_1 d_{ij} + \beta_2 d_{ij}^2 + \phi_{cross}\delta + u_{ij}$$

where δ equals one if it is a cross border pairing and zero otherwise. Table 8 reports the results. The border effect measured as ϕ_{cross} is largest for the constructed productivity series. With the average correlation between U.S. pairs at 0.27, a decline of 0.07 is somewhat small. The result for the estimated productivity series is statistically significant. The values of ϕ_{cross} found for the other productivity measures are smaller and are not statistically significant.

4.4.3 Estimation by Semi-Parametric Methods

The correlation regressions reported in the previous section may be sufficient proof that (1) the border effect is relatively small and that (2) the correlation between industries is dependent on what inputs the industries use. This section reports additional evidence using the method of Conley and Dupor. One advantage of their method is that it allows for changes in input usage over time. For example, the subcomponents of an industry might change. These changes will be reflected in the industry's input usage and will cause changes in the distance measure of input similarity.

Figure 3 plots correlation functions for all three productivity measures. For each productivity measure, three estimates of $C\left(d\right)$ are reported. One correlation function (the thick black line) is the estimate based on the assumption of no border effect. The second correlation function (the line with circles) reports the correlation between two industries separated by the border. The third correlation function reports the correlation between two industries located in the same country. The thick solid line is the estimate of C(d) found by estimating the following equation:

$$\Delta z_i \Delta z_j = \sum_{k=1}^{4} b_k H_k\left(d_{ij}\right)$$

for all pairings of i and j and with the restriction that $b_{k+1} > b_k$. Appendix C defines $\{H_k\left(\right)\}_{k=1}^{4}$, the set of basis functions for the correlation function, and describes the estimation procedure in more detail. The estimation is a straightforward application of the methods in Chen and Conley and no allowance is made for border effects. The sign restriction on b_k ensures that the correlation matrix is positive definite, which is required to construct confidence intervals. The gray interval is the bootstrap confidence interval.

The confidence interval is constructed by using a procedure described in Chen and Conley. To construct a bootstrap confidence interval, one needs to simulate data. The current simulations use the covariance matrix Ω_t of the productivity fluctuations z_t . However, the covariance matrix depends on the time-varying distances between industries. As such, a vector of i.i.d errors u_t with variance one can be constructed as

$$u_t = \text{chol}\left(\Omega_t\right)^{-1} z_t$$

where chol denotes the matrix operator that maps between a positive definite matrix Σ and its upper triangular Cholesky factorization. A simulation run is constructed by drawing with replacement from the set of the errors $\{u_s\}_{s=1}^{T}$ for each time period a value u_t^* and then multiplying it by the Cholesky factorization of the corresponding variance covariance matrix to get a simulated productivity series

$$z_t^* = \text{chol}\left(\Omega_t\right) u_t^*$$

For each of the 500 simulation runs, the coefficient estimates of C(d) are stored. These simulations are then used to construct a 90 percent confidence interval for the covariance function.[22]

The second set of results allows for two border effects. The first controls for cross-border pairs of the same industry and the second controls for all cross-border pairs of different industries.

$$\Delta z_i \Delta z_j = \phi_1 \delta_1 + \phi_2 \delta_2 + \sum b_k H_k\left(d_{ij}\right)$$

[22] The confidence interval is constructed as follows. First, generate 500 simulations of the statistic of interest x_i where x^* is the empirical estimate of the same statistic. Calculate the differences between the simulated statistics and the empirical statistic. Denote the 5^{th} percentile of these differences as ζ_{low} and the 95^{th} percentile as ζ_{high}. The resulting confidence interval is $[x^* - \zeta_{high}, x^* + \zeta_{low}]$.

where δ_1 equals one when i and j indicate the equivalent industries in the two different countries and δ_2 equals one when i and j indicates non-equivalent industries that are located in different countries. In addition, the restriction of the b_k's is not imposed because these off-diagonal constants imply that the resulting correlation matrix is not necessarily positive-definite. The thin line reports the value of $\sum b_k H_k(d)$ and the line with circles reports the value of $\phi_2 + \sum b_k H_k(d_{ij})$. Hence the difference between the two lines is the value of ϕ_2, the effect of the border.

The figure reports $C(d)$ over the entire range of observed distances. In addition, the dashed lines indicate the interval (0.23,0.70) that contains 90 percent of the non-zero distances. The estimates of C(d) are all fairly steep. For example, within-country industries that use similar inputs (a distance of 0.25) have an estimated correlation for labor productivity of 0.36 which declines to 0.10 when the distance increases to 0.70.

Table 9 reports the cross-border coefficients and the associated sampling uncertainty. The first result is a test of the null hypothesis of no border effect between the same industry in the two countries. These results are generated by using the same bootstrap simulations of the data generating process that made no allowance for border effects. As an additional check, a 90 percent confidence interval for the cross border coefficient is estimated by an alternative bootstrap procedure in which the vector of growth rates is sampled with replacement. This process is typically less efficient (Horowitz 2002) but is valid under the assumption of no serial correlation.

For labor productivity, one would fail to reject the null hypothesis of no same-industry border effect at the 90 percent or higher significance level. For MFP and the estimated productivity series, one would reject the null hypothesis that ϕ_1 equals zero at the 95 percent significance level. For all three productivity measures, one would reject the null hypothesis of no border effect for non-identical industries at the 95 percent significance level. Similar results are found with the 90 percent confidence intervals generated by the alternative bootstrap procedure. On the basis of these tests, the statistical evidence supports the existence of a border effect; cross-border industries are less correlated than similar industries located in the same country. The evidence is weaker for cross-border pairs of the same industry.

Having established statistical significance, the next question concerns the border's economic significance. As mentioned above, the dependence on input similarity shows a fairly strong decline. Industries that use similar inputs (a distance of 0.23) have an estimated labor productivity correlation 0.26 more than industries that are quite dissimilar (a distance of 0.70). Crossing the border results in a 0.14 decline in correlation. Hence, for labor productivity, cross-border pairs that use similar inputs are more correlated than within country pairs that use dissimilar inputs. The border effect is yet smaller for the multifactor and estimated productivity series. Therefore, although the border effect does exist, it is much smaller than Costello's evidence suggests.

