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Estimating TFP in the Presence of Outliers and Leverage Points: An Examination of the KLEMS Dataset

by Ryan Macdonald

Micro-economic Analysis Division
R.H. Coats Bldg.,18-F,100 Tunney's Pasture Driveway
Ottawa, Ontario K1A 0T6

Telephone: 1-800-263-1136

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How to obtain more information:
National inquiries line: 1-800-263-1136
E-mail inquiries: infostats@statcan.ca

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Abstract

This paper examines the effect of aberrant observations in the Capital, Labour, Energy, Materials and Services (KLEMS) database and a method for dealing with them. The level of disaggregation, data construction and economic shocks all potentially lead to aberrant observations that can influence estimates and inference if care is not exercised. Commonly applied pre-tests, such as the augmented Dickey-Fuller and the Kwaitkowski, Phillips, Schmidt and Shin tests, need to be used with caution in this environment because they are sensitive to unusual data points. Moreover, widely known methods for generating statistical estimates, such as Ordinary Least Squares, may not work well when confronted with aberrant observations. To address this, a robust method for estimating statistical relationships is illustrated.

Keywords: productivity, outliers, time series

Executive summary

Care needs to be exercised when estimating economic relationships with the Capital, Labour, Energy, Materials and Services (KLEMS) database. Although the dataset comprises high quality estimates of economic variables constructed from the supply and use tables of the National Accounts, aberrant observations, such as outliers and leverage points, constitute an important feature of the dataset.

Aberrant observations can occur for several reasons. First, changes in classification and methodology can lead to discontinuities over time. Second, disaggregation into finer industry classifications produces data where coherency may be of lower quality. Third, macroeconomic or other shocks may cause abrupt, unusual movements in the underlying data sources.

This paper provides a first step for addressing aberrant observations. It is broadly divided into two parts. The first part examines how pre-tests for unit roots or stationarity perform when applied to the KLEMS data. The results imply that, due to the complexity of the data and the presence of aberrant observations, commonly applied tests, used individually or aggregated over the panel of industries, may not provide adequate inference.

The second part focuses on how aberrant observations affect parametric total factor productivity (TFP) growth estimates, and on how to identify them. When aberrant observations are present, commonly applied estimation methods such as Ordinary Least Squares (OLS) can be affected. This paper examines their impact by employing an estimation technique that is less sensitive to unusual observations. The results of the two estimation methods are compared to illustrate the impact of unusual data points.

Over the course of the second part of the paper a number of questions pertinent to dealing with aberrant observations are addressed:

- What techniques are available for dealing with aberrant observations in the KLEMS database?

  Several estimators that are insensitive (or less sensitive) to aberrant observations are available, including Least Median Squares, M-estimators, Least Trimmed Squares and S-estimators. These estimators use functions of the data that, in a variety of ways, account for the influence of aberrant observations. In this paper an S-estimator is used because it is insensitive to aberrant observations in the dependent and independent variables.

- How do aberrant observations affect OLS estimates, and does this matter economically?

  On average, OLS estimates are found to underestimate TFP growth relative to the S-estimator by as much as 0.35 percentage points, and by as much as 4.3 percentage points for particular industries. These magnitudes are non-trivial, particularly when compounded over 43 years.

- Are aberrant observations equally distributed across years?

Analysis of the timing of aberrant observations shows that they tend to be grouped around certain events. In particular, the first oil shock in the early 1970s, the 1980–1981 recessions and the 1990 recession are shown to be important sources of aberrant observations.

- What causes aberrant observations?

Macroeconomic shocks are the most important source of aberrant observations. It appears that when industries are placed under stress, either by rapidly increasing input costs with inelastic demand or by reducing aggregate demand, the response function of the industries is different from ‘regular’ expansionary periods. The responses vary widely across industries and, for the purposes of estimating TFP, represent adjustments that are likely beyond the scope of traditional assumptions regarding productivity growth.

- How important are aberrant observations in the KLEMS dataset?

Aberrant observations are an important feature of the KLEMS dataset. In this paper, which uses a Cobb-Douglas production function, up to 21% of sample observations are found to be aberrant in some way. Failure to account for these observations can affect parameter estimates and lead to inaccurate inference. Researchers, when they use the KLEMS dataset, need to consider whether special techniques should be employed to take into account the aberrant observations.

1. Introduction

The expansion of the Capital, Labour, Energy, Materials and Services (KLEMS) database by Statistics Canada provides researchers with a rich dataset for examining economic relationships. The database has been back cast from 1997 to 1961 using industry classifications defined in the 1997 North American Industry Classification System (NAICS 1997). Previously the database contained Standard Industry Classification 1980 (SIC 1980) aggregations from 1961 to 1997 and NAICS 1997 aggregations from 1997 to 2003.

The expanded database now spans 43 years, from 1961 to 2003, providing more data points from which inference may be drawn. It contains nominal and real values, as well as the accompanying price indices, for gross output, gross domestic product (GDP), capital services, labour services and intermediate inputs. Additionally, labour productivity and multi-factor productivity estimates are available.

The disaggregate industry data provide an opportunity to expand economists' and policy makers' understanding of how industries behave and evolve in Canada. In particular, the expanded, disaggregate dataset provides a rich data source from which an updated set of industry specific parametric total factor productivity (TFP) estimates can be generated, and from which other economic relationships can be investigated.

However, the time series in the dataset cover a large number of industries that are subject to a variety of economic and non-economic shocks over time. Changes in methodology, measurement error and aggregate and idiosyncratic economic shocks can all potentially make inference based on the data difficult. Moreover, because some industries can be more sensitive to economic events than others, the industry-level data can be noisy, especially when compared with aggregate time series.

The KLEMS database is generated in part from the supply and use tables of the National Accounts, whose construction involves the reconciliation of many data sources. Over time, industries and commodity classifications change and series have to be spliced. New sources of information (e.g., on prices) become available and have to be integrated within the tables. Despite great care being exercised to provide continuity in the series, some irregular points exist that may cause the quality of the series to be less than ideal for some purposes.

Idiosyncratic and aggregate economic shocks also affect the KLEMS data. Idiosyncratic shocks refer to economic events that affect a particular industry or sector, but not the whole business sector. These types of shocks may come from, for example, technological advancement, changes in regulatory structure, changes in tariffs or non-tariff barriers, increased foreign competition in a particular industry, changes in tax or subsidy rates and changes in consumer preferences. Aggregate economic shocks, on the other hand, refer to events that affect a majority of, if not all, the industries in Canada.

As the paper progresses, it will become clear that unusual observations, which are referred to as aberrant observations since there are many reasons why they can emerge, are an important part of the industry data generating processes. As a result, it is important to examine the underlying data in order to understand how these types of data features may affect estimation and, therefore, inference.[1] While this is true of any dataset, when the KLEMS database is employed it is particularly important. The underlying data are noisy and subject to economic and non-economic shocks. These problems make it difficult to ascertain the 'true' underlying parameter estimates using commonly known estimation techniques, such as Ordinary Least Squares (OLS).

Changing estimation strategies can overcome the difficulties that aberrant observations pose in some settings, one of which is demonstrated here. A comparison between OLS and one estimator that is less sensitive to aberrant observations is made to illustrate this point. The difference between the two sets of estimates illustrates, ceteris paribus, how aberrant observations influence OLS estimates. This does not mean that OLS estimates are incorrect; rather, it suggests that prior to estimation researchers should take time to consider whether the whole sample period is relevant for examining a particular economic relationship.

Although aberrant observations can have a large effect on parameter estimates and inference, this does not mean that the data are poor quality. Rather, it means that researchers using the data need to be aware of how aberrant observations manifest themselves. Aberrant observations often indicate that something out of the ordinary occurred to a particular industry in a given year. Their presence should not be used to infer that the data are somehow inaccurate or unusable.

The remainder of this paper examines how to empirically deal with aberrant observations when estimating TFP from a simple production function. In Section 2, the KLEMS data used for estimation are described. Section 3 outlines the economic model employed, while Section 4 discusses unit root testing. Section 4 illustrates the difficulty that noisy disaggregate data pose for practitioners. Although it is not a treatise on unit root testing issues, it is an important section for readers who are interested in testing the unit root hypothesis with KLEMS data—an important first step in any econometric exercise using time series data. Section 5 discusses the econometric model that is used to generate the parametric TFP estimates. The estimation methods are discussed in Section 6. Because the data are subject to aberrant observations, OLS does not perform well. An S-estimator is therefore employed to provide robust estimates and to juxtapose the OLS estimates. Finally, Section 7 examines the estimates and Section 8 concludes.

2. KLEMS data

This study uses real gross domestic product (GDP), capital and labour services data from the Capital, Labour, Energy, Materials and Services (KLEMS) database held at Statistics Canada. There are 88 business sector industries and one non-business sector industry in the data set that correspond to the P-level NAICS 1997 industry aggregations.[2]

For each industry, real GDP is taken directly from the input–output tables created by the Industry Accounts Division of Statistics Canada.

1. The term aberrant observation is used in the paper to refer to a class of observations that are noticeably different from the remaining sample.
2. The data are also available in three other aggregations: Business Sector, M-Level and S-Level.

Capital services are a measure of the contribution of the capital stock to domestic value added calculated for the Canadian Productivity Accounts. For each industry, investment data and the perpetual inventory method are used to create capital stocks for a range of assets. The capital services for each industry are then calculated as the weighted average of the individual stocks employed. The relative cost of capital is used to weight the various assets. Differing depreciation rates across assets, which affect the cost of capital, ensure that assets that lose value quickly generate higher service values to cover their cost (see Baldwin and Gu forthcoming; Schreyer, Diewert and Harrison 2005; Gellatly, Tanguay and Yan 2002; and Harchaoui and Tarkhani 2003).

Labour services are a measure of the contribution of labour input to domestic value added calculated for the Canadian Productivity Accounts. Typically econometric studies use hours worked as a measure of labour input. However, this misses differences in skill and human capital across industries and occupations. The estimates of labour services calculated for the productivity accounts use relative wage rates to aggregate hours worked into a labour input series for each industry. The labour services series assume that workers are paid their marginal product. As a result, workers with higher wages contribute more to output for each hour worked than workers with lower wages (Gu et al. 2002).

3. Model specification

Total factor productivity (TFP) measures the contribution to economic growth that does not come from tangible inputs. Often it is viewed as a measure of underlying, disembodied technical change. However, it can also be viewed as capturing a wide rage of factors that include measurement error or variables that could be included in a production function but are difficult to measure, such as changes in management structure, network externalities or the contribution to output from research and development or public infrastructure.

TFP may be estimated in one of two ways—parametrically and non-parametrically. Both approaches rely on the assumption that an industry production function exists. Non-parametric estimates typically estimate labour and capital share of income, and then use the shares as weights in a production function where a constant returns to scale assumption is imposed. Using capital and labour input estimates, scaled by their corresponding weights, an estimate of how much gross domestic product (GDP) should increase given the change in inputs is calculated. The estimate is invariably different from actual GDP growth and the difference is defined as TFP growth (see, for example, Jorgenson and Stiroh 2000; Jorgenson, Gollop and Fraumeni 1987).

Parametric estimates are based on an assumed functional form for the GDP production function. Capital and labour input are used to econometrically produce estimates of their elasticities. TFP estimates, however, are dependent on how the data are employed. If the log-levels of the data are used, then a time trend can be used to capture TFP. However, if the data are log-differenced, the time trend in the level model becomes constant so that the intercept in the differenced model captures TFP growth. The decision about whether to use log-levels or log-differences ultimately depends on the time series nature of the data.

In this study a Cobb-Douglas production function is used to generate a parametric estimate of TFP:

$$\ln GDP_t = TFP(t) + \beta_K \ln K_t + \beta_L \ln L_t \qquad (1)$$

where *GDP* is real GDP at time *t*, *K* is capital services and *L* is labour services. The parameters β_K and β_L capture the elasticity of GDP with respect to capital and labour services, respectively. They are interpreted as the elasticities of capital and labour services. Two forms of the model are employed. The first does not constrain the parameters while the second imposes constant returns to scale on the production function:

$$\beta_K + \beta_L = 1. \qquad (2)$$

How TFP is estimated (as a time trend using log-level data versus as a constant using log-differences) depends on the functional form of $TFP(t)$. A priori it is uncertain what functional form the data will allow, and the choice will ultimately depend on whether the data are viewed as containing a unit root or a deterministic trend.

4. Unit root testing

This section is not intended to be an exhaustive exploration of time series analysis or unit root testing issues. Rather, it provides an overview of why it is important to take account of unit roots, and of how aberrant observations and structural change can affect unit root tests applied to series from the Capital, Labour, Energy, Materials and Services (KLEMS) database.[3]

When economic series exhibit a stochastic increase or decrease over time it is possible to generate statistically significant coefficient estimates from multivariate analysis solely because the series used for estimation have a trend. This feature of time series analysis—which is first illuminated in Yule (1926) and later popularized by Granger and Newbold (1974)—is referred to as spurious regression. The results from a spurious regression rely on the trending series, and not on an underlying economic relationship, to provide statistically significant parameter estimates. Spurious regression is typically associated with series that follow a unit root process and it forces time series practitioners to take care when examining these types of relationships. As a result, a great deal of attention is focused on unit root testing.

A series is said to follow a unit root when innovations in the series are permanent. Permanent innovations occur when the auto regressive parameter in the univariate relationship between Y_{t-1} and Y_t is equal to one. It differs from a series that follows a deterministic trend over time where innovations create temporary divergences from the trend.

3. For more information see Maddala and Kim (1998) for a readable discussion of these issues.

When time series practitioners analyse a multivariate relationship, the first problem they face is determining which type of trend is present in the data. This problem is complicated by two factors:

1. Under the null hypothesis that a time series follows a unit root process, the test statistic can converge to a non-standard limiting distribution; and,
2. Unit root tests often have low power.

The first complication has been overcome through simulation techniques that provide critical values. The second complication, however, remains an issue. Unit root tests attempt to find permanent changes in time series data. When one-off events, such as a recession, affect the level of the series, they can lead to erroneous inference from unit root tests (Perron 1989, Madalla and Kim 1998). That is, commonly applied tests can falsely suggest the presence of a unit root. Ultimately, the analyst needs to ask whether these intermittent events lead to structural breaks that need to be accounted for. This will be a serious problem when the KLEMS data is analysed.

Second, based on the outcome of unit root tests, practitioners must decide how to treat the data. If the series in question follow a unit root, there is often an additional test for cointegration. This is a test of whether or not a linear combination of processes that follow a unit root process is stationary.[4] If this is the case, then it is still possible to use the log-levels of the data to form estimates of the long-run relationship between the variables. If the series in question follow deterministic trends, then including deterministic variables leads to valid regression results. However, if the series are not cointegrated, or if some series appear stationary while others appear to follow a unit root process, regression analysis using the log-level data can lead to spurious results.

4.1 Aberrant observations and unit root tests

Time series practitioners, whether interested in forecasting or parameter estimates, invariably include a discussion of stationarity in their analysis. Typically, if a series exhibits a trend, a unit root test is applied to the time series and a test statistic is compared with some set of critical values. Often a second unit root test is applied, and the outcome compared with the initial test. This is referred to as confirmatory analysis (Maddala and Kim 1998). Based on the results of the unit root test(s) the data are employed without transformation, are transformed to account for non-stationarity or, in the case of multi-variate analysis, further pre-testing for cointegration may be performed.