Further Hypothesis Testing One might be interested in knowing how well the estimated model matches the unconditional covariance matrix. To test this hypothesis, I us a classical likelihood ratio statistic. The statistic suggests that unexplained influences on the comovement remain. Overall, however, the input-based measure of similarity appears to be a useful organizing principle.

The first measure of model fit is an R^2 statistic. These distance based regressions do have fairly low R^2 statistics: with values of 0.03 for labor productivity, 0.04 for multi-factor productivity, and 0.03 for the estimated productivity measure. However, statistical testing of the null hypothesis of no explanatory power would be rejected because of the large number of observations. An F-test of no statistical significance would have 5 and $(30 * (30 - 1)/2) * 36$ degrees of freedom. As such, given the number of data points, even for the low R^2 statistics reported here, one would reject the restriction of no explanatory power.

If the distance matrix were fixed at a constant value, then the distance based covariance matrix could be viewed as a restricted version of the sample covariance matrix.[23] Furthermore, assuming that the vector of productivity fluctuations are normally distributed implies the following likelihood ratio test (Hamilton, 1994):

$$L(\Omega_U) - L(\Omega_R) = \frac{T}{2}\log\left|\Omega_U^{-1}\right| - \frac{1}{2}\sum_{t=1}^{T} z_t \Omega_U^{-1} z_t - \frac{T}{2}\log\left|\Omega_R^{-1}\right| + \frac{1}{2}\sum_{t=1}^{T} z_t \Omega_R^{-1} z_t$$

[23] I continue to normalize the productivity growth rates by dividing by the sample standard deviations.

With 15 industries in each of the two countries, the number of degrees of freedom is large, with 465 coefficients in the sample covariance Ω_U. The distance-based measure has only the 30 diagonal terms, and the 4 distance coefficients. Hence, the current application has 431 degrees of freedom with a resulting 95 percent critical value of 480.40. Fixing the distance matrix at the 1987 values and assuming no border effects, the estimated likelihood ratio is 536.44 for labor productivity, 504.67 for the multifactor productivity, and 442.93 for the estimated productivity. On the basis of these values, one would reject the null hypothesis that input-usage alone can explain the correlation matrix for either multifactor or estimated productivity. Therefore, as with the low R^2 statistics reported above, the evidence supports unexplained variation in the correlation matrix. Understanding what additional factors or refinements could explain this variation is a topic for future research.

5 Conclusions

The study has made three contributions to understanding industry-level productivity comovement. First, for Canada and the United States, cross-border productivity fluctuations are more highly correlated than had been previously reported. Second, the similarity of input usage can help explain the pattern of covariances between industries, confirming earlier work. Third, a border effect exists. The correlation in productivity growth between similar industries in Canada and the United States is smaller than the correlations between similar industries within a country. In contrast to some border-effect estimates, the difference between cross-border correlations and within-country correlations of similar industries is not overwhelming. In particular, for a given industry, its correlation with a same-country industry that uses dissimilar inputs is less than its correlation with a cross-border industry that uses similar inputs.

These results suggest directions for further theoretical and empirical research. In particular, understanding what factors generate the dependence on input usage could lead to a better understanding of the sources of productivity fluctuations. Perhaps the dependence on input similarity reflects a measurement problem. Improvements in the quality of intermediate inputs could be measured as improved productivity by the users rather than by the producers of the input.

As discussed in Engel and Rogers (2001), the 'first generation' of border-effect papers document the size of the border effect. As Engel and Rogers did for prices, a 'second generation' of papers should explore the economic forces behind border effects for productivity. For productivity, one could follow the example of Evans (2003), who uses firm-level data to better understand border effects for trade. In particular, she examines variations in sales between domestic and foreign multinationals to determine the importance of nationality versus location. If the data were available, a similar study for productivity growth would be informative. In particular, if one could obtain firm-level information on intermediate input usage, then one might begin to understand the dependence on input usage.

A Concerns about Missing Data on Materials Inputs

For many countries, the available data sets (such as the OECD STAN data set), do not have data on intermediate input use. In the United States, no statistical agency publishes data on intermediate input use at frequencies higher than annual. Because productivity growth is measured as the growth of output minus the growth of inputs, missing inputs could therefore lead to a contaminated productivity series. Two different strategies can attempt to deal with this problem. First, production functions can be assumed to be separable. Observed inputs such as labor and capital move together with the missing inputs. The problem with the separability assumption is that counterexamples are easy to find. For example, suppose that the workers vary their effort. When they have work to do, they work. When there is nothing to do, they are still counted as working. In that case, to produce more output, a firm may increase the amount of intermediate inputs without changing the amount of employed labor. Hence, the production function is not separable. The other strategy is to use output that has be constructed with the contribution of intermediate inputs removed – that is, value-added data.

Basu and Fernald (1995), however, showed that these intermediate inputs can still contaminate productivity measures constructed with value-added data. One can use data on intermediate inputs and gross output to measure value added in several different ways. One approach measures value added as the growth rate of output minus the growth rate of intermediate inputs, weighted by expenditure-share. Basu and Fernald discuss other approaches and show that these other methods have more biases. Abstracting away from energy and services, one can express valued added as follows. Assuming constant returns to scale, real gross output can be written as a combination of materials and value added:

$$dy = (1 - s_m)\, dv + s_m dm,$$

where s_m denotes the expenditure on materials as a fraction of total input expenditure. This equation can be rewritten as an expression for value added:

$$dv = \frac{1}{1 - s_m} \left(dy - s_m dm \right).$$

This equation is sensible with perfect competition because it implies that if gross output and materials both increase by one percent, value added will also increase by the same amount. In addition, looking at value added makes sense when looking at aggregate measures, such as GDP.

Notice, however, the implication for the measure of productivity when the elasticity of output with respect to materials γ_m differs from the expenditure share, such as when the industry has increasing returns to scale.

$$\begin{aligned} dv &= \frac{1}{1-s_m}\left((\gamma_k dk + \gamma_l dl + \ \gamma_m dm\ ) - s_m dm\right) + \frac{1}{1-s_m}dz \\ &= \frac{\gamma_k}{1-s_m}dk + \frac{\gamma_l}{1-s_m}dl \ + \ \frac{\gamma_m - s_m}{1-s_m}dm + \frac{1}{1-s_m}dz \end{aligned}$$

But in estimating this equation, one will actually estimate the following equation

$$dv = \gamma_k^v dk + \gamma_l^v dl \ + dz^v \tag{8}$$

where

$$dz^v = \frac{\gamma_m - s_m}{1-s_m}dm + \frac{1}{1-s_m}dz$$

Hence, as long as γ_m does not equal the expenditure share s_m, then the productivity measure will be contaminated with material usage data. Material usage is likely correlated across industries within a country because of demand linkages and aggregate shocks such as monetary policy. Therefore one might expect to find larger border effects when examining productivity calculated with value-added data than with gross output data.[24]

[24] Estimating the coefficients in equation (8) may mitigate the problem of using value added data if the instruments are correlated with the omitted variable (dm). With the instruments correlated with material usage, the estimated coefficients should be biased in such a way to reduce the amount of material usage in the residual.

A.1 The Implications of Not Having Data on Materials Inputs

As mentioned earlier, an advantage of the KLEMS data set over other data sets is that the KLEMS data set has information on intermediate inputs. This section reports two sets of results to describe the effect of excluding the intermediate inputs data. In the first set, the measure of output is the value-added measure expressed as the growth rate of gross output minus the share-weighted growth rates of materials and services. The only inputs are labor and energy. Therefore, for the value-added data, productivity is calculated as the residual from the following regression:

$$\begin{aligned}(\Delta y - s_m \Delta m - s_s \Delta s) &= \Delta v \\ \Delta v &= \gamma_l \Delta l + \gamma_e \Delta e + z\end{aligned}$$

An alternative is to measure output as gross output but still have as inputs only labor and energy.

$$\Delta y = \gamma_l \Delta l + \gamma_e \Delta e + z$$

This equation is similar to the equations estimated in Conley and Dupor (2003) and Costello (1993).

In terms of simple correlations, the different measures do not make a substantial difference. The first rows of Table A1 report the average correlation between cross-border pairs of the same industry for the estimated productivity and these two new measures. The number of significant correlations is also similar.

For the border effect, the magnitudes of ϕ_1 and ϕ_2 are qualitatively similar. For the measures without intermediate inputs, non-identical industries have a somewhat larger border effect. For all three measures, the correlation patterns depend on the similarity of input use.

B Tests for Weak Instruments

Because input choice is likely correlated with productivity changes, estimation of production functions is often done by instrumental variables. However, in selecting instrumental variables, a researcher must find variables that are both uncorrelated with the productivity changes and correlated with the explanatory variables. A growing literature has documented that if the instruments are only weakly correlated with the explanatory variables then parameter estimates may be imprecisely estimated. This section applies the tools developed in this literature to the estimation done here.

This section first reports regression-based tests of whether the instrument variables are uncorrelated with the explanatory variables. In other words, a test of whether the instruments are weak. For a single explanatory variable x with instruments z, the standard approach for weak instruments is to estimate the following equation:

$$X_1 = Z\beta_1 + u$$

and report the F-statistic of whether β_1 (a vector) equals zero. Although this approach is informative for a single explanatory variable, two explanatory variables requires a different approach. In particular, one wants to know the extent to which the instruments can explain each explanatory variable independent of the other explanatory variable. As such I define two new variables $\tilde{x}_1$ and $\tilde{x}_2$ where each variable is defined as the part of the original variable that is orthogonal to the other variable. In other words,. $\tilde{x}_1$ is the residual from a regression of x_1 on x_2. In addition I define as vector $\tilde{z}_1$ as the part of z orthogonal to x_2.

$$\begin{aligned} \tilde{x}_1 &= \tilde{z}_1\beta_1 + u \\ \tilde{x}_2 &= \tilde{z}_2\beta_2 + u \end{aligned}$$

Table A2 reports the F-statistics for testing independently the null hypotheses $\beta_1 = 0$ and $\beta_2 = 0$. These statistics tell us how much information is contained in z to explain x_1 independent of x_2 (and vice versa). This statistic is analogous to the partial R^2 statistic that is reported by Shea. I report the F-statistic because it is more readily interpretable than the partial R^2 statistic.

To reject, at the standard 10 percent significance levels, the null hypothesis that the instruments are not informative about an explanatory variable, the F-test statistic must be greater than two. On the basis of these statistics, we can conclude that these instruments have some information regarding the explanatory variables. Stock and Staiger argue that standard critical values are too low and propose as a rule-of-thumb that the F-test statistic should be above 10. Therefore, given these low F-statistic values, estimating industry-specific coefficients would likely ask too much of these instruments. The approach adopted here of estimating the same coefficients for many different industries does have the potential of resulting in a more efficient estimate.

An additional check would be to look at the robustness of the estimates. One way to assess robustness is to ask whether any of the industries have particular leverage in determining the coefficient estimates. The rest of Table A3 reports results for dropping a particular industry from the estimation routine. For the U.S. industries, the printing industry has a lot of leverage because dropping it results in the nondurable estimate of returns-to-scale μ falling to 0.8. However, because the F statistic for the printing industry is relatively large when compared with the other nondurable industries, I have greater confidence in the estimate with the printing industry than without. Likewise, the transportation industry seems responsible for the high value of ξ^d for the durable industries. None of the Canadian industries appear to have high leverage. The estimated coefficients are similar for all measures.

B.1 An Alternative Estimation Strategies

The test for weak instruments suggests a need for caution in using these coefficient estimates. Some confidence is gained because the paper's three measures of productivity – labor, multifactor, and estimated – imply similar comovement results. To build further confidence, this section reports results for a productivity measure that is calculated using the ordinary least squares estimates of the production parameters. These estimates, by definition, do not suffer from the weak instrument problem; but, the estimates may be biased because of the endogeneity of input choice. Even if inputs were endogenous the sign and size of the resulting bias is uncertain. Although input choice may be correlated with productivity movements, the direction of the correlation depends on a firm's economic environment. A standard RBC model, for example, would imply that input usage would increase immediately in response to a positive technology shock. On the other hand, in a sticky price model (Gali 1999) or in a flexible price model with real rigidities (Vigfusson 2004), the response to a positive technology shock may be an immediate fall in input usage. Hence, theory can not determine the sign of the bias implied by using endogenous regressors. Furthermore, even if the parameter estimates were biased, it is unclear that these biases would imply my main comovement findings.