Throughout this process, practitioners sometimes pay little attention to the underlying data prior to applying unit root tests. This can lead to serious problems when aberrant observations or structural changes are present in time series. Unit root tests tend to have low power, and will often fail to distinguish between unit root processes and structural breaks, trend changes or other changes in the underlying data generating process (Perron 1989, Maddala and Kim 1998). Aberrant observations can capture, or occur around, these events and may come from a number of sources including measurement error, business cycle turning points and economic shocks

4. More generally, a cointegration test examines whether a linear combination of I(d) variables form a series that is I(d-1).

(Franses 1998, Chang, Tiao and Chen 1988, and Fox 1972). As a result, the presence of structural breaks or aberrant observations can affect parameter estimates and may lead to poor inference about the presence of unit root processes.

Consequently, it is important for researchers to examine their data for aberrant observations or changes in the underlying data generating process that, for whatever reason, may have an undue influence on regression parameters used in pre-testing. Moreover, when these difficulties are encountered, it may be important to apply professional judgement. This does not mean that any transformation is applicable; rather, it suggests that when a series that appears to follow a linear trend (stochastic trend) generates a parametric test result that implies the series follows a unit root process (is trend stationary) researchers need to ask why the contradiction is arising.

4.2 Sample industry unit root tests

It becomes increasingly important to analyse the time series when disaggregate data are employed. Because the disaggregate data can be more susceptible to shocks, and may have different trends, trend changes or level shifts than aggregate series, the problem can be compounded. Within the KLEMS database, many industries are subject to these types of shocks, which makes unit root testing difficult.

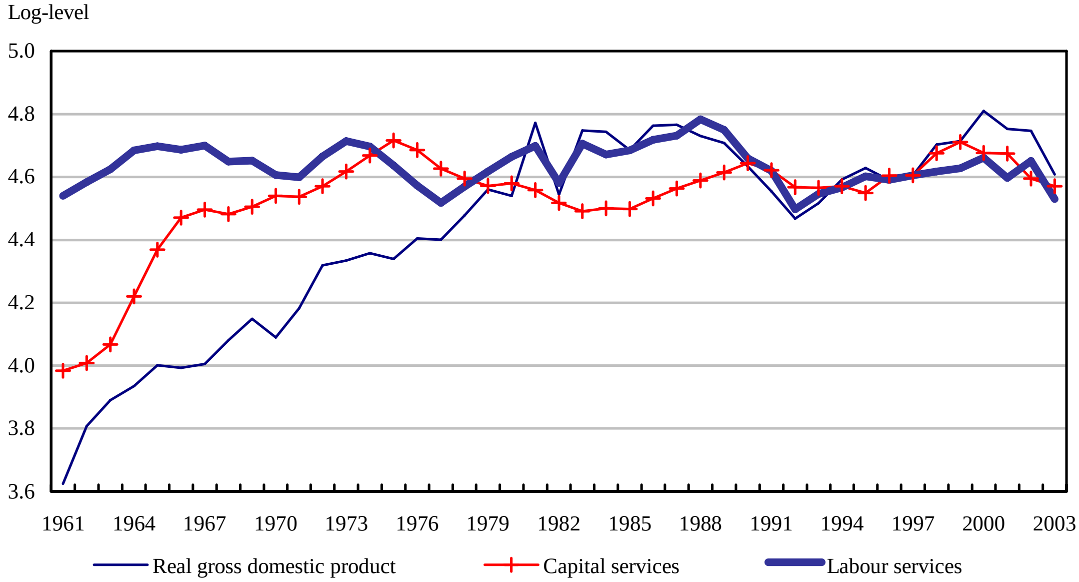
For example, the level of real gross domestic product (GDP), capital services and labour services for Textile and Textile Product Mill Manufacturing, Railroad Rolling Stock Manufacturing and Computer and Peripheral Equipment Manufacturing are shown in Figures 1 to 3. In the Textile and Textile Product Mill Manufacturing industries, there is an increase in real GDP until the 1981 recession, after which GDP levels off. Capital services increase rapidly at the start of the period, but, by the late 1960s level off, remaining fairly constant thereafter. The level of labour services appears to fluctuate around a trend.

In the Railroad Rolling Stock Manufacturing industries, real GDP and labour services are subject to permanent looking level shifts at a number of points. In particular there are increases in real GDP and labour services at the start of the period, around the 1981 recession and at the end of the period. The level of capital services increases from 1961 until 1980 when the level begins decreasing. The declining level of capital services continues from 1981 to the end of the sample.

In the Computer and Peripheral Equipment Manufacturing industries, labour services increase over time. However, there is a permanent-looking decline in 1971, after which the level of labour services becomes more volatile. The level of real GDP mimics the movements in labour services over the early part of the period. Following the 1971 decline, it increases rapidly as capital services begin accelerating. Capital services increase more rapidly, and are subject to a smaller decline in the early 1970s, than labour services. Following the decrease in the early 1970s, capital services increase for the majority of the sample.

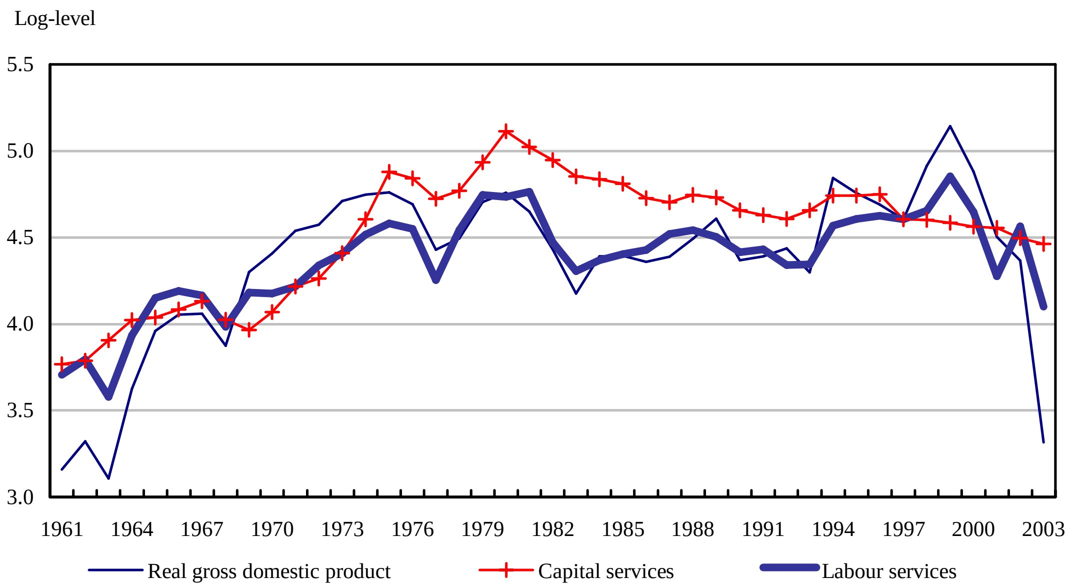
Figures 1 to 3 illustrate the difficulty that the disaggregate KLEMS dataset poses. The data are volatile, some series appear to follow unit root processes over the sample period, while others appear to follow linear tends. Still other series appear to contain structural breaks in their levels or trends. In the presence of these types of shocks, traditional unit root tests can perform poorly.

Figure 1
Textile and textile product mill manufacturing



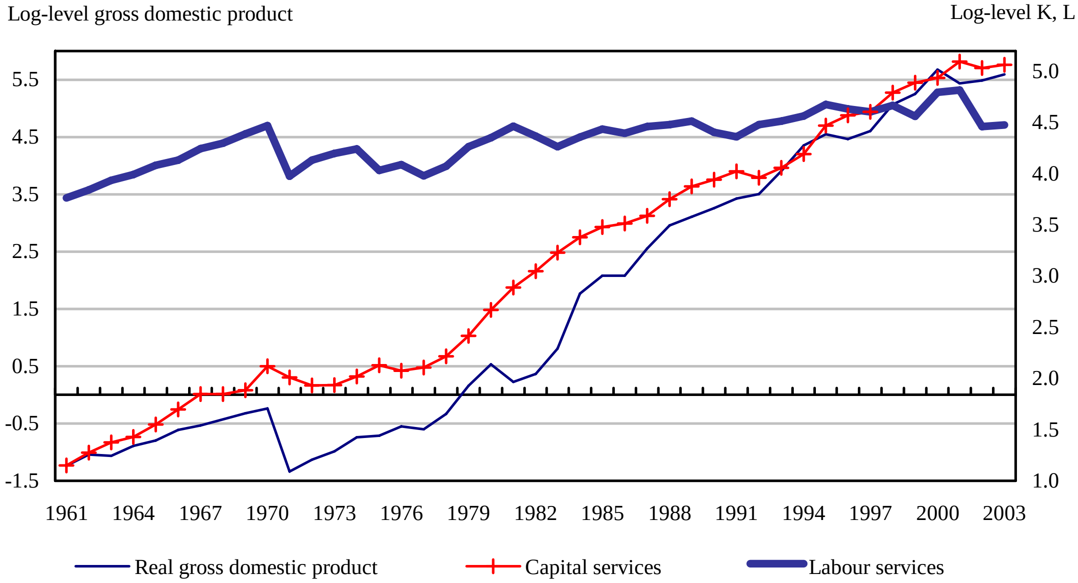
Source: Statistics Canada.

Figure 2
Railroad rolling stock manufacturing



Source: Statistics Canada.

Figure 3
Computer and peripheral equipment manufacturing



Source: Statistics Canada.

To illustrate, two sets of unit root/stationarity tests are applied to the series in Figures 1 to 3. The first is the augmented Dickey-Fuller (ADF) unit root test (Table 1). For the majority of series the ADF test fails to reject the null hypothesis that a unit root is present. Only for Textile and Textile Product Mill Manufacturing GDP, capital and labour services and Computer and Peripheral Equipment Manufacturing labour services is the null hypothesis rejected.

Table 1
ADF[1] unit root tests

	Ho: Series contains a unit root		
	Textile and textile product mills	Railroad rolling stock manufacturing	Computer and peripheral equipment manufacturing
ln GDP[2]	-2.99*	-2.27	0.53
ln L	-3.00*	-2.80*	-2.55
ln K	-4.69*	-2.33	-0.04

1. Augmented Dickey-Fuller.
2. Gross domestic product.
Note: *Denotes rejection of the null hypothesis at the 10% significance level.
Source: Statistics Canada.

While the results appear plausible for the Textile and Textile Product Mill Manufacturing series, they are not completely consistent with prior expectations for all of the other series. In particular, in the Computer and Peripheral Equipment Manufacturing industry the real GDP series may be described as consisting of three segments—from 1961 to the early 1970s, from the mid-1970s to the early 1980s, and from the mid-1980s to the end of the sample. During the first two sub-periods the data appear to follow a linear trend, which is interrupted by a rapid transition that is driven by economic events that are known to have had wide ranging implications. A similar argument can be made for Railroad Rolling Stock Manufacturing capital services, which increase until the 1980–1981 recession and decline afterwards. In these cases, a unit root process may be incorrectly attributed to series that experience a structural change due to specific economic events.

Because it is difficult to statistically test the unit root hypothesis, practitioners often seek confirmation of their results by conducting an additional unit root test (see Madalla and Kim 1998, 126–128). When the outcomes of the additional unit root test and the original unit root test are the same, the outcome is viewed as more credible. The confirmation is seen as providing additional evidence that the series follows, or does not follow, a unit root process. However, the second test can, and often does, contradict the first test. In these instances there is limited guidance available.

Following the vein of confirmatory analysis, a KPSS (Kwaitkowski, Phillips, Schmidt and Shin 1992) test is applied to each of the real GDP, capital and labour services series. Under the null hypothesis in the KPSS test, the series follows a linear trend.

The results are presented in Table 2. The KPSS tests imply that all series except for Textile and Textile Product Mill Manufacturing and Computer and Peripheral Equipment Manufacturing labour services follow a unit root process. The results differ from the ADF tests for Textile and Textile Product Mill Manufacturing GDP and capital services, Railroad Rolling Stock Manufacturing labour services and Computer and Peripheral Equipment Manufacturing labour services. For all other time series tested, the results of the tests appear to confirm each other, strengthening the notion that they contain a unit root.

Table 2
KPSS[1] stationarity test

	Ho: Series is stationary		
	Textile and textile product mills	Railroad rolling stock manufacturing	Computer and peripheral equipment manufacturing
ln GDP[2]	0.20*	0.16*	0.17*
ln L	0.08	0.19*	0.06
ln K	0.15*	0.20*	0.12*

1. Kwaitkwoski, Phillips, Schmidt and Shin.
2. Gross domestic product.
Note: *Denotes rejection of the null hypothesis at the 10% significance level.
Source: Statistics Canada.

The results imply that a mixture of deterministic and stochastic trends is present. If these results are viewed as credible, then any model that is consistent across industries will have to reconcile the apparent differing nature of the input and response series. However, a closer inspection of the data will reveal that the low power of the unit root tests is likely leading to false test results, making inference difficult. As Perron (1989) shows, when there is a one-time structural break, or a one-time change in the trend of a time series that is stationary around that trend, unit root tests can falsely indicate the presence of a unit root.

4.3 A closer inspection of textile and textile product mill manufacturing

A visual inspection of the time series in Figures 1 to 3 provides an example that is similar in structure to the argument made by Perron (1989). Textile and Textile Product Mill Manufacturing GDP appears to follow a linear trend that changes around 1980, which is consistent with one of the examples Perron discusses. As a result, the stationarity hypothesis for this series is examined more closely. In particular, the KPPS test result is examined in greater detail because it provides an opportunity to succinctly show the impact of the trend change.

The KPSS test statistic is a test of parameter constancy. The test statistic follows from the econometric model where:

$$y_t = \alpha_t + \beta t + e_t$$
$$\alpha_t = \alpha_{t-1} + u_t$$

and $u_t \sim iid(0, \sigma_u^2)$. When $\sigma_u^2 = 0$, the series follows a linear trend, while $\sigma_u^2 > 0$ implies that the parameter follows a random walk. [5] The test statistic is formed using the residuals from the regression $\ln GDP_t = \alpha + \beta t + \varepsilon_t$ where t is a linear trend (model 1). The residuals from model 1 are used to create a series of partial sums:

$$S_t = \sum_{t=1}^{n} e_t \quad n = 1 \ldots T .$$

If the series follows a linear trend then there should not be permanent divergence between the actual time series and the fitted model. Therefore, all the partial sums of the residuals should be near 0. To form the test statistic, note that the partial sums can be written as:

$$S_t = S_{t-1} + e_t .$$

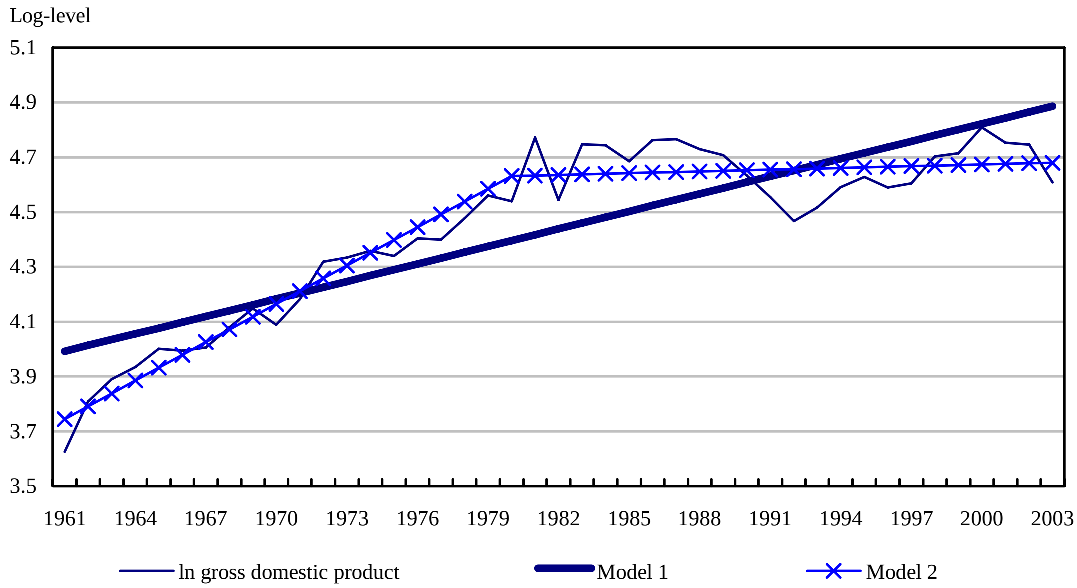
When a unit root is present, permanent changes in the level of the series will lead to partial sums whose variance is non-zero. The test statistic is, therefore, formed by combining an estimate of the variance of the partial sums with an estimate of the long run variance of the estimated residuals. The asymptotic critical values are provided in Kwaitkowski et al. (1992). The test is provided in a number of statistical software routines, which also provide the asymptotic critical values. (For more information, see Kwaitkowski et al. 1992, Franses 1998, and Madalla and Kim 1998.)

However, misspecification of the null model can also lead to residual partial sum series with a non-zero variance. Although the KPSS null model 1 for textile GDP in Table 2 implies the presence of a unit root in Textile and Textile Product Mill Manufacturing GDP, Figure 4 suggests that there is a change in the trend of the series around 1980. If the null model (model 1)

5. The test description is a condensed version of Maddala and Kim's (1998) description. For more information see Maddala and Kim (1998).

is mis-specified, then the residuals and test will be affected. Therefore, rather than using a null model, which assumes the same trend for the whole sample, suppose that the null model allows for a change in the trend in 1980. Specifically, consider the null model (model 2) $\ln GDP_t = \alpha + \beta_1 t + \delta_2 \beta_2 (t - t_L) + \varepsilon_t$ where t and t_L are time trends for the whole period and post-1980, respectively, and δ_2 is an indicator variable that has a value of zero from 1961 to 1979 and one from 1980 to 2003.[6]

Figure 4
Null models for textile and textile product mill manufacturing GDP[1]



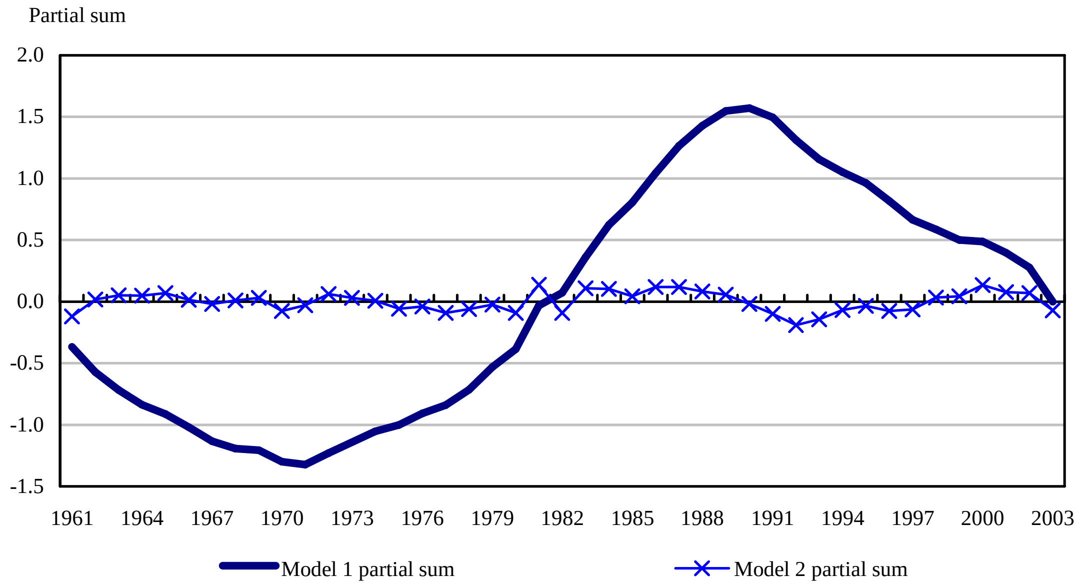
1. Gross domestic product.
Source: Statistics Canada.

The fitted values from the two models are plotted against the log of textile GDP in Figure 4, where it is clear that the fitted values from model 2 track real GDP better than model 1. Moreover, the partial sum of the residuals from model 1 and model 2 are distinctly different (Figure 5). The variance of the partial sum series from model 1 appears greater than zero, implying that the series is non-stationary and leading to the test result in Table 2. However, the variance of the partial sum series from model 2 appears near zero, implying the series is trend stationary with a break. The KPSS test statistic from model 2 is 0.05, which is insignificant at the 10% level, implying that the series is trend stationary.

The different results between model 1 and model 2 suggest that the misspecification of null model 1, rather than the presence of a unit root, is the dominant factor in the rejection of the trend hypothesis in Table 2. Results like this should give researchers reason to pause and consider their results when examining the KLEMS database.

6. This is Model B from Perron (1989).

Figure 5
Partial sums for null model errors



Source: Statistics Canada.

The examination of textile GDP suffices to show that researchers using the KLEMS database need to be cautious. The unit root literature demonstrates that commonly applied unit root tests have low power and are influenced by trend changes and level shifts (Perron 1989, Maddala and Kim 1998). Since these, among other, types of shifts are present in the KLEMS database, simply applying these unit root tests will be problematic.

4.4 Panel unit root tests

Up to this point, a selection of sample industries have been analysed in isolation. However, the KLEMS database contains a panel of industries. If researchers attempt to determine individually whether each series contains a unit root, or which industries are cointegrated, they will be drawn into a long, complicated process that, in the end, will not allow for broad conclusions about the economy. Instead, they will end up modelling each industry separately and be forced to make assumptions about where breaks occur in order to increase the power of their tests. This approach is fraught with danger and exposes researchers to data mining criticisms.

However, if all industries in the panel are treated as having the same structure it is possible to apply unit root tests to the whole panel simultaneously. Unit root tests based on the ADF and KPSS tests are available for this purpose. They attempt to increase the power of these tests by exploiting the cross-section of industries. In effect, test statistics for each industry are combined to form a panel test statistic that has better power than the individual tests.

Two panel unit root tests, the IPS (Im, Pesaran and Shin 1995) and Hadri’s LM test (Hadri 2000) are conducted here. The IPS test aggregates ADF tests from each industry. Under the null hypothesis, all series contain a unit root while under the alternative, at least one series is stationary. Hadri’s LM test assumes all industries are stationary under the null hypothesis and non-stationary under the alternative. The residuals from an auxiliary regression on a trend are used from a test statistic, which follows the KPSS test. The IPS test results are presented in Table 3 and Hadri's LM test results are presented in Table 4.

Table 3
IPS[1] panel unit root tests

H_O: All series contain a unit root H_A: At least one series does not contain a unit root			
	ln GDP[2]	ln L	ln K
Lags			
1	-1.26	-1.02	-1.27
2	-1.19	-1.07	-1.11

1. Im, Pesaran and Shin.
2. Gross domestic product.
Source: Statistics Canada.

Table 4
Hadri's LM panel unit root test

H_O: All time series are stationary			
	ln GDP[1]	ln L	ln K
Homoskedastic errors	114.4*	105.5*	141*
Heteroskedastic errors	100.9*	94.4*	117.4*
Serially dependent errors	29.4*	26.1*	35.0*

1. Gross domestic product.
Note: * Denotes rejection of the null hypothesis at the 10% significance level.
Source: Statistics Canada.

The IPS test supports the null hypothesis that all series contain a unit root, while Hadri's LM test rejects the null hypothesis that the series are trend stationary. The tests provide confirmation of each other and imply that the panel series should be treated as if they follow a unit root process. However, as noted above, the data are noisy, subject to numerous types of structural breaks and to aberrant observations. As a result, it is likely that the panel unit root tests are being affected in a manner analogous to the KPSS and ADF tests in the previous section.

Unfortunately, knowing this does not leave researchers with guidance about how best to treat the data. From the three industries analysed in detail it certainly appears that a complicated data generating process (DGP) is present. It is also clear that in some cases, such as Textile and Textile Product Mill Manufacturing GDP, a linear trend with a break approximates the DGP well. In other cases, such as Railroad and Rolling Stock Manufacturing, it is less clear that a linear approximation matches the data. As a result the 'correct' method for estimating total factor productivity will depend on the extent to which the researcher is comfortable with the test results, and the extent to which all series follow the same type of trend (stochastic or deterministic).

4.5 Data transformation

In this paper the unit root test results are viewed as suspect. Given the examination of the sample industries and the differing nature of the DGPs across industries, simply accepting the outcome of the panel unit root tests appears risky. Therefore, the following two assumptions are made:

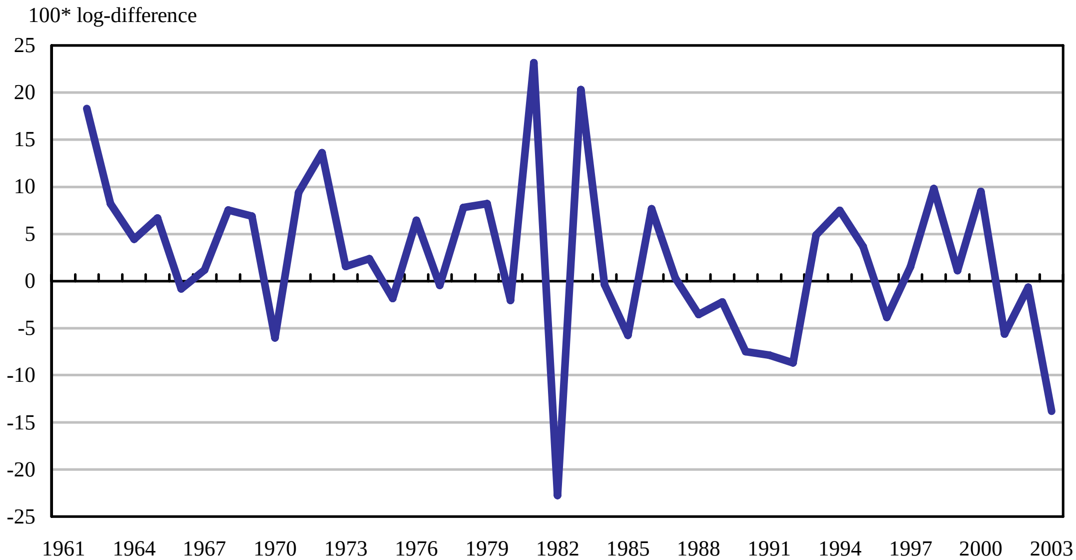
1. All series can be rendered covariance stationary by applying the first difference (1-L) filter to the data; and,
2. The contemporaneous changes will adequately capture the economic relationship between the variables of interest.

These assumptions are strong, and assume away issues associated with structural breaks and serial error correlation. These are important issues that can have consequences for parameter estimates. However, this paper assumes that these problems are secondary when compared with the impact of the aberrant observations in the dataset.

For example, the log-differences of GDP from the sample industries exhibit large magnitude observations, which make it doubtful that accurate identification of mean shifts can be accomplished without first addressing their influence (Figures 4 to 6). While this paper recognizes that mean shifts and differencing issues are important, it focuses on how to deal with and identify the aberrant observations. Once this is accomplished, it should be possible to revisit issues associated with structural breaks and over differencing. However, for the purposes of this paper, these issues are beyond the scope of analysis.

For the remainder of the paper, therefore, analysis focuses on log-level data that are first differenced and multiplied by 100. For small changes, this will approximate the growth rate of the series. However, as Figures 4 to 6 show, the industry level data are subject to aberrant changes that may be quite large and, as such, the growth rate approximation will be inaccurate in these cases.

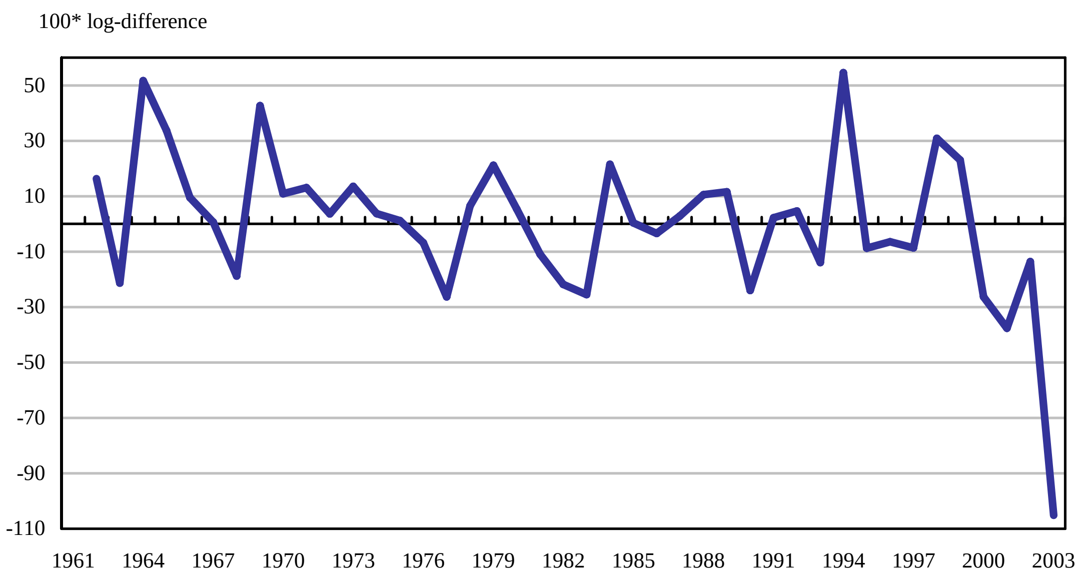
Figure 6
Textile and textile product mill manufacturing gross domestic product



Source: Statistics Canada.

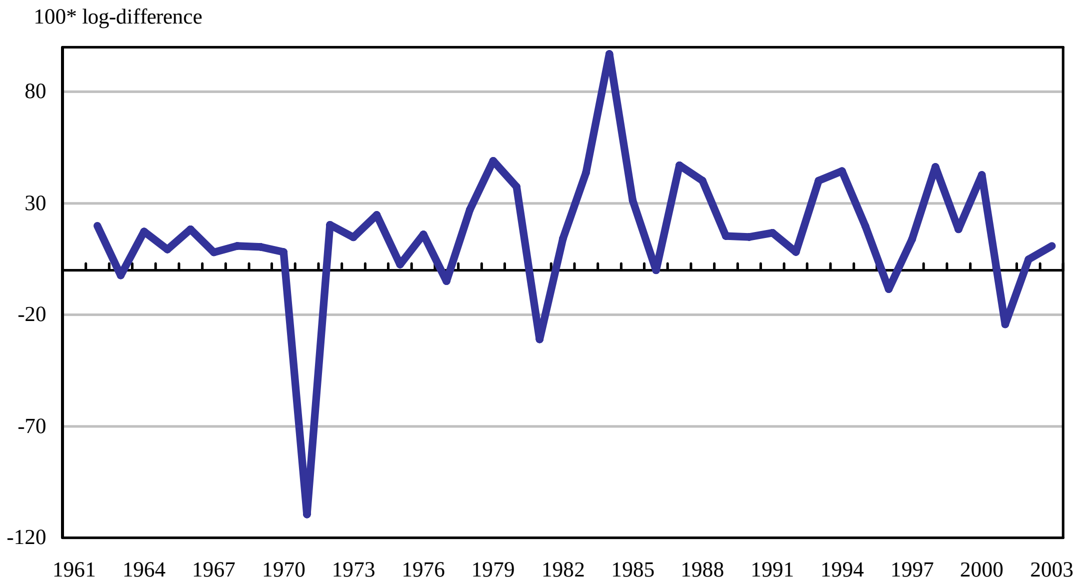
Employing the (1-L) filter makes the data appear covariance stationary; however, it also exposes aberrant data points that may affect some types of estimators. When the data are log-differenced business cycle turning points, oil shocks, idiosyncratic shocks, aggregate economic shocks, measurement error and methodology changes can all affect GDP, capital and labour services from year to year. Occasionally these changes are large, relative to the history of the industry, and have the ability to bias commonly applied estimators.