The parameter estimates are reported in Table A4. The greatest change in the coefficient estimates is the values of the utilization coefficients. Particularly for Canada, the estimates are very small. For both Canadian and American industries, the returns-to-scale are somewhat closer to one. Given the small changes in the coefficients the cross-border correlations reported in Table A5 are not that different. The largest changes are that the Printing industries are somewhat more highly correlated and the cross-border correlations between the American and Canadian Fabricated Metals and Industrial Machinery are somewhat smaller.

C Details on the Estimation

The following section describes the calculation behind the estimation procedure used to calculate the covariance between industries as a function of economic distance. The covariance is written as the weighted sum of the basis functions $H_k\left(\right)$:

$$C\left(d_{ij}\right) = \sum b_k H_k\left(d_{ij}\right)$$

where $H_k\left(\right)$ arises from the spectral representation of the covariance function. The spectral representation is implemented here with the following specification

$$H_k\left(d_{ij}\right) = \int h\left(\omega d_{ij}\right) B^1_{m,k}\left(d_{ij}\right) d\omega$$

where $B^1_{m,k}\left(d_{ij}\right)$ is the first derivative of the k-th b-spline of order m.[25] (The B-splines used here are of second order and hence appear as a set of over lapping bell curves.) The function $h\left(x\right)$ is defined as

$$h\left(x\right) = 2^{(l-2)/2}\Gamma\left(k/2\right)\frac{J_{(l-2)/2}\left(x\right)}{x^{(l-2)/2}}$$

where $J_{(l-2)/2}\left(x\right)$ is a Bessel function of the first kind and l is the dimension of the location vector. In the current application, l equals the number of inputs in the input-output table. The covariance matrix is computed by using the values of $\{b_k\}$ and the distance between industries. The off-diagonal elements of the covariance matrix are defined as a function of the distance between the two industries $C(d_{ij})$. The diagonal elements are defined as $\sigma^2_j + C(0)$ where $C(0)$ is the value of $\Sigma b_k H_k\left(0\right)$ and σ^2_j is the industry-specific covariance term. The own-industry covariances are computed as

$$\sigma^2_j = \max\left(\frac{1}{T}\sum_{t=1}^{T}\Delta z^2_{jt} - C\left(0\right), 0\right)$$

[25] Judd (1998, p 227-28) gives a concise discussion of b-splines.

The values of b_k are computed as the solution to the following least squares problem, subject to the constraint that b_1 is non-negative and that $b_{k+1} \geq b_k$.

$$\min \sum_{t=1}^{T} \sum_{i=1}^{n-1} \sum_{j \neq i} \left(\Delta z_{it}^{c} \Delta z_{jt}^{c} - \sum b_k H_k \left(d_{ij}^{c} \right) \right)^2$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{n-1} \sum_{j \neq i} (\left(\Delta z_{it}^{u} \Delta z_{jt}^{u} - \sum b_k H_k \left(d_{ij}^{u} \right) \right)^2$$

$$+ \sum_{t=1}^{T} \sum_{i=1}^{n-1} \sum_{j \neq i} (\Delta z_{it}^{c} \Delta z_{jt}^{u} - \phi_2 - \sum b_k H_k \left(d_{ij}^{a} \right))^2$$
$$+ \sum_{t=1}^{T} \sum_{i=1}^{n-1} (\Delta z_{it}^{c} \Delta z_{it}^{u} - \phi_1 - \sum b_k H_k \left(d_{ii}^{a} \right))^2$$

where Δz_j^c is the productivity measure from Canadian industry j, Δz_j^u is the productivity measure from the American industry j, d_{ij}^c is the distance between Canadian industries i and j, d_{ij}^u is the distance between American industries i and j, and d_{ij}^a is the distance between Canadian industry i and American industry j. When ϕ_1 and ϕ_2 are set equal to zero, these conditions on the coefficient estimates ensure that the resulting variance covariance matrix is a valid positive-definite matrix (Yaglom, 1987).

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D Tables

Table 1: A List of the Durable and NonDurable Industries Studied Here

Durable	SIC Code	NonDurable	SIC Code
Lumber	24	Food	20
Furniture	25	Textiles	22
Glass Stone & Clay	32	Apparel	23
Primary Metals	33	Paper	26
Fabricated Metals	34	Printing	27
Industrial Machinery	35	Chemicals	28
Electrical Machinery	36	Rubber and Plastics	30
Transportation (Equipment)	37		

Table 2 Coefficient Estimates

	Returns to Scale μ		Utilization ϕ	
	Point Estimate	95 percent Confidence Interval	Point Estimate	95 percent Confidence Interval
United States				
Nondurable	0.98	(0.95,1.11)	0.025	(-0.06,0.11)
Durable	0.93	(0.81,1.04)	0.10	(0.00,0.19)
Canada				
Nondurable	1.42	(1.25,1.58)	0.025	(-0.05,0.10)
Durable	1.16	(1.07,1.25)	0.038	(-0.04,0.11)

Notes: Coefficients are estimated using two-step GMM.
The partition of industries into durable and nondurable are reported in Table 1.