Figure 7
Railroad rolling stock manufacturing gross domestic product



Source: Statistics Canada.

Figure 8
Computer and peripheral equipment gross domestic product



Source: Statistics Canada.

5. *Econometric specification*

The preliminary data analysis suggests that using first differenced data will be more fruitful than assuming that the series are cointegrated or stationary around a linear trend. After applying the (1-L) transformation, there are two basic econometric models that are used to generate total factor productivity (TFP) estimates using the Cobb-Douglas specifications from Section 2. First, (1) becomes:

$$\Delta \ln GDP_{i,t} = \alpha_i + \beta_{i,K} \Delta \ln K_{i,t} + \beta_{i,L} \Delta \ln L_{i,t} + \varepsilon_{i,t}. \quad (3)$$

Second, after imposing the constant returns to scale constraint (2), equation (1) reduces to:

$$\Delta \ln LP_{i,t} = \alpha_i + \beta_{i,K} \Delta \ln \left(\frac{K_{i,t}}{L_{i,t}} \right) + \varepsilon_{i,t} \quad (4)$$

where LP is defined as labour productivity such that:

$$LP_{i,t} = \Delta \ln \left(\frac{GDP_{i,t}}{L_{i,t}} \right).$$

In each econometric specification, TFP is captured by a constant, α_i, that varies across industries. Real gross domestic product (GDP), capital services and labour services are indexed across time and industries, where t=1 … 42 log-differences from 1962 to 2003 and i = 1 … 88 business sector industries at the P-level aggregation from the Capital, Labour, Energy, Materials and Services (KLEMS) database.

The interpretation of the elasticity coefficients is analogous to their interpretation in the log-level model described in Section 2. After applying the (1-L) filter, $\beta_{i,K}$ and $\beta_{i,L}$ capture the elasticity of capital and labour services. In each version, which are hereafter described as the Cobb-Douglas (C-D) and Labour Productivity (LP) versions, it is not assumed a priori that the elasticities of capital and labour are equal across all industries. The elasticities are, therefore, also indexed across the 88 industries.

While panel data investigations often hypothesize that regression coefficients are equal for all units, this hypothesis requires verification when the KLEMS dataset is employed. In many applications, such as investigations using the Panel Study on Income Dynamics (PSID), or provincial or state panels, the hypothesis is likely a good approximation. In these studies the units, which are either people or economic areas, tend to have a lot in common, making the hypothesis that their slope parameters in regression equations are equal plausible.[7]

With the KLEMS data, the hypothesis warrants further analysis because economic theory suggests that the units (industries) likely have different elasticities of capital and labour services. In particular, industries that are more capital intensive, such as manufacturing or mining, oil and gas extraction, likely have a higher elasticity of capital than industries that are more labour intensive, such as finance, insurance and real estate. Given these differences, the hypothesis that the elasticities should be equal across industries appears overly restrictive.

Nevertheless, the hypothesis that the elasticities could be equal is examined in a fixed effects model. Typically an F-test for the constraint is used to statistically test the hypothesis. However, this approach will encounter difficulties when the KLEMS dataset is employed. First, by estimating the relationship using a traditional fixed effects model, the error variance is assumed to be equal across all industries. Figures 4 to 6 suggest that this is a strong assumption, which likely does not fit the data. Second, the presence of aberrant observations will lead to non-normal residuals which will bias the test results. A Weighted Least Squares (RLS) estimator is employed to mitigate this; however, the differing magnitude industry variances will remain an issue.[8]

7. To be precise, the assumption is that while there may be some variation between units, the variation is not sufficiently large to reject the null hypothesis that the coefficients are equal across units.
8. RLS reduces the impact of outliers and leverage points by changing the weights in the OLS (ordinary least squares) regression. RLS minimizes $\min \sum_{t=1}^{T} w_t e_t^2$ where w_t is chosen such that aberrant observations get a small weight while 'good' data gets a large weight. Note that traditional OLS assumes $w_t = 1 \quad \forall t$. In this paper a simple weighting scheme is employed: $w_t = \begin{cases} =1 & Non-Aberrant \\ =0 & Aberrant \end{cases}$. More complex schemes can be employed if desired. For more information, see Chen (2002), Rousseeuw and Leroy (1987).

Since the hypothesis that the elasticities of capital and labour are equal across industries appears overly restrictive, estimates are initially produced for each industry individually. This means that 88 individual regressions are performed. Once completed, the parameter estimate distributions, as well as the RLS F-test, are employed to revisit the hypothesis that the parameters are equal across industries.

6. Estimation in the presence of aberrant observations

Preliminary analysis indicates that aberrant observations are present in the dataset. Their presence will have important consequences for how the Capital, Labour, Energy, Materials and Services (KLEMS) data are employed to generate total factor productivity (TFP) estimates. In particular, aberrant observations have the ability to influence parameter estimates and inference when Ordinary Least Squares (OLS) is used (see Sapra 2003; Tsay, Pena and Pankratz 2000; Chen and Liu 1993; Pena 1990; Rousseeuw and Leroy 1987; Tsay 1986; and Rousseeuw 1984).

To overcome the influence, a high breakpoint estimator is used in this paper. The breakpoint of an estimator is a measure of its sensitivity to aberrant observations. It represents the proportion of the sample employed for estimation that can be aberrant before the estimator is affected.

6.1 The OLS estimator

The OLS estimator is not a high breakpoint estimator. The objective function for OLS estimation minimizes the residual sum of squares:

$$\min \sum_{t=1}^{T} e_t^2 .$$

Because aberrant observations can lead to large errors, the minimization problem necessarily directs the plane of a linear regression toward a single observation that is arbitrarily large. As a result, by including a single aberrant observation, it is possible to change the OLS slope and intercept parameter estimates.[9] Because a single data point can affect the OLS estimator, its breakdown point is zero percent (Rousseeuw and Leroy 1987).

The OLS zero breakdown point makes its estimates inappropriate for inference, or identifying aberrant observations when they are present. Importantly for analysis in this paper, biased OLS parameter estimates can hide aberrant observations in diagnostic statistics that are designed to reveal them. In particular, for sufficiently large aberrant observations, OLS is drawn toward the problematic data point and, as a result, residual diagnostic statistics based on an OLS regression can signify that the actual aberrant observation is a good data point while signalling that 'good' data is problematic. Moreover, when there is more than one aberrant observation, or a group of aberrant observations, the aberrant observations can interact in complex ways, enhancing or cancelling each other's influence. As a result, one outlier may hide the presence of another,

9. See Rousseeuw and Leroy (1987).

which is known as the masking effect. Similarly, a group of aberrant observations can draw the plane of the regression towards them, which is known as the swamping effect. In this instance, OLS estimates make it difficult to assess which data points are 'good' versus which are aberrant (Hadi 1992, Rousseeuw and van Zomeren 1990, and Rousseeuw and Leroy 1987).

6.2 The S-estimator

To overcome these problems, an estimator that is robust to aberrant observations is required. Several choices are available including Least Median Squares, M-estimators, Least Trimmed Squares and S-estimators. These estimators use functions of the data that, in a variety of ways, reduce the influence of aberrant observations.

They are often referred to as robust estimators because they are insensitive to aberrant observations. In some cases, such as S-estimators, they have a breakdown point of 50%, meaning that up to half of the sample can be aberrant before the estimator is affected. This is a marked improvement over the OLS estimator which is sensitive to the presence of a single aberrant observation.[10]

In this paper, Rousseeuw and Yohai's (1984) S-estimator is used. The S-estimator is a high break point estimator that selects parameter estimates with the goal of minimizing the dispersion of the residuals. Importantly, this estimator is robust with respect to aberrant observations in the dependent variable and independent variables.

The S-estimator minimizes the dispersion of the regression residuals such that

$$\hat{\theta}_S = \arg\min_{\theta} S(\theta)$$

where $S(\hat{\theta})$ is an estimate of the distribution dispersion.

The S-estimate is selected by applying an algorithm to the full sample of data. The algorithm selects a subsample of the data to calculate regression coefficients. These coefficients are used to iteratively solve an additional equation and generate an estimate of $S(\hat{\theta})$. When the algorithm is applied repeatedly, vectors of dispersion estimates are created. Because aberrant observations necessarily increase the dispersion of the residuals, a robust set of parameter estimates can be found by selecting the regression coefficients that correspond to the smallest $S(\hat{\theta})$.[11] The algorithm provides robust parameter estimates that are asymptotically equivalent to the estimates from a standard Gaussian regression model.

10. Note that a least absolute deviations (LAD) estimator is subject to the same breakdown point as the Ordinary Least Squares estimator. Although the estimator provides the median in a univariate sample, and can be robust to aberrant observations in the dependent variable, for a sufficiently large aberrant observation in the independent variable the slope of the LAD estimator will pass through the problematic point. For more information, see Rousseuw and Leroy (1987).
11. For a technical discussion about the algorithm used to compute the S-estimates used in this paper see the SAS9 user manual discussion on Proc RobustReg.

6.3 Identifying outliers and leverage points

Since aberrant observations may only be present in a subset of the variables used for analysis, a distinction is made between aberrant observations in the independent variables (leverage points) and aberrant observations in the response variable (outliers). As noted above, it is necessary to employ robust estimators when identifying leverage points and outliers (Hadi 1994, 1992; Rousseuw and van Driesen 1999).

Leverage point detection is accomplished by measuring the robust distance of an observation from a robust central location. The following robust distance statistic is used here:

$$RD(x_i) = \left[\left(x_i - T(x_i) \right)' C(x_i)^{-1} \left(x_i - T(x_i) \right) \right]^{0.5}$$

where $T(x_i)$ and $C(x_i)$ are robust multivariate estimates of the central location and scatter matrix, respectively.[12] The leverage points are then defined as robust distances that are greater than the corresponding critical value, which is based on the Chi-squared distribution

$$Crit(p) = \left(\chi^2_{p,1-\alpha} \right)^{0.5}$$

where p is the number of explanatory variables and α is the pre-designated significance level. When $RD(x_i)$ is greater than $Crit(p)$, a leverage point is deemed to be present. While the choice of significance level is arbitrary, in this paper all tests for leverage points are conducted at the 5% level.

Outlier detection is based on the residuals from a regression, and will, consequently, be affected by functional form, parameter constraints and the explanatory variables that are included. The S-estimates are used to form a residual vector $\hat{\varepsilon}$. For each $\hat{\varepsilon}_t$ in $\hat{\varepsilon}$, the absolute value of the residual is compared with twice the scale parameter estimate $S(\hat{\theta}_S)$. When the absolute value of $\hat{\varepsilon}_t$ is greater than this cut off the observation is deemed an outlier.

12. Derivations and notation follow Chen (2002). The estimates of $RD(x_i)$ are created using the SAS9, which employs Rousseuw and Van Dreissen's (1999) algorithm for computing robust multivariate statistics. For more information please refer to Chen (2002).

7. Parametric TFP estimates

The examination of the parameter estimates from the Cobb-Douglas (C-D) and labour productivity (LP) equations in this section illustrates the degree to which Ordinary Least Squares (OLS) estimates derived from the Capital, Labour, Energy, Materials and Services (KLEMS) database are biased, due to outliers and leverage points. The comparison begins with the sample industries followed by an analysis of the full business sector panel. For the analysis at this point, only 88 of the 89 industries in the KLEMS database are employed. The final industry, the non-business sector, is not included. It is, however, added back to the panel in subsequent sub-sections where the number and timing of aberrant observations are analysed.

The analysis focuses on how aberrant observations impact OLS estimates, and on how changing estimation techniques can reveal aberrant observations. It does not focus on whether or not the equation is properly specified. In particular, the specification may miss dynamics in total factor productivity (TFP), capital utilization over the business cycle or the impact of scale economies. These aspects, which are important issues that can generate omitted variable bias, are not the focus of the econometric examination. Rather, the econometric examination is designed to illustrate the impact that aberrant observations can have on parametric estimates if they are not accounted for. The TFP specification employed is commonly used in the literature, and is consistent with non-parametric TFP specifications.

Before examining the panel of industries, the sample industries are used to illustrate, ceteris paribus, the impact that changing the estimation strategy has. Subsequently the full business sector panel is examined and a number of broad conclusions are drawn about the sources of aberrant observations.

7.1 Sample industry TFP estimates

For Textile and Textile Product Mill Manufacturing, the OLS tfp estimate from the C-D equation is 2.43% which is 0.43 percentage points higher than the S estimate of 2.0% (Table 5). There is a difference between the elasticity estimates; however, it is of a smaller magnitude than the difference between the tfp estimates.

While OLS overestimates tfp for Textile and Textile Product Mill Manufacturing, the remaining sample industries are underestimated by OLS. In Computer and Peripheral Equipment Manufacturing, the OLS estimate of tfp is 8.88% while the S-estimate is 13.17%, a difference of 4.30 percentage points. This is the largest difference found in the business sector. Moreover, the S-estimate for the elasticity of labour is 0.46, which is 0.63 percentage points lower than the OLS estimate of 1.09. Importantly, while the constant returns to scale hypothesis does not appear to fit the data well when OLS is employed, the S-estimate appears to support the constraint.

Table 5
Cobb-Douglas equation parameter estimates

Textile and textile product mill manufacturing	OLS[1]	S-estimator
tfp	2.43	2.00
$\hat{\beta}_L$	1.11	1.05
$\hat{\beta}_K$	-0.04	-0.01
Computer and peripheral equipment manufacturing	OLS[1]	S-estimator
tfp	8.88	13.17
$\hat{\beta}_L$	1.09	0.46
$\hat{\beta}_K$	0.59	0.55
Railroad rolling stock manufacturing	OLS[1]	S-estimator
tfp	-1.12	1.06
$\hat{\beta}_L$	1.19	1.09
$\hat{\beta}_K$	0.22	0.12

1. Ordinary least squares.
Source: Statistics Canada.

For Railroad Rolling Stock Manufacturing, the difference is less pronounced. However, the *tfp* estimate changes sign when aberrant observations are accounted for. The OLS estimate of *tfp* in this industry is -1.12% per year. By accounting for the aberrant observations in the data, the S-estimate of *tfp* rises 2.18 percentage points to 1.06%. The S-estimates for the elasticity of capital and labour services are lower than the OLS estimates.

The Textile and Textile Product Mill Manufacturing LP *tfp* growth estimates are similar to the C-D estimates (Table 6). The OLS estimate suggests *tfp* growth is 2.48%, which is 0.42 percentage points higher than the S-estimate of 2.06. The estimate for the elasticity of capital services is near zero from both estimation methods, however, the OLS estimate is nearly three times larger than the S-estimate.

Unlike the C-D equation where OLS underestimates *tfp* growth in the Computer and Peripheral Equipment Manufacturing industry, the OLS LP *tfp* growth estimate of 14.15% is 0.89 percentage points larger than the S-estimate of 13.26%. As with the C-D estimates, the OLS elasticity of capital estimate of 0.06 is lower than the S-estimate of 0.54.

For Railroad Rolling Stock Manufacturing the OLS *tfp* growth estimate from the LP equation is -0.47%, which is negative like the C-D estimate, but less than half the magnitude. The S-estimate increases 1.74 percentage points to 1.27%, which is similar to the unrestricted C-D estimate. The elasticity of capital estimate rises from -0.14 to 0.04 when the S-estimator is employed.

Table 6
Labour productivity equation estimates

Textile and textile product mill manufacturing	OLS[1]	S-estimator
tfp	2.48	2.06
$\hat{\beta}_K$	-0.08	-0.03
Computer and peripheral equipment manufacturing	OLS[1]	S-estimator
tfp	14.15	13.26
$\hat{\beta}_K$	0.06	0.54
Railroad rolling stock manufacturing	OLS[1]	S-estimator
tfp	-0.47	1.27
$\hat{\beta}_K$	-0.14	-0.04

1. Ordinary least squares.
Source: Statistics Canada.

The sample industries illustrate the impact that outliers and leverage points can have on parametric estimates when the KLEMS database is employed. OLS estimation using these data is going to be affected by the aberrant observations. While it appears that in the Computer and Peripheral Equipment Manufacturing industry the *tfp* growth estimate improves when constant returns to scale are imposed on the production function, this should not be generalized. The OLS LP estimate of the elasticity of capital for that industry is lower than the S-estimate and *tfp* estimates for the remaining sample industries continue to be influenced by aberrant observations.

7.2 Industry panel TFP estimates

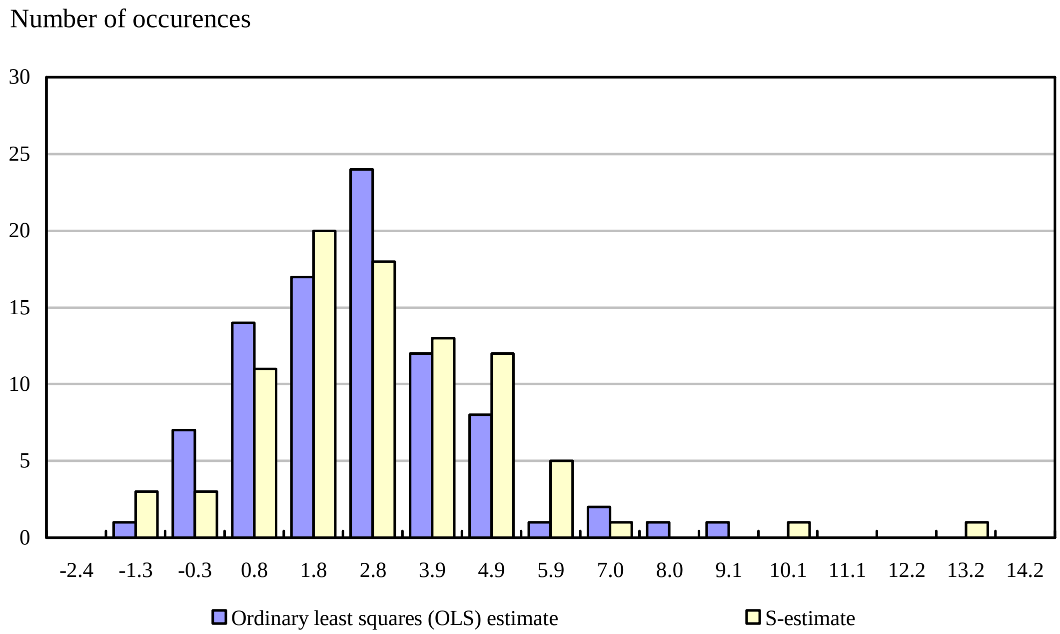
The OLS and S-estimator parametric estimates from the sample industries are sufficient to show the impact that aberrant observations can have on a particular industry. However, the sample industries do not provide sufficient information to make generalizations about the impact of outliers and leverage points on the panel of business sector industries.

Analysing the business sector is difficult because, as noted above, the differing capital intensities across industries suggest that the elasticity of capital is also different across industries. Therefore, the data are not initially pooled and regressions are performed for each of the industries separately. The estimates from the OLS and S-estimators are grouped together, and their distributions are examined. The majority of the analysis focuses on these distributions because the aberrant observations in the dataset make it difficult to conduct residual based tests. Despite this, Weighted Least Squares (RLS) is used to statistically test the validity of the cross equation restrictions. However, the RLS procedure employed here necessarily constrains the variances of the industries to be equal; a constraint that is likely too strong.

Analysis focuses on the cross-industry parameter estimate distributions because they make it possible to informally test a number of hypotheses. First, if the outliers and leverage points tend to affect all industries in a similar manner, the central point of the OLS and S-estimator distributions will differ. Second, if OLS tends to miss large parameter estimates, which is the case for the C-D *tfp* growth estimates, the tails of the S-estimate distribution will be thicker than the tails of the OLS estimate distribution. Third, if the hypothesis that *tfp* growth, or the elasticities of capital and labour services, is equal across industries is valid, the distributions should exhibit little variance. They should be closely bunched around their respective central locations.[13]

The C-D OLS *tfp* growth estimates appear to be negatively affected by aberrant observations, providing more low estimates than the S-estimator (Table 9). The OLS estimator also appears to be unable to adequately estimate *tfp* growth in those industries where it is largest. The average growth rate from the OLS estimates is 2.08% while the S-estimator mean is 2.43%.

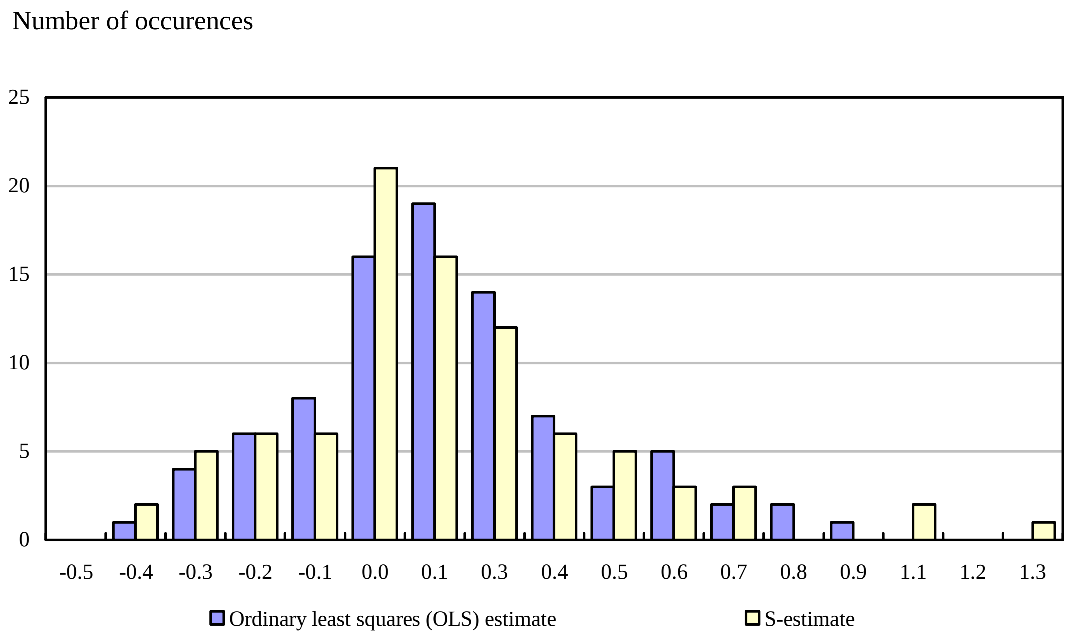
Figure 9
Distribution of Cobb-Douglas production function TFP[1] estimates



1. Total factor productivity.
Source: Statistics Canada.

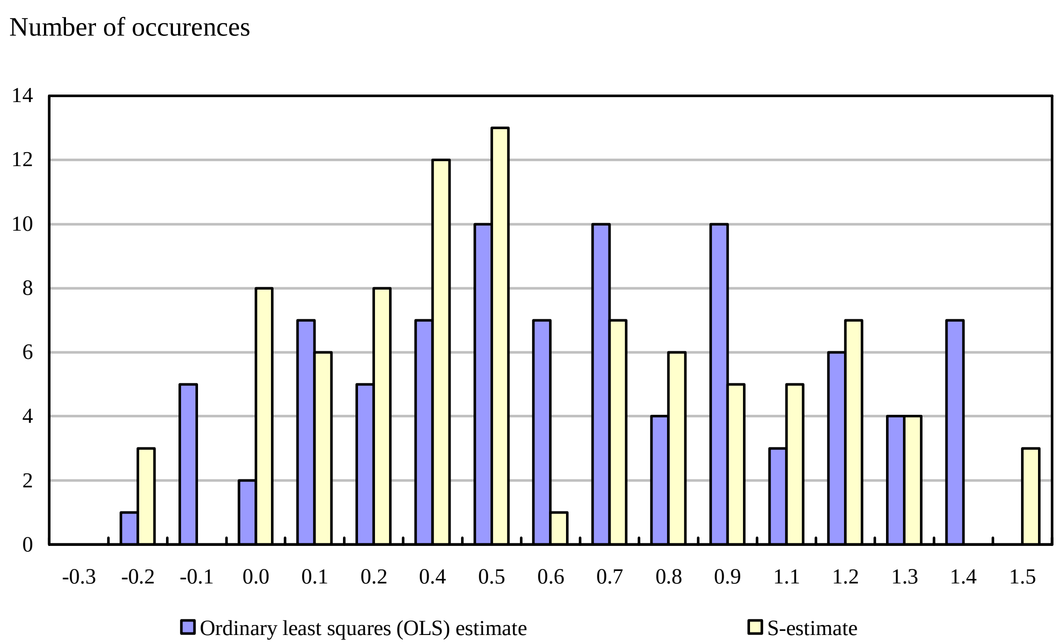
13. For a complete table of parameter estimates see Appendix A.

Figure 10
Distribution of Cobb-Douglas production function elasticity of capital estimates



Source: Statistics Canada.

Figure 11
Distribution of Cobb-Douglas production function elasticity of labour estimates



Source: Statistics Canada.

However, since OLS appears to underestimate the largest *tfp* growth rates, the comparison of the means of the S-estimate and OLS *tfp* growth rates may reflect the impact of a small number of large positive observations. If the five largest positive growth rates are trimmed and the average of the industry *tfp* growth rates is re-calculated, a consistent picture emerges; the OLS industry *tfp* growth rate average is 1.80 while the S-estimator average is 2.10. In each case OLS underestimates average *tfp* growth.

If OLS is applied to the KLEMS database the resulting *tfp* growth rate estimates will tend to underestimate *tfp* growth and fail to capture those industries where *tfp* growth is largest. Moreover, the differences appear to be non-random since the OLS estimates are, on average, lower than the S-estimates.

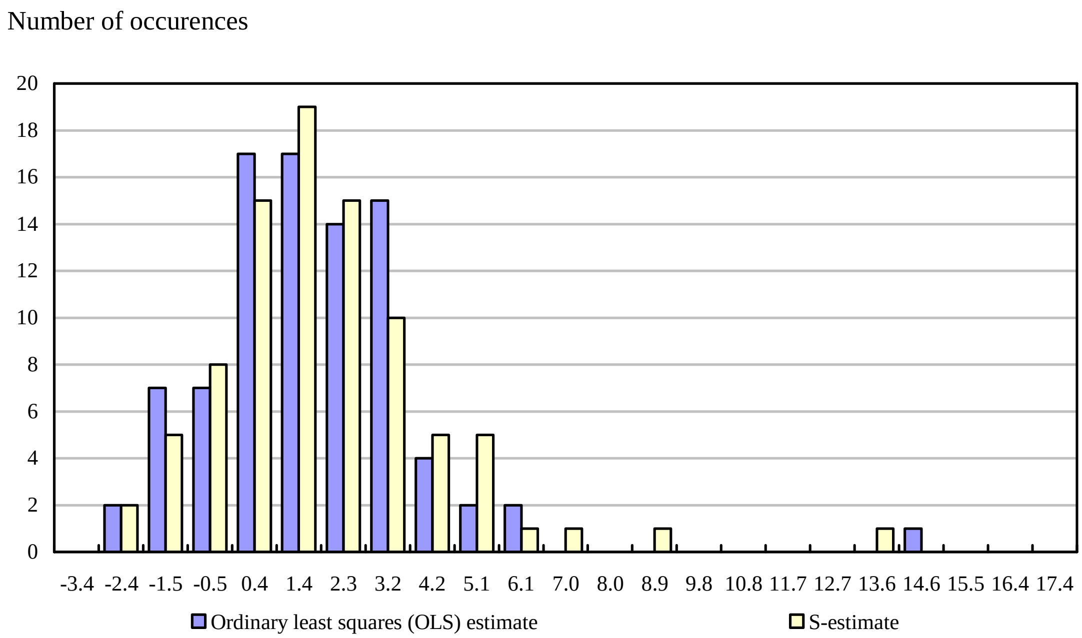
For the C-D elasticity of capital estimates, it appears that OLS may be underestimating the elasticity while simultaneously failing to recognize the largest values (Figure 10). However, the OLS and S-estimate means are similar: 0.10 and 0.11, respectively. Calculating a trimmed mean by removing the top five estimates does not alter this.

The similarity between the OLS and S-estimates is unexpected, given the presence of leverage points and outliers in the dataset. The apparent contradiction may be explained by the implied low average elasticity. The near zero average may result from small year-to-year differences. However, it is also possible that, while the OLS and S-estimates are different in many industries, the difference is random rather than systematic.

Unlike the *tfp* growth and elasticity of capital estimates, the C-D elasticity of labour estimates suggests that OLS is overestimating the average elasticity of labour (Figure 11). On average, OLS provides an estimate of 0.59 which is 0.07 percentage points higher than the S-estimate average of 0.52. The same difference is found if the top five estimates are trimmed from the sample.