Table 3 Correlations Between Productivity Growth Rates for American and Canadian Industry pairs

Industry	Productivity Measure		
SIC Code	Labor	Multifactor	Estimated
20 Food	**0.26**	**0.15**	**0.09**
22 Textiles	**0.26**	**-0.12**	**0.00**
23 Apparel	-0.14	0.36*	0.12
24 Lumber	-0.09	0.12	0.46*
25 Furniture	-0.04	0.50*	0.54*
26 Paper	0.62*	0.49*	0.42*
27 Printing	0.44*	0.33*	0.24
28 Chemicals	**0.55***	**0.56***	**0.51***
30 Rubber and Plastics	0.29*	0.54*	0.47*
32 Glass Stone & Clay	0.43*	0.64*	0.64*
33 Primary Metals	**0.51***	**0.33***	**0.18**
34 Fabricated Metals	**0.26**	**0.37***	**0.33***
35 Industrial Machinery	0.30*	0.35*	0.30*
36 Electrical Machinery	0.58*	0.44*	0.39*
37 Transportation Equipment	0.60*	0.62*	0.38*

* denotes correlations that are statistically significant at the 90 percent significance level.
Bold text denotes industries examined in Costello (1993).
Sample Period 1961-1997

Table 4: Comparing the Standard Deviation of Various Productivity Measures

Industry	United States			Canada			Ratio of US to Canadian Industries		
	Std Dev of MFP	Ratio of Std Dev to MFP Labor	Estimated	Std Dev of of MFP	Ratio of Std Dev.to MFP Labor	Estimated	LP	MFP	Estimated
20 Food	2.4	1.0	1.0	0.9	2.2	1.1	1.2	2.8	2.4
22**Textiles**	2.0	1.3	1.0	2.4	1.6	1.0	0.6	0.8	0.8
23 Apparel	1.1	3.5	1.1	1.7	1.9	1.3	1.3	0.7	0.6
24 Lumber	3.4	1.3	1.0	2.4	1.6	0.7	1.2	1.5	1.9
25 Furniture	1.8	1.4	1.1	3.1	1.5	1.0	0.6	0.6	0.7
26 Paper	3.0	0.7	1.0	2.9	1.2	0.7	0.6	1.0	1.4
27 Printing	1.7	1.4	1.0	2.3	1.2	0.9	0.9	0.7	0.8
28 **Chemicals**	4.0	1.0	1.0	2.3	1.8	0.9	1.0	1.8	1.9
30 Rubber and Plastics	2.3	1.3	1.0	2.9	1.5	0.9	0.7	0.8	0.9
32 Glass Stone & Clay	2.3	0.9	0.9	3.4	1.2	0.9	0.5	0.7	0.7
33 **Primary Metals**	2.9	1.2	1.0	1.9	2.6	0.8	0.7	1.5	1.8
34 **Fabricated Metals**	1.8	1.3	1.0	1.9	1.9	0.9	0.7	0.9	1.0
35 Industrial Machinery	3.0	1.2	1.1	3.0	1.6	0.8	0.7	1.0	1.4
36 Electrical Machinery	3.0	1.3	1.0	2.6	1.7	0.9	0.9	1.1	1.3
37 Transportation Equipment	2.9	1.6	1.0	2.4	2.6	0.7	0.8	1.2	1.8
Average	2.5	1.4	1.0	2.4	1.7	0.9	0.8	1.1	1.3

Standard Deviation Of Multifactor Productivity Growth Multiplied by 100.

Bold text denotes industries examined in Costello (1993).

Table 5: Fraction of Variance Explained by Aggregate and Input-Specific Technologies.

Industry	United States					
	Labor		MFP		Estimated	
	Agg	Input Specific	Agg	Input Specific	Agg	Input Specific
20 Food	0.19	0.10	0.08	0.13	0.08	0.08
22**Textiles**	0.14	0.20	0.07	0.23	0.07	0.19
23 Apparel	0.10	0.08	0.18	0.30	0.16	0.26
24 Lumber	0.06	0.11	0.03	0.15	0.03	0.11
25 Furniture	0.17	0.13	0.17	0.27	0.15	0.22
26 Paper	0.18	0.40	0.07	0.40	0.07	0.31
27 Printing	0.21	0.31	0.15	0.54	0.16	0.45
28 **Chemicals**	0.09	0.26	0.05	0.40	0.05	0.25
30 Rubber and Plastics	0.17	0.16	0.13	0.26	0.13	0.22
32 Glass Stone & Clay	0.22	0.57	0.10	0.59	0.12	0.58
33 **Primary Metals**	0.12	0.23	0.06	0.28	0.06	0.23
34 **Fabricated Metals**	0.25	0.25	0.20	0.48	0.21	0.41
35 Industrial Machinery	0.09	0.13	0.07	0.24	0.06	0.16
36 Electrical Machinery	0.08	0.14	0.07	0.31	0.07	0.23
37 Transportation Equipment	0.07	0.07	0.08	0.17	0.08	0.13
Average	0.14	0.21	0.10	0.32	0.10	0.26
Industry	Canada					
	Labor		MFP		Estimated	
20 Food	0.15	0.13	0.14	0.44	0.26	0.36
22**Textiles**	0.07	0.09	0.06	0.24	0.08	0.15
23 Apparel	0.09	0.10	0.11	0.34	0.09	0.16
24 Lumber	0.08	0.11	0.06	0.26	0.09	0.20
25 Furniture	0.05	0.07	0.04	0.16	0.06	0.11
26 Paper	0.10	0.26	0.05	0.39	0.09	0.37
27 Printing	0.09	0.18	0.06	0.38	0.10	0.31
28 **Chemicals**	0.08	0.21	0.07	0.60	0.09	0.36
30 Rubber and Plastics	0.07	0.10	0.06	0.26	0.08	0.17
32 Glass Stone & Clay	0.07	0.21	0.04	0.38	0.06	0.29
33 **Primary Metals**	0.05	0.11	0.10	0.51	0.16	0.52
34 **Fabricated Metals**	0.10	0.14	0.11	0.46	0.16	0.34
35 Industrial Machinery	0.05	0.07	0.05	0.22	0.09	0.20
36 Electrical Machinery	0.05	0.07	0.06	0.28	0.09	0.19
37 Transportation Equipment	0.03	0.02	0.07	0.13	0.14	0.13
Average	0.07	0.12	0.07	0.33	0.11	0.26

Bold text denotes industries examined in Costello (1993).

Table 6: A subsection of the U.S. Input Output Table 1987

	Industries							
Inputs	22	26	28	29	33	35	36	37
Other	22	22	29	82	34	18	20	17
20 Food	0	0	0	0	0	0	0	0
22 Textiles	**29**	1	0	0	0	0	0	0
26 Paper	0	**29**	2	0	0	0	1	0
28 Chemicals	21	8	**33**	1	3	0	2	1
29 Petroleum	0	0	1	**8**	0	0	0	0
33 Primary Metals	0	0	0	0	**27**	10	7	5
34 Fabricated Metals	0	0	1	0	1	4	4	7
35 Industrial Machinery	0	0	0	0	2	**15**	1	5
36 Electrical Machinery	0	0	0	0	0	7	**16**	4
37 Transportation Equipment	0	0	0	0	0	0	0	**23**
Labor	22	26	25	5	26	39	39	26

Notes: Each table entry reports the percentage of total inputs used by the industry listed in the column produced by the industry listed in the row.
Bold text denotes the input share produced by the own-industry.