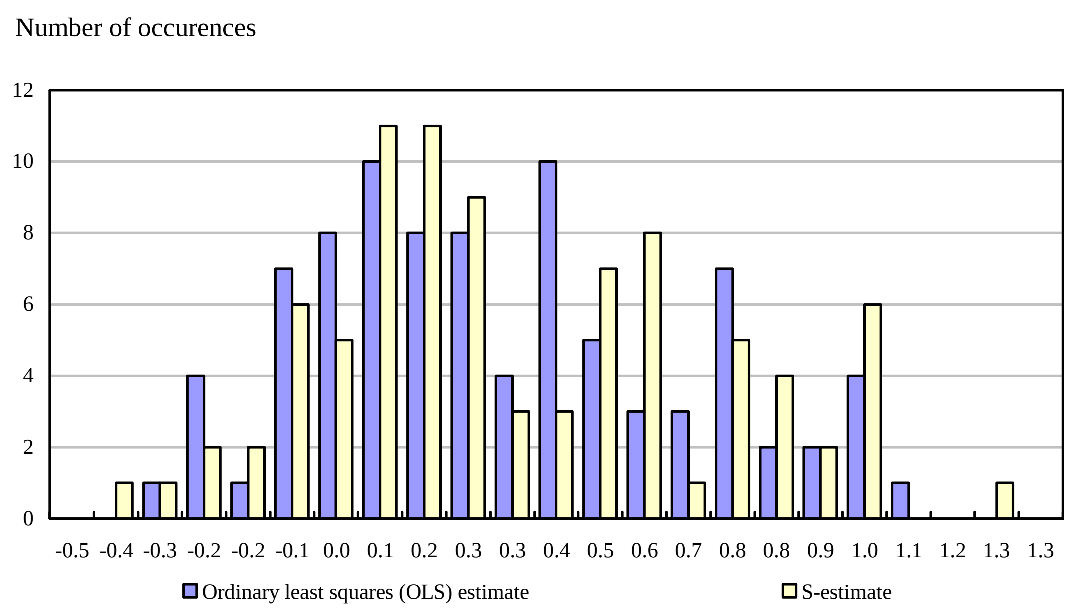
The LP *tfp* growth estimates present a slightly different profile than the C-D estimates. With the constant returns to scale constraint, the distributions become more centralized, although the OLS estimates continue to underestimate *tfp* growth relative to the S-estimates. The average of the OLS *tfp* growth estimates is 1.23% which is 0.15 percentage points lower than the 1.38% average from the S-estimates. As with the C-D estimates, there are a small number of large *tfp* growth estimates. When the five largest *tfp* growth estimates from the OLS and the S-estimator are removed, the averages drop to 0.89% and 1.0%, respectively. Despite the estimates being less dispersed when constant returns to scale are imposed, the estimates still differ noticeably between industries, and continue to suggest that a systematic difference is present.

Figure 12
Distribution of labour productivity function TFP[1] estimates



1. Total factor productivity.
Source: Statistics Canada.

Figure 13
Distribution of labour productivity function elasticity of capital estimates



Source: Statistics Canada.

The OLS and S-estimator elasticity of capital estimates from the LP equation are noticeably different across industries. Despite this, the averages are similar (OLS: 0.28; S-Estimates: 0.31) and close to capital's share of income in the business sector. Moreover, the implied elasticity of labour is 0.72 (OLS) or 0.69 (S-Estimates), which is close to labour's share of business sector income. Like the C-D estimates, the LP elasticity estimates do not imply that there is a consistent bias in OLS estimates across industries.

The analysis of the parameter distributions from the C-D and LP equations illustrate that OLS tends to underestimate *tfp* growth relative to the S-estimator. The underestimation occurs at both the average of the estimates and for large parameter estimates in particular industries. This pattern suggests that large negative innovations, which do not represent the majority of the data, can have noticeable impacts on parametric *tfp* growth estimates. In particular, OLS estimates are derived from the averages of the independent and dependent variables. If irregular infrequent negative events, such as recessions, affect these averages, then the OLS *tfp* growth estimates will also be biased. Moreover, if particular industries are more sensitive to infrequent economic shocks, then the difference in their estimates of *tfp* growth should be larger.

The distributions imply that OLS estimates, by using all available data, are influenced by periods of irregular economic activity. The S-estimator, however, focuses on observations that represent a majority of the data and is not subject to the same problem. The difference brings to the forefront an important issue about estimating *tfp*.

During recessionary periods the response functions of economic agents can be different from their expansionary response functions. As a result, if a researcher is trying to capture long-run growth derived from increases in intangible, or hard to measure, inputs it may be unreasonable to include recessionary periods in the dataset used for estimation. While a full discussion of this issue is beyond the scope of this paper, subsequent sections will show that the number of outliers and leverage points tend be bunched around aggregate shocks, implying that these periods are important sources of unusual observations.

The distributions of the parameter estimates from both equations imply that *tfp* growth, as well as the elasticities of capital and labour, differ across industries. The estimates tend to be dispersed rather than tightly grouped around a central location. In the presence of these types of parameter estimate differences, the validity of cross-equation constraints is uncertain. Nevertheless, the hypothesis is formally tested for *tfp* growth and the elasticities from both equations.

The C-D equation rejects the hypothesis that *tfp* growth and the elasticity of labour are equal across industries (Table 7). However, the F-test fails to reject the hypothesis for the elasticity of capital, which is at odds with the dispersion of the parameter estimates from the individual regressions. For the LP equation the hypothesis that *tfp* growth and the elasticity of capital are equal is rejected at the 5% level.

Table 7
Weighted least squares (RLS) cross equation constraint F-tests

Hypothesis	F-test
Cobb-Douglas equation	
$tfp_i = tfp$	1.60 (0.00)
$\hat{\beta}_{K,i} = \hat{\beta}_K$	1.03 (0.41)
$\hat{\beta}_{L,i} = \hat{\beta}_L$	2.04 (0.00)
Labour productivity equation	
$tfp_i = tfp$	1.84 (0.00)
$\hat{\beta}_{K,i} = \hat{\beta}_K$	2.72 (0.00)

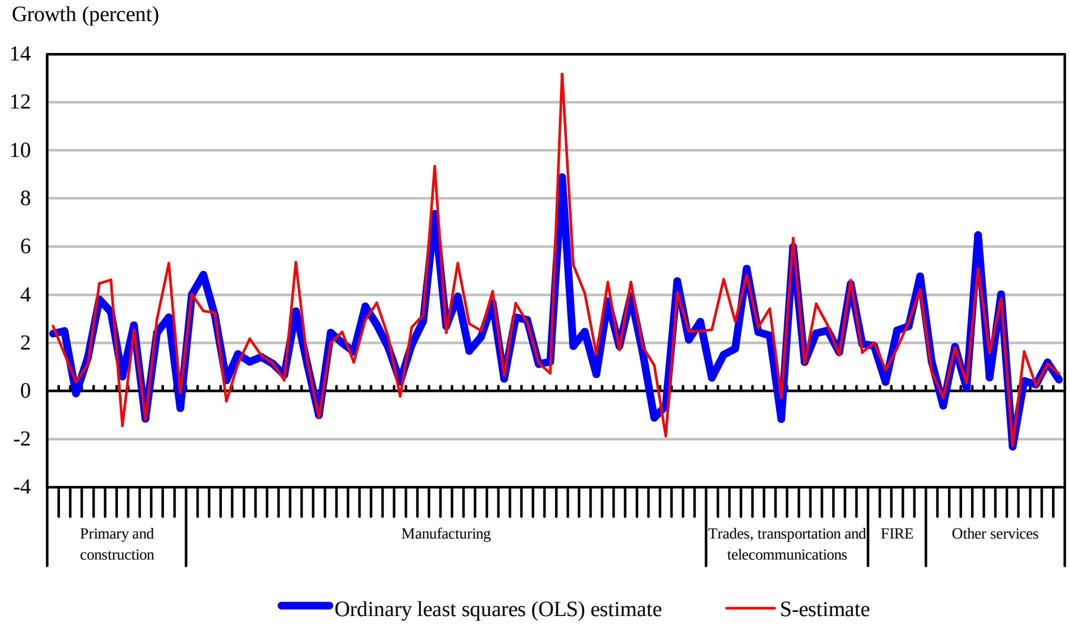
Note: P-values in parentheses.
Source: Statistics Canada.

With the exception of the elasticity of capital in the C-D equation, the F-tests support the notion that the parameter estimates differ across industries. The failure to reject the null hypothesis for the elasticity of capital in the C-D equation is puzzling, considering the dispersion of the individual estimates. It may be the result of the RLS technique reducing the variability of the change in capital stock, which tends to have little variation to begin with, making parameter estimates statistically insignificant. For the majority of the elasticity of capital parameter estimates this may be the case; however, there are a minority of estimates that remain significant at the 5% level.

Nevertheless, the dispersion of the parameter estimates and the F-test results provide a strong indication that the data should not be pooled, and that parameters should not be constrained across equations. Whether or not the data are treated as a panel or used in individual regressions will depend on whether or not researchers believe the variances of the individual equations can reasonably be constrained to be equal.

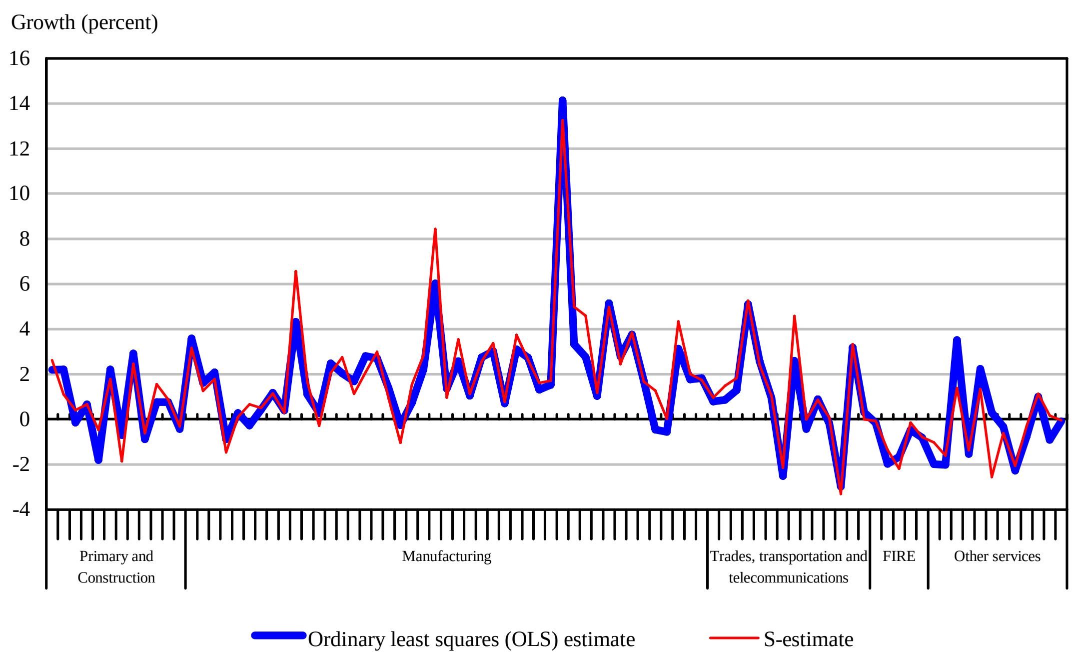
It is worth noting that the pattern of parametric tfp growth rate estimates differs across industries, depending on whether the constant returns to scale constraint is imposed (Figures 14 and 15). While both equations show that manufacturing sector tfp growth tends to be higher than other sectors, when constant returns to scale is imposed on the production function the primary and service industry estimates become low or negative.

Figure 14
Cobb-Douglas equation production function TFP[1] estimates by industry



1. Total factor productivity.
Source: Statistics Canada.

Figure 15
Labour productivity equation production function TFP[1] estimates by industry



1. Total factor productivity.
Source: Statistics Canada.

As a result, the contribution to business sector productivity from different sectors depends on whether the constant returns to scale constraint is valid. If it is, then business sector productivity is driven almost completely by manufacturing and tends to be held back by other sectors. However, if the assumption is invalid then only select industries, rather than sectors, will detract from productivity growth.

The distinction is important because it is demonstrated in Baldwin, Durand and Hosein (1999) that sectors with the highest productivity growth experience a decrease in their aggregate weight over time. As a result, if the constant return to scale constraint is valid, in order to maintain a particular level of business sector productivity growth over time, it may be necessary to experience an ongoing and accelerating increase in manufacturing productivity growth.

It is also worth noting that the mix of industries where the largest difference between OLS and S-estimator *tfp* growth rate estimates are present differs between the C-D and LP equations (Tables 8 and 9). While there are some industries in common, the magnitude of the biases in the C-D OLS estimates tends to be larger than the biases in the LP OLS estimates.

Nevertheless, in both cases the size of the bias is non-trivial, and suggests that economic shocks do not affect all industries equally. Importantly, the largest magnitude differences from the C-D and LP equations suggests that the OLS estimates tend to underestimate *tfp* growth, supporting the supposition that infrequent negative shocks, such as recessions, play a significant role in biasing OLS *tfp* growth estimates. Furthermore, the impact of these shocks differs across industries, implying that their reactions are not equal. Rather, the relationship between inputs and value added appears to vary considerably.

Table 8
Cobb-Douglas TFP[1] estimate differences: S- versus OLS[2] estimates

Industry	Difference
Computer and peripheral equipment manufacturing	4.30
Electronic product manufacturing	3.38
Retail trade	3.14
Natural gas distribution, water and other systems	2.25
Railroad rolling stock manufacturing	2.18
Metal ore mining	-2.05
Wineries	2.03
Wholesale trade	2.00
Resin, synthetic rubber, and artificial and synthetic fibres and filament	1.98
Household appliance manufacturing	1.59
Sugar and confectionery product manufacturing	-1.51
Waste management and remediation services	-1.39
Pharmaceutical and medicine manufacturing	1.39
Coal mining	1.34
Ship and boat building	-1.23
Accommodation and food services	1.23
Postal service and couriers and messengers	1.23

1. Total factor productivity.
2. Ordinary least squares.
Source: Statistics Canada.

Table 9
Labour productivity TFP[1] estimate differences: S- versus OLS[2] estimates

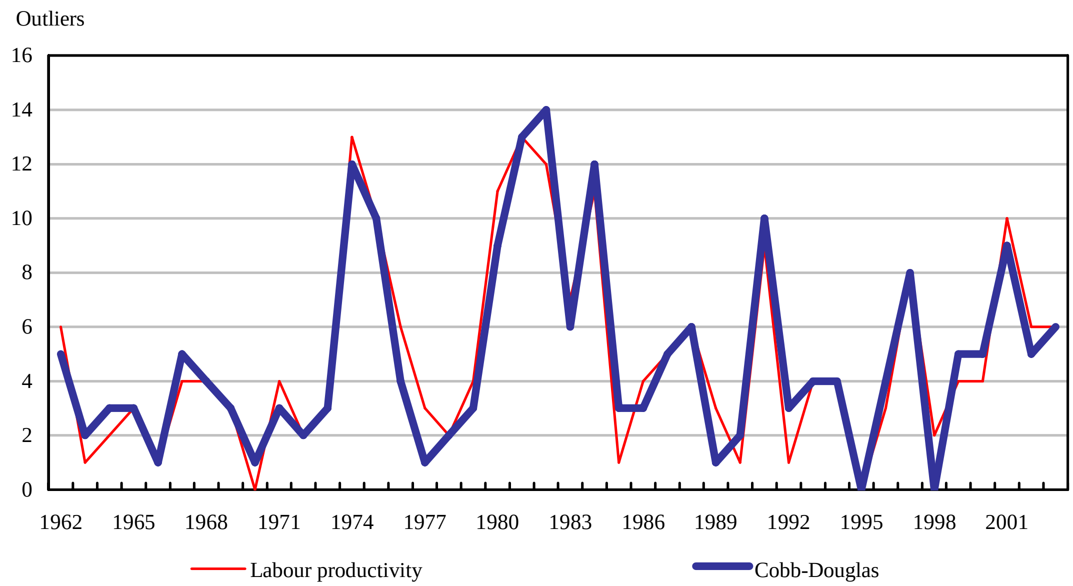
Industry	Difference
Educational services (except universities)	-2.84
Resin, synthetic rubber, and artificial and synthetic fibres and filament	2.41
Wineries	2.24
Other professional, scientific and technical services	-2.14
Pipeline transportation	1.99
Household appliance manufacturing	1.82
Railroad rolling stock manufacturing	1.74
Electronic product manufacturing	1.67
Oil and gas extraction	1.33
Other transportation equipment manufacturing	1.21
Metal ore mining	-1.15
Forestry and logging	-1.10
Grant-making, civic, and professional and similar organizations	1.07
Pharmaceutical and medicine manufacturing	0.96
Advertising and related services	0.94
Seafood product preparation and packaging	0.94

1. Total factor productivity.
2. Ordinary least squares.
Source: Statistics Canada.

The distributions, and magnitudes of the largest differences, suggest that infrequent events, such as recessions, are leading to aberrant observations.[14] This implies that the number of aberrant observations should increase around these types of infrequent economic shocks. This is, in fact, what occurs (Figures 16 and 17). During the first oil shock in the early 1970s, the 1980–1981 recessions, the 1990 recession and towards the end of the sample the number of outliers in real GDP and labour productivity by industry increase.

Moreover, the number of leverage points in the capital services, labour services, and the capital–labour ratio also respond during unusual economic circumstances.[15] The number of leverage points increases in the mid-1960s, during the 1980–1981 recession, the 1991 recession and towards the end of the sample.

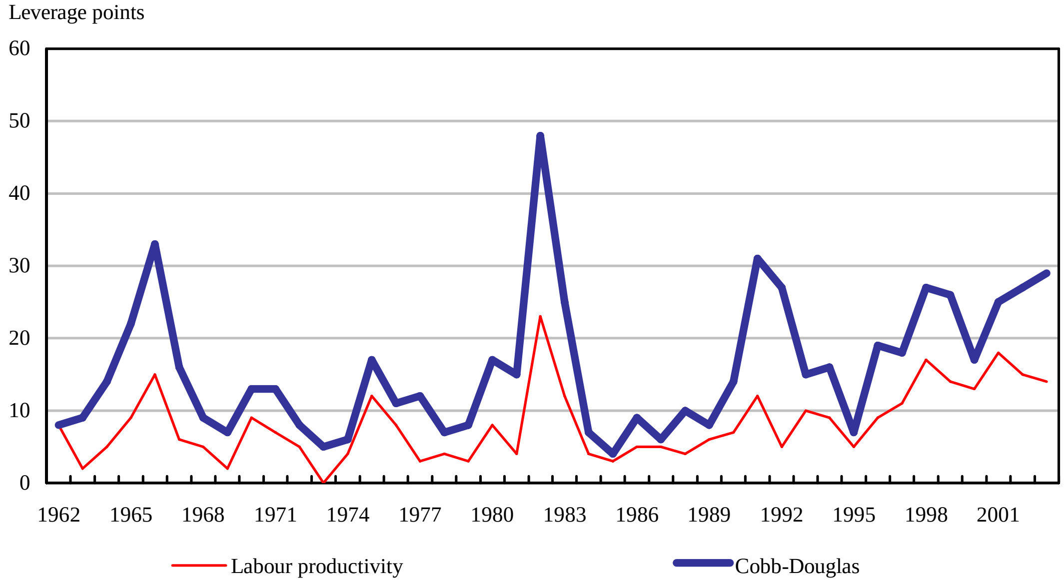
Figure 16
Outliers by year



Source: Statistics Canada.

14. At this point the Non-business Sector is added back into the data set so that the total number of outliers and leverage points can be examined. Its inclusion does not affect the results, so, in the interest of completeness it is included in the compilation of the total number of outliers and leverage points found in the data set.
15. For a list which presents outliers and leverage points by industry, by year, see Appendixes B and C.

Figure 17
Leverage points by year



Source: Statistics Canada.

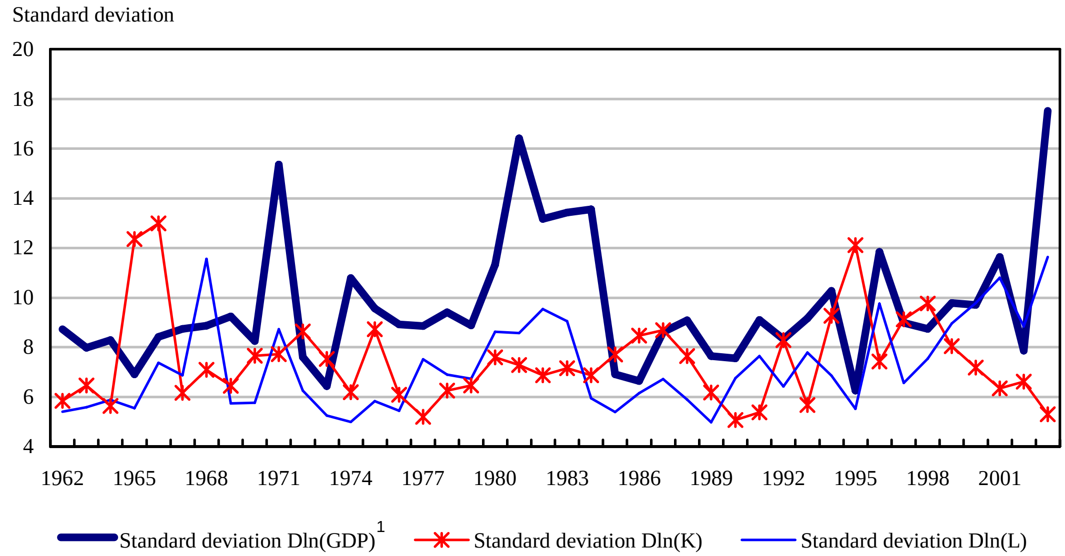
As Figures 16 and 17 demonstrate, outliers and leverage points are not infrequent. For the C-D and LP equations, there are 206 outliers out of a total 3,738 observations. Outliers, therefore, are present in 5.5% of the response variables in the sample. For the C-D equation, there are 665 leverage points (17.8% of the sample observations), while the LP equation has 340 (9.1% of the sample observations).

While the proportion of leverage points and outliers in the sample are noteworthy, it is important to remember than they do not have to occur in the same year. Although there are bunches of aberrant observations around particular economic events, the actual number of aberrant observations that need to be accounted for in the sample is calculated as the number of years in which at least one type (outlier or leverage point) of aberrant observation is present. When the data are combined in this fashion there are a 506 aberrant observations (13.5% of sample observations) present when the LP equation is used and 812 (21.7% of sample observations) when the C-D equation is used. These totals illustrate that outliers and leverage points constitute an important dimension of the KLEMS database.

The magnitude of the largest biases also suggests that some industries are affected more than others by infrequent economic shocks. If this is true, then the reaction of the industries should vary more when irregular shocks affect the system. It is possible to informally test this hypothesis by forming a time series of the standard deviations across the industry log-differences each year. If some industries are more sensitive to economic shocks, then the standard deviation should increase when these shocks occur.

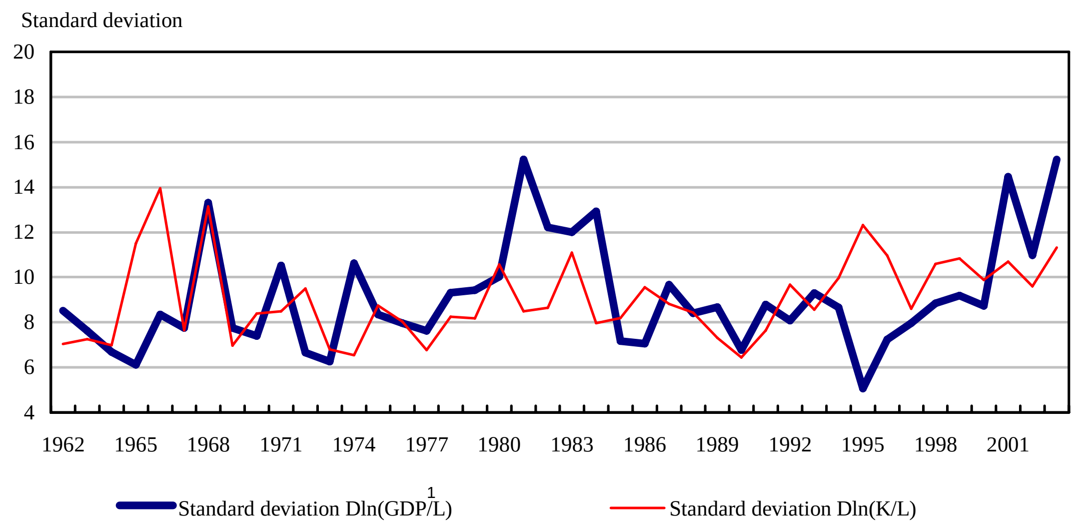
When the time series are examined, the hypothesized pattern emerges (Figures 18 and 19). The effect is stronger for the dependent variables than for the inputs. Nevertheless, there is an increase in the dispersion of industry GDP and labour services during macroeconomic shocks in the early 1970s and early 1980s and in 2003. However, there is little response during the 1991 recession.

Figure 18
Cobb-Douglas equation



1. Gross domestic product.
Source: Statistics Canada

Figure 19
Labour productivity equation



1. Gross domestic product.
Source: Statistics Canada

8. *Concluding remarks*

With any data source, it is important to look at the underlying data in order to understand how data features, such as outliers and leverage points, may affect estimation and, therefore, inference. With the Capital, Labour, Energy, Materials and Services (KLEMS) database, it is very important. The underlying data are noisy, subject to methodology changes, measurement error, idiosyncratic and aggregate economic shocks. These problems make it difficult to ascertain the 'true' underlying parameter estimates using commonly known estimation techniques such as Ordinary Least Squares (OLS).

The problem is compounded when the data are used for unit root testing because commonly applied unit root tests, such as the Augmented Dickey-Fuller or Kwaitkowski, Phillips, Schmidt and Shin tests, have low power. They are, in effect, unable to distinguish between an aberrant response, or trend shift, and a unit root process. The KLEMS dataset is sufficiently noisy, and has a sufficient number of aberrant observations in all variables and industries, that unit root testing with traditional unit root tests is difficult.

A comparison between OLS and S-estimates implies that OLS underestimates *tfp* growth because of aberrant observations in the KLEMS dataset. The timing of the aberrant observations suggests that aggregate shocks, such as recessions, could be responsible for a significant portion of the outliers and leverage points present in the dataset. An examination of the periods when the majority of the aberrant observations are present, and of the dispersion of the industry input and GDP log-differences, provides support for this hypothesis.

The timing of aberrant observations, and their impact on OLS estimates, also suggests that not all observations over time are ideal for estimating total factor productivity (TFP). TFP is often viewed as the additional value added generated in the production process once tangible inputs are accounted for. The interpretation is well suited to periods of 'normal' economic activity. However, during periods of stress, such as the oil shock of the early 1970s, and the 1980–1981 and 1990 recessions, the interpretation may not match the evolution of inputs and value added as closely.

In particular, activities such as labour hoarding may lead to changes in input levels that are not commensurate with changes in value added. Moreover, the notion that the economy reacts differently between expansions and recessions is explicitly formulated in regime switching time series models such as Hamilton's (1989) Markov Switching model.

When researchers estimate TFP, therefore, it may be worthwhile asking whether all time periods provide information of equal value. To a large extent, the answer will depend on the assumed functional form of the TFP function, and on how researchers choose to interpret TFP estimates.

While aggregate shocks, such as the first oil shock, the 1980–1981 recessions and the 1991 recession appear to explain a large portion of the aberrant observations, they do not explain all the outliers and leverage points. Idiosyncratic shocks, measurement error and methodology changes likely account for the remainder, however, this is supposition only at this point.

Nevertheless, the analysis shows that a robust estimator can provide parametric *tfp* growth estimates from a noisy database that is subject to a combination of different types of outliers and leverage points.

Appendix A Cobb-Douglas equation leverage points and outliers

Cobb-Douglas equation		
	Outliers	Leverage points
Crop and animal production	…	1979, 1981, 1985, 1986
Forestry and logging	1975, 1976, 1983, 1987	1964, 1965, 1969, 1973, 1974, 1975, 1982, 1995, 1996
Fishing, hunting and trapping	1968, 1994	1965, 1967, 1978, 1979, 1980, 1981, 1986, 1988, 1992
Support activities for agriculture and forestry	1987	1964, 1965, 1973, 1974, 1980, 1982, 1983, 1991, 1997, 1999, 2003
Oil and gas extraction	1975	1966, 1968, 1980, 1986, 1987, 1988, 1989, 1990, 1991, 1992, 1993, 2001
Coal mining	1968, 1984, 1992, 2002, 2003	1962, 1966, 1967, 1968, 1970, 1971, 1980, 1982, 1983, 2000
Metal ore mining	1964, 1973, 1984	1966, 1967, 1969, 1970, 1971, 1972
Non-metallic, mineral mining and quarrying	1982, 1984, 2003	1975, 1982, 1991, 1996, 1998, 2000
Support activities for mining and oil and gas extraction	1962, 1987, 1988	1992
Electric power generation, transmission and distribution	1982	1966, 1979, 1984, 1989, 1999
Natural gas distribution, water and other systems	1962, 1997, 2002	1975, 1986, 1993, 1997, 1999, 2000, 2001, 2002, 2003
Construction	1978, 1980, 1991	1962, 1965, 1967, 1976, 1977, 1982, 1987, 1991
Animal food manufacturing	1973, 1974, 1982	1967, 1980, 1982, 1983, 1988, 1996, 1998, 2000, 2002, 2003
Sugar and confectionery product manufacturing	1965, 1974	1964, 1974, 1980, 1981, 1983, 1985, 1994, 1996, 2000, 2001, 2002
Fruit and vegetable preserving and specialty food manufacturing	…	1977, 1992, 1996, 1998
Dairy product manufacturing	1971	1963, 1980, 1996, 2000
Meat product manufacturing	2000	1982, 1996, 1997, 1998, 1999, 2001, 2002, 2003
Seafood product preparation and packaging	1974, 1978	1962, 1966, 1967, 1978, 1988

Cobb-Douglas equation leverage points and outliers (continued)

Cobb-Douglas equation		
	Outliers	Leverage points
Soft-drink and ice manufacturing	1992	1967, 1970, 1997, 1998, 2001
Breweries	…	1968, 1969, 1970, 1990, 1996, 1998, 2002, 2003
Wineries	1964, 1975, 1976	1994, 1998, 2001
Distilleries	1996, 1997	1969, 1970, 1978, 1979, 1980, 1992, 1996, 1997, 1999, 2001, 2002, 2003
Tobacco manufacturing	1994, 1999	1974, 1975, 1986, 1987, 2000, 2001, 2002, 2003
Textile and textile product mill manufacturing	1981	1964, 1965, 1966, 1977, 1982, 1983, 1992, 2002, 2003
Clothing manufacturing	1988, 1999, 2001	1977, 1982, 1983, 1986, 1990, 1991, 1992, 2000, 2001, 2002, 2003
Leather and allied product manufacturing	2000	1972, 1981, 1982, 1992, 1993, 1999, 2001, 2002
Wood product manufacturing	1981, 1983	1969, 1970, 1974, 1975, 1982, 1990, 1991
Pulp, paper and paperboard mills	1975, 1983, 2001	1966, 1975, 1976, 1982, 1989, 1998
Converted paper products manufacturing	1975, 1982, 1993	1975, 1977, 1982, 1985, 1988, 1989, 1994, 1996
Printing and related support activities	1976, 1991	1983, 1989, 1990, 1991, 2003
Petroleum and coal products manufacturing	1962, 1973, 1982, 1983	1967, 1982, 1993, 2003
Basic chemical manufacturing	1975, 1991	1975, 1976, 1983, 2003
Resin, synthetic rubber, and artificial and synthetic fibres and filament	1981, 1982, 1983, 2001, 2003	1975, 1976, 1981, 1982, 1991, 1993, 1998, 1999, 2000, 2003
Pesticides, fertilizer and other agricultural chemical manufacturing	1974, 2001, 2003	1965, 1966, 1967, 1979, 1980, 1981, 1982, 1983, 1996, 1997, 1999
Pharmaceutical and medicine manufacturing	1991, 2001	1966, 1979, 1982, 2001, 2003
Miscellaneous chemical product manufacturing	1981, 1982, 1997	1965, 1966, 1971, 1983, 1991, 1993, 1994, 1996, 1998, 2002, 2003