Table 7 : OLS Regressions on Distance-Based Correlations

	R^2 of Regression			F-test of No Explanatory Role for Inputs		
	U.S.	Canada	Cross	U.S.	Canada	Cross
Labor	0.11	0.22	0.02	6.1	14.5	2.3
P-values				*<0.01*	*<0.01*	*0.1059*
Multifactor	0.23	0.17	0.07	15.4	10.5	7.6
P-values				*<0.01*	*<0.01*	*<0.01*
Estimated	0.26	0.20	0.10	18.1	12.7	11.4
P-values				*<0.01*	*<0.01*	*<0.01*

Notes: For the U.S. and Canada regressions, there are 2 and 15*7-3 degrees of freedom
For the Cross Border regression, there are 2 and15*14-3 degrees of freedom

Table 8: Estimated Coefficients for Border Effect

	β_0	β_1	β_2	ϕ_{CROSS}	R^2	F-test
Labor Productivity	0.44	-0.40	0.01	-0.04	0.04	4.57
	2.91	*-0.54*	*0.01*	*-1.44*		
MFP	0.79	-1.77	1.62	-0.01	0.06	6.17
	5.36	*-2.42*	*1.83*	*-0.55*		
Estimated Productivity	0.81	-2.05	1.68	-0.07	0.12	14.7
	5.39	*-2.74*	*1.84*	*-2.55*		

Notes: Numbers in italics are t-statistics for the hypothesis that coefficient equals zero. F-test is that β_1 and β_2 equals zero.

Table 9: Testing for A Border Effect

Productivity:	Labor	MFP	Estimated
Cross-Border Decline: Identical Industries	-0.07	-0.16	-0.14
$P\left(\phi_{1,sim} < \phi_{1,est} \vert H_0\ \phi_1 = 0\right)$	0.11	0.01	0.02
90% Confidence Interval	(-0.20 0.01)	(-0.31 -0.04)	(-0.28 -0.04)
Cross-Border Decline: Non-identical Industries	-0.15	-0.12	-0.11
$P\left(\phi_{2,sim} < \phi_{2,est} \vert H_0\ \phi_2 = 0\right)$	0	0	0
90% Confidence Interval	(-0.21 -0.09)	(-0.19 -0.04)	(-0.16 -0.06)
Confidence Interval for $\phi_{1,sim} - \phi_{2,sim}$	(-0.03 0.14)	(-0.16 0.03)	(-0.16 0.07)

Notes: Hypothesis Tests are generated using 500 Simulations of Distance-Based Correlation Matrix DGP with no Border Effect. Confidence Intervals are generated by drawing with replacement . from vector time series of productivity growths. 500 Simulations

E Figures

Figure 1: Histogram of Distances

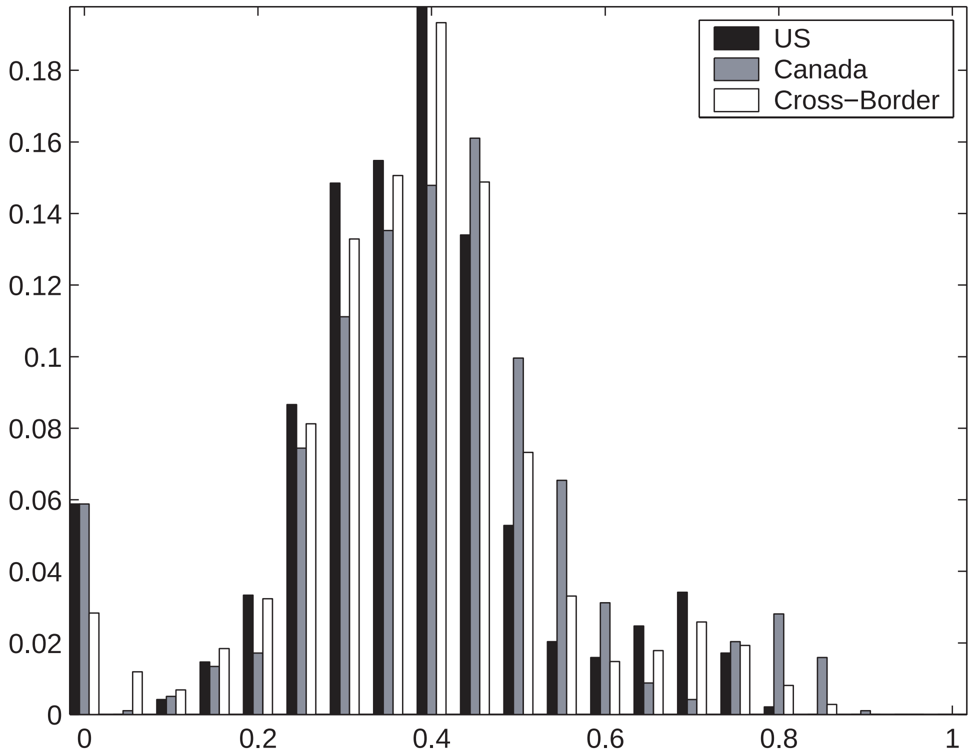


Figure 2: The Correlation of Productivity Growth as Function of Similar Input Use