Cobb-Douglas equation leverage points and outliers (continued)

Cobb-Douglas equation		
	Outliers	Leverage points
Rubber product manufacturing	1980, 1986, 1997	1970, 1971, 1981, 1982, 1989, 1990
Cement and concrete product manufacturing	1967, 1997	1964, 1965, 1966, 1973, 1982, 1983, 1984, 1991, 1992, 1998
Miscellaneous non-metallic mineral product manufacturing	1980	1966, 1967, 1970, 1982, 1990, 1991, 1992, 1993
Primary metal manufacturing	1979, 1984	1982, 1983, 1990, 1992, 1993, 1994, 2001, 2002, 2003
Fabricated metal product manufacturing	1975, 1986, 1996	1965, 1966, 1982, 1983, 1990, 1991, 1992, 2000
Machinery manufacturing	1984, 1993	1982, 1983, 1990, 1991, 1992, 2002
Computer and peripheral equipment manufacturing	1971, 1981, 1984, 2001	1971, 1972, 1975, 1976, 1982, 1983, 1992, 2000, 2002
Electronic product manufacturing	1972, 1999, 2001, 2002	1966, 1982, 1999, 2001, 2002, 2003
Household appliance manufacturing	1975, 1987, 1988	1971, 1978, 1982, 1991
Electrical equipment and component manufacturing	2000	1966, 1982, 1983, 1991, 1998, 1999, 2000
Motor vehicle manufacturing	1967, 1980, 1988	1963, 1964, 1965, 1983, 1985, 1986, 1988
Motor vehicle body and trailer manufacturing	1964, 1982	1965, 1975, 1976, 1977, 1980, 1981, 1982, 1983, 1990, 1991, 2001
Motor vehicle parts manufacturing	2001	1964, 1965, 1966, 1970, 1980, 1994
Aerospace product and parts manufacturing	1983, 1984	1966, 1971, 1972, 1978, 1979, 1980, 1982, 2002, 2003
Railroad rolling stock manufacturing	1994, 2002, 2003	1963, 1975, 2001, 2003
Ship and boat building	2000, 2002	1962, 1964, 1971, 1979, 1981, 1982, 1991, 1999, 2001, 2002
Other transportation equipment manufacturing	1981, 1982, 2001, 2003	1965, 1967, 1968, 1969, 1970, 1982, 1994, 1995, 2001, 2003
Furniture and related product manufacturing	1974, 1981, 1982	1977, 1982, 1990, 1991, 1992

Cobb-Douglas equation leverage points and outliers (continued)

Cobb-Douglas equation		
	Outliers	Leverage points
Wholesale trade	1982	1963, 1982, 1983, 1992, 1994, 1997, 2001
Retail trade	1980, 1982, 1990, 1991	1982, 1991
Air transportation	1991	1966, 1982, 1983, 1991
Rail transportation	1982, 1984	1982, 1983, 1990, 1997, 1998, 1999
Water transportation	1989	1981, 1982, 1983, 1986, 1996, 1998, 1999
Truck transportation	1974, 1979, 1980, 1991	1962, 1970, 1971, 1982, 1983, 1984, 1997, 1998
Transit and ground passenger transportation	1979, 1981, 1984, 1991	1964, 1965, 1966, 1975, 1976, 1977, 1982
Pipeline transportation	1972, 1980	1966, 1969, 1978, 1980, 1981, 1998, 1999, 2000, 2001, 2003
Scenic and sightseeing transportation and support activities for transportation	2000	1982, 1984, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003
Postal service and couriers and messengers	1969, 1976, 1977, 1981, 1993	1963, 1965, 1967, 1968, 1980, 1981, 1992, 1994
Warehousing and storage	1962, 1963	1996, 1998, 1999, 2001, 2002
Motion picture and sound recording industries	1969, 1981, 1993	1967, 1968, 1982, 1991, 1992, 1993, 1997, 2001, 2002, 2003
Broadcasting and telecommunications	1975	1966, 1973, 1975, 1988, 2003
Publishing Industries, information services and data processing service	1991	1968, 1988, 1989, 1990, 1991, 1997, 1998, 1999, 2002
Monetary authorities and depository credit intermediation	…	1981, 1987, 1991, 1992, 1993, 1998, 1999, 2002, 2003
Insurance carriers	1996	1984, 1993, 1994, 2003
Lessors of real estate	1970, 1994, 1999	1977, 1986, 1987, 1992, 1993, 1997, 1998
Rental and leasing services and lessors of non-financial intangible assets	1966	1964, 1982, 1991, 1997, 1999

Cobb-Douglas equation leverage points and outliers (concluded)

Cobb-Douglas equation		
	Outliers	Leverage points
Other finance, insurance and real estate and management of companies	1981, 1985, 1988, 1990	1972, 1976, 1977, 1978, 1984, 1988, 1993, 1994, 1997, 2002
Advertising and related services	1985, 1999	1966, 1976, 1992, 1994, 1995, 1999, 2001
Architectural, engineering, legal and accounting services	1974, 1992	1965, 1966, 1982, 1992, 1994
Other professional, scientific and technical services	1971, 1980	1965, 1966, 1971, 1982, 1983, 1992, 1998, 1999, 2002
Administrative and support services	1968, 1988	1962, 1964, 1966, 1983, 1992, 1998, 1999, 2002
Waste management and remediation services	1965, 1967, 1974	1966, 1967, 1970, 1971, 1987, 1991
Educational services (except universities)	1967, 1974, 1996, 1997	1962, 1963, 1975, 1976, 1984, 1993, 1994, 1996, 1997, 1998, 1999
Health care services (except hospitals) and social assistance	1975	1963, 1964, 1965, 1966, 1971, 1976, 1999, 2001, 2002, 2003
Arts, entertainment and recreation	1974, 1987	1963, 1965, 1966, 1967, 1968, 1972, 1973, 1975, 1980, 1981, 1989
Accommodation and food services	1982, 1991	1963, 1965, 1966, 1968, 1972, 1977, 1982, 1991, 2003
Repair and maintenance	1969, 1974, 1984	1966, 1982, 1991, 1998, 1999, 2000
Grant-making, civic, and professional and similar organizations	1962, 1963, 1965, 1967, 1974	1964, 1965, 1966, 1971, 1974, 1981, 1992, 1993, 1995, 1996, 1997
Personal and laundry services and private households	1981, 1984, 1985	1966, 1980, 1991, 1994, 1995, 1996, 1998
Non-business sector	1968	1962, 1965, 1966, 1967, 1996, 1997, 1998, 2002

… not applicable

Appendix B Labour productivity equation leverage points and outliers

Labour productivity equation		
	Outliers	Leverage points
Crop and animal production	1967	1985
Forestry and logging	1974, 1975, 1976, 1983, 1987	1975, 1978, 1995, 1996
Fishing, hunting and trapping	1968, 1994	1965, 1980, 1986, 1988
Support activities for agriculture and forestry	1987, 1997	1974, 1997
Oil and gas extraction	1975, 1980, 1981	1966, 1968, 2001
Coal mining	1968, 1984	1962, 1967, 1968, 1983
Metal ore mining	1971, 1973, 1984	1969, 1982
Non-metallic mineral mining and quarrying	1982, 1984, 2003	1982, 1997
Support activities for mining and oil and gas extraction	1962, 1986, 1987, 1988	1994, 2000
Electric power generation, transmission and distribution	1975, 1981, 1982, 1989	1966, 1989, 2000
Natural gas distribution, water and other systems	1962, 1978	1975, 1997, 2002
Construction	1978, 1980, 1991	1962, 1967, 1976, 1982, 1987, 1991
Animal food manufacturing	1973, 1974, 1982	1980, 1983, 1988, 1996, 2000
Sugar and confectionery product manufacturing	1965, 1974, 1980	1964, 1974, 1981, 1985, 1994, 2000, 2001, 2002
Fruit and vegetable preserving and specialty food manufacturing	…	1992, 1996, 1998
Dairy product manufacturing	1971, 1980, 2002	1980
Meat product manufacturing	1962, 1989, 2000	1997, 1998, 1999, 2001, 2003
Seafood product preparation and packaging	1974	1976, 1977, 2000
Miscellaneous food manufacturing	1976, 1991, 1999, 2001	1964, 1970

Labour productivity equation leverage points and outliers (continued)

Labour productivity equation		
	Outliers	Leverage points
Soft-drink and ice manufacturing	1992, 2002	1970, 1997, 1998, 1999, 2001
Breweries	…	1969, 1990, 1998, 2002, 2003
Wineries	1964, 1975, 1976	2001
Distilleries	1997	1970, 1979, 1980, 1999, 2001, 2002, 2003
Tobacco manufacturing	1974, 1975, 1994	1974, 1975, 1986, 2001, 2003
Textile and textile product mill manufacturing	1981, 1982	1983, 2002
Clothing manufacturing	1988, 1999, 2001	1983, 1993, 1997, 2000, 2001
Leather and allied product manufacturing	2000	1981, 1982, 1991, 1993, 2002
Wood product manufacturing	1983	1970, 1974
Pulp, paper and paperboard mills	1975, 1983, 2001	1975, 1982, 1988, 1989
Converted paper products manufacturing	1993	1975, 1982, 1985, 1988, 1989, 1996
Printing and related support activities	1976, 1991	1983, 1989, 1990, 1991, 2003
Petroleum and coal products manufacturing	1962, 1982, 1983	1982, 1993
Basic chemical manufacturing	1975, 1991	1983, 1995, 2003
Resin, synthetic rubber, and artificial and synthetic fibres and filament	1981, 1983, 2001, 2003	1975, 1976, 1993, 1999, 2000, 2003
Pesticides, fertilizer and other agricultural chemical manufacturing	1974, 2003	1966, 1979, 1980, 1983, 1997
Pharmaceutical and medicine manufacturing	1991, 1996, 2001, 2003	1966, 1979, 1982, 1994, 2001
Miscellaneous chemical product manufacturing	1981, 1982, 1997	1983, 1991, 1998, 2003
Plastics product manufacturing	1980, 1981	1982

Labour productivity equation leverage points and outliers (continued)

Labour productivity equation		
	Outliers	Leverage points
Rubber product manufacturing	1980, 1984, 1986, 1993, 1997	1970, 1971, 1981, 1982, 1989, 1990
Cement and concrete product manufacturing	1967, 1997	1971, 1986, 1987
Miscellaneous non-metallic mineral product manufacturing	1980	1966, 1967, 1970, 1982, 1990
Primary metal manufacturing	1979, 1983, 1984	1975, 1982, 1990, 2002
Fabricated metal product manufacturing	1975	1962, 1982, 1992, 1993, 2000
Machinery manufacturing	1984, 1993, 2002	1982, 1990, 1991
Computer and peripheral equipment manufacturing	1971, 1981, 1984, 2001	1971, 1972, 1975, 1992, 2000, 2002
Electronic product manufacturing	1972, 1999, 2001, 2002	1999, 2001, 2002, 1982, 2003
Household appliance manufacturing	1975, 1987, 1988	1987, 1971, 1978, 1991
Electrical equipment and component manufacturing	2000	2000, 1982, 1983, 1991, 1998
Motor vehicle manufacturing	1967, 1980, 1988	1971, 1986
Motor vehicle body and trailer manufacturing	1964, 1982	1982, 1965, 1991
Motor vehicle parts manufacturing	2001	1970, 1980
Aerospace product and parts manufacturing	1983, 1984	1972
Railroad rolling stock manufacturing	1994, 2002, 2003	1963, 2002, 2001, 2003
Ship and boat building	1997	1962, 1991, 2001, 2002
Other transportation equipment manufacturing	1981, 1982, 2001, 2003	1982, 2001, 2003
Furniture and related product manufacturing	1974, 1981, 1982	…
Miscellaneous manufacturing	1984, 1986, 1997	1972, 1995, 2000

Labour productivity equation leverage points and outliers (continued)

Labour productivity equation		
	Outliers	Leverage points
Wholesale trade	1982	1994
Retail trade	1979, 1980, 1986, 1990, 1991	1991, 1976, 1987, 1993, 2000
Air transportation	1991	1991
Rail transportation	1982	1982, 1983, 1997, 1999
Water transportation	1989	1982, 1983, 1993, 1994, 1996, 1999
Truck transportation	1974, 1979	1962, 1970, 1971, 1983, 1984
Transit and ground passenger transportation	1979, 1981, 1984	1964, 1965, 1975, 1976, 1982
Pipeline transportation	1980, 1981, 1982	1980, 1966, 1978, 1998, 2001, 2003
Scenic and sightseeing transportation and support activities for transportation	2000, 2002	1982, 1984, 1998
Postal service and couriers and messengers	1969, 1976, 1977, 1981	1965, 1968, 1994
Warehousing and storage	1998	1998, 1996, 2001
Motion picture and sound recording industries	1969, 1993,	1967, 1968,
Broadcasting and telecommunications	1975	1975, 2003
Publishing industries, information services and data processing service	1991	1989, 1990, 1991, 1998, 2002
Monetary authorities and depository credit intermediation	…	1987, 1992, 1998, 1999,
Insurance carriers	1996	1993, 1999
Lessors of real estate	1994, 1999	1977, 1986, 1993, 1998
Rental and leasing services and lessors of non-financial intangible assets	1966, 2001	1962, 1963, 1964, 1977, 1997
Other finance, insurance and real estate and management of companies	1981, 1985, 1988	1976, 1978, 1984, 1994, 1997, 2002

Labour productivity equation leverage points and outliers (concluded)

Labour productivity equation		
	Outliers	Leverage points
Advertising and related services	1976, 1977	1966, 1994, 1995, 1999, 2001
Architectural, engineering, legal and accounting services	…	1965, 1966, 1982, 1994
Other professional, scientific and technical services	1971, 1980	1965, 1966, 1992, 1998
Administrative and support services	1968, 1988	1962, 1966, 1998, 1999, 2002
Waste management and remediation services	1965, 1974	1966, 1970, 1971
Educational services (except universities)	1962, 1974, 1996, 1998	1962, 1996, 1998, 1975, 1976, 1984, 1999
Health care services (except hospitals) and social assistance	1973	1976, 1999, 2001, 2002, 2003
Arts, entertainment and recreation	1974, 1987	1965, 1966, 1967, 1968, 1972, 1975, 1980
Accommodation and food services	1972, 1977	1972, 1965, 1966
Repair and maintenance	1969, 1974, 1984, 1991	1966, 1998, 1999, 2000, 2001
Grant-making, civic, and professional and similar organizations	1962, 1963, 1965, 1967, 1974	1965, 1964, 1981, 1993, 1996, 1997
Personal and laundry services and private households	1997	1966, 1995, 1996, 1998
Non-business sector	1968	1967

… not applicable

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