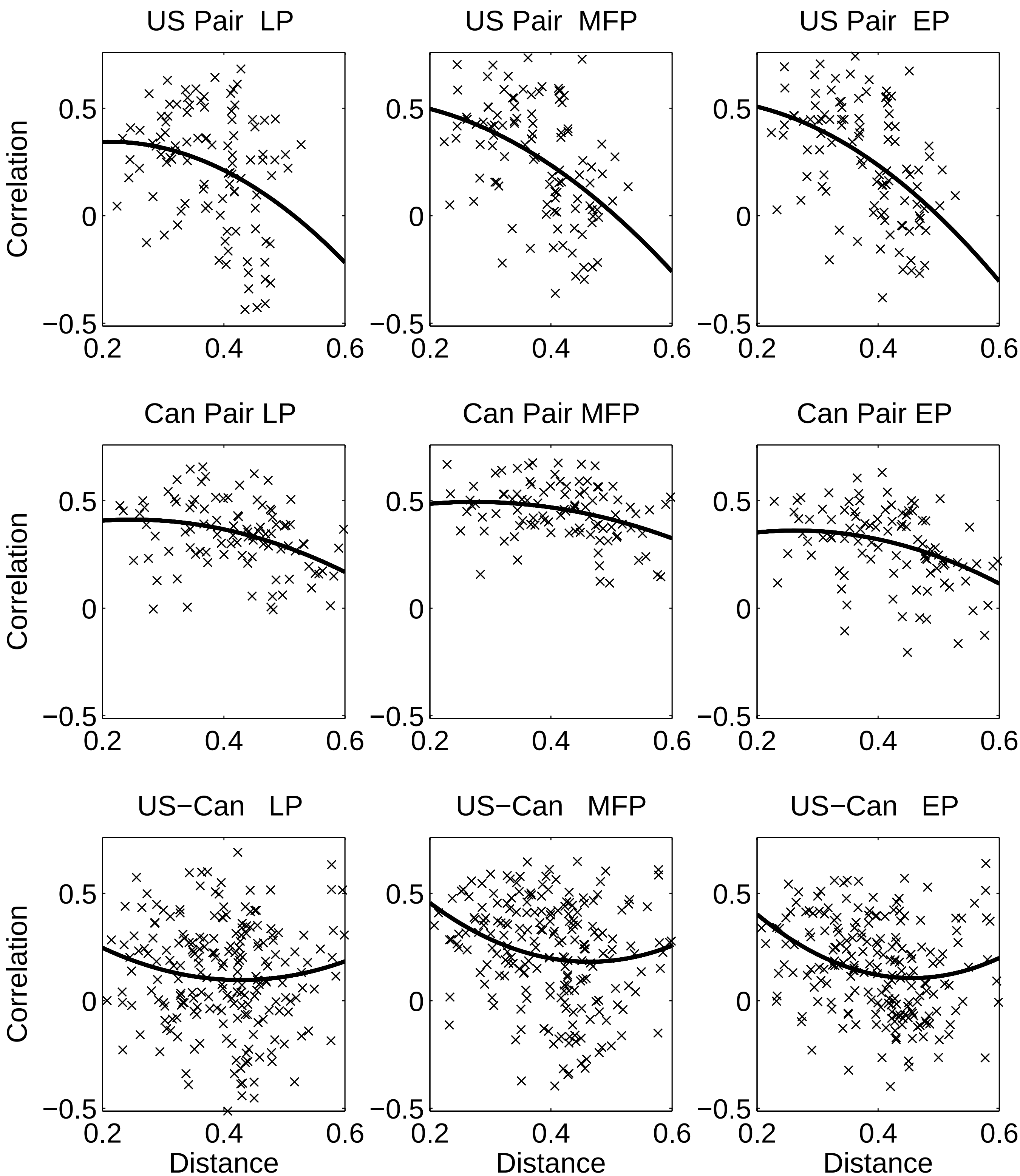


Figure 3 Correlation Between Industries As Function Of Input Similarity

Figure 3a: Labor Productivity

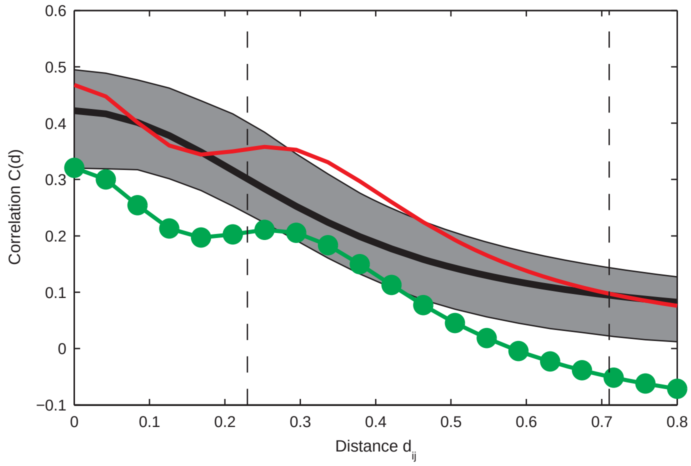


Figure 3b: Multifactor Productivity

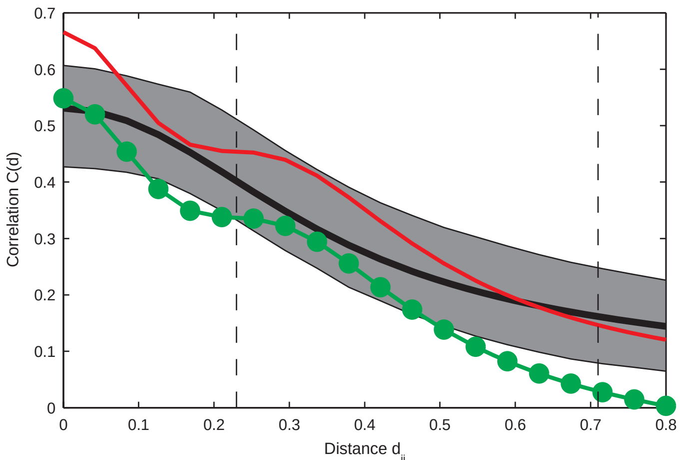
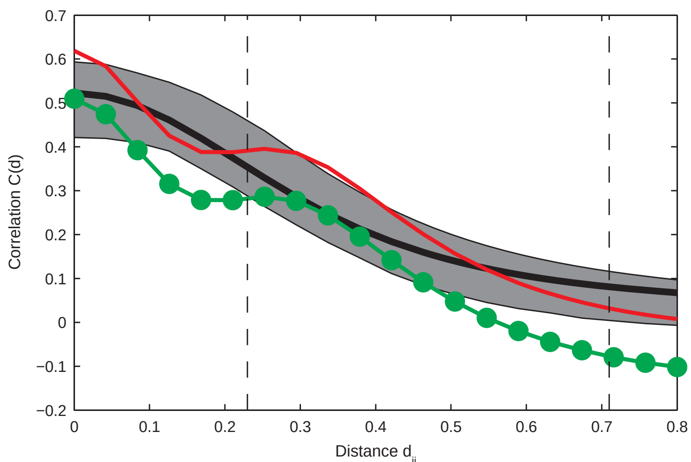


Figure 3c: Estimated Productivity



Notes: Thick Line, C(d) estimated under null hypothesis of no border effect
Thin Line: Estimate of C(d) absent a border effect, Circles: Estimate of C(d) $+\phi_2$ (include a border effect)
Grey Area 90 percent confidence interval of C(d) under null of no border effect.
Dashed Lines. Interval Between 0.23 and 0.7 that includes 90 percent of non-zero distances

F Appendix Tables

Table A1: Effect of Not Having Intermediate Inputs Data

	Baseline	Value Added	Gross Output No Intermediate Inputs
Average Correlation	0.3192	0.3158	0.3212
Significant Correlations	7	8	9
ϕ_1	-0.092	-0.113	-0.059
ϕ_2	-0.081	-0.113	-0.124
d		C(d)	
0	0.511	0.507	0.461
0.126	0.372	0.404	0.345
0.253	0.354	0.357	0.335
0.379	0.281	0.260	0.266
0.505	0.162	0.147	0.155
0.632	0.087	0.079	0.085
0.758	0.047	0.042	0.047

Table A2 Tests for Instrumental Variable Relevance and Industry leverage for Point Estimates

Industry	United States: F-test for instrumental variable relevance		United States: Estimated values when this industry dropped				Canada: F-test for instrumental variable relevance		Canada: Estimated values when this industry dropped			
	F_μ	F_ϕ	μ^n	ϕ^n	μ^d	ϕ^d	F_μ	F_ϕ	μ^n	ϕ^n	μ^d	ϕ^d
20 Food	0.9	0.8	1	-0.01	0.95	0.09	0.4	0.6	1.4	0.03	1.2	0.04
22 Textiles	1	1.2	1	-0.01	0.94	0.09	1.9	2.0	1.5	0.01	1.2	0.03
23 Apparel	2.1	0.3	0.98	0.05	0.93	0.10	0.6	1.7	1.4	0.05	1.2	0.05
24 Lumber	2.7	0.9	0.97	0.03	0.98	0.09	3.8	0.5	1.4	0.02	1.2	0.03
25 Furniture	2.5	1.4	0.98	0.02	0.97	0.10	1.6	1.5	1.4	0.03	1.2	-0.03
26 Paper	2.2	1.1	0.97	0.03	0.94	0.08	3	1.3	1.3	0.03	1.2	0.02
27 Printing	2	2.3	0.81	0.18	0.95	0.10	0.4	0.4	1.4	0.03	1.2	0.04
28 Chemicals	1.1	2.2	1	-0.01	0.93	0.09	1.3	0.6	1.4	0.01	1.2	0.04
30 Rubber and Plastics	1.3	1.2	0.95	-0.01	0.93	0.09	2.9	1.8	1.4	0.02	1.2	0.04
32 Glass Stone & Clay	1.9	0.7	0.99	0.014	0.96	0.09	0.7	1.9	1.4	0.03	1.1	0.06
33 Primary Metals	1.7	0.7	0.98	0.02	0.93	0.11	0.8	0.2	1.4	0.02	1.2	0.01
34 Fabricated Metals	0.8	0.6	0.99	0.02	0.9	0.10	0.4	0.9	1.4	0.03	1.2	0.04
35 Industrial Machinery	1.1	0.4	0.98	0.02	0.93	0.09	0.6	1.2	1.4	0.03	1.2	0.03
36 Electrical Machinery	1.9	2.6	0.98	0.03	0.85	0.14	2.3	3.1	1.4	0.02	1.1	0.07
37 Transportation Equipment	0.9	2.3	0.97	0.02	0.97	0.05	0.3	1.4	1.4	0.03	1.2	0.05
Average Result	1.6	1.2	0.97	0.03	0.94	0.09	1.4	1.3	1.4	0.03	1.2	0.03

Table A3 Comparing Coefficient Estimates

	Returns to Scale μ		Utilization ϕ	
	GMM	OLS	GMM	OLS
United States				
Nondurable	0.98	0.96	0.025	0.04
Durable	0.93	1.09	0.10	0.06
Canada				
Nondurable	1.42	1.28	0.025	-.0.003
Durable	1.16	1.21	0.038	0.009

Notes:
The partition of industries into durable and nondurable are reported in Table 1.

Table A4 Correlations Between Productivity Growth Rates for American and Canadian Industry pairs

Industry	Productivity Measure			
SIC Code	Labor	Multifactor	Estimated	OLS
20 Food	**0.26**	**0.15**	**0.09**	0.12
22 Textiles	**0.26**	**-0.12**	**0.00**	-0.04
23 Apparel	-0.14	0.36*	0.12	0.23
24 Lumber	-0.09	0.12	0.46*	0.48*
25 Furniture	-0.04	0.50*	0.54*	0.42*
26 Paper	0.62*	0.49*	0.42*	0.49*
27 Printing	0.44*	0.33*	0.24	0.31*
28 Chemicals	**0.55***	**0.56***	**0.51***	0.55*
30 Rubber and Plastics	0.29*	0.54*	0.47*	0.54*
32 Glass Stone & Clay	0.43*	0.64*	0.64*	0.53*
33 Primary Metals	**0.51***	**0.33***	**0.18**	0.10
34 Fabricated Metals	**0.26**	**0.37***	**0.33***	0.25
35 Industrial Machinery	0.30*	0.35*	0.30*	0.21
36 Electrical Machinery	0.58*	0.44*	0.39*	0.28*
37 Transportation Equipment	0.60*	0.62*	0.38*	0.32*

* denotes correlations that are statistically significant at the 90 percent significance level.
Bold text denotes industries examined in Costello (1993).
Sample Period 1961-1997