Measuring Capital and Multifactor Productivity: The Role of Asset Depreciation and Initial Capital Stock Estimates

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Abstract

This paper suggests a meaningful way to compare how the depreciation and retirement of assets are estimated in the national accounts of different countries and shows large differences. Applying the same assumptions in the US as in other G7 countries would reduce the US net capital stock by up to 1/3 and increase US GDP by up to 0.5 per cent. The growth rates of capital services and MFP would be less affected. This paper also considers two commonly used methods to estimate initial capital stocks and the impact they may have on measured capital and MFP. They assume that either investment growth rates or capital-stock-to-output ratios are constant over time. The first one is misleading because it fails to account for trends and fluctuations in real-estate investment. The second one works well for the US but may be less reliable for other countries. Overall, this paper calls for a more frequent review of asset depreciation patterns by statistical agencies, and for extending investment series to the maximum extent before relying on crude methods to estimate initial capital stocks.

Capital measurement plays a fundamental role in national accounts, both to assess the economic wealth and the state of infrastructure in a given country, and to better understand the sources of economic and productivity growth. Nevertheless, measuring capital stocks is challenging because it requires estimating initial capital stocks, accessing good-quality data on past investment flows, and cumulating them while accounting for the depreciation and retirement of assets. This statistical process is known as the Perpetual Inventory Method

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(PIM).[2]

Statistical agencies in different countries tend to use very different assumptions regarding the depreciation and retirement of assets. While some existing studies conclude that depreciation patterns may differ across countries, industries and time, the reasons for these differences remain largely unexplained (Erumban, 2008). They may be related to structural factors such as climate, construction techniques (for buildings and structures) and government investment incentives, differences in data sources, or measurement errors as depreciation and retirement patterns used by statistical agencies tend to be based on thin empirical evidence or old research (Bennett *et al.*, 2020).

Unexplained differences in depreciation and retirement patterns across countries may harm the cross-country comparability of capital stocks and macroeconomic indicators relying on the consumption of fixed capital (CFC). This is obviously the case for economic aggregates that are measured net of depreciation, such as net investment (the difference between gross investment and CFC) and net domestic product (the difference between GDP and CFC). In addition, since CFC also enters the calculation of the output and value added of non-market activities, uncertainty around CFC estimates may also affect prominent gross indicators such as GDP.

This article discusses the impact on the measurement of capital and multifactor productivity (MFP) of using different asset depreciation and retirement patterns, and different assumptions to estimate initial capital stocks. Given the limited resources that most statistical agencies allocate to these questions, an important objective of this article is to illustrate the potential impact of mismeasuring capital depreciation and initial capital stocks on headline macroeconomic aggregates.

By using the distribution of cohort depreciation rates[3] for a given asset type across countries as a measure of uncertainty, this article assumes that all available estimates measure the same unobserved cohort depreciation rate, and that all differences across countries may be related to measurement errors. This is an extreme assumption, but it provides a useful upper bound of the uncertainty on capital and MFP measurements.[4] By highlighting this uncertainty, this paper aims at

2 Detailed descriptions of the PIM and how it is applied in different international databases to measure capital and multifactor productivity (MFP) include (OECD, 2009) and (Gouma and Inklaar, 2023).

3 To avoid any ambiguity, the term depreciation (without any further qualification) is reserved to describe how the value (i.e. the market price) of a single productive asset declines over time due to the shortening of its remaining service life. Depreciation is reflected in the age-price profile of a single asset. Nevertheless, the depreciation process does not consider that assets belonging to the same cohort (i.e. purchased at the same time) may be retired from the productive capital stock at a different age. Cohort depreciation corresponds to the combined effect of (single-asset) depreciation and retirement. It determines how the value of a stock of assets declines over time if depreciation and retirement are not compensated by investment (GFCF) or other positive changes in volume. The terms cohort depreciation, combined depreciation and retirement, and consumption of fixed capital all have the same meaning and are used interchangeably in this paper.

4 Alternatively, a pure Monte Carlo analysis could have been considered. Nevertheless, there is no obvious statistical distribution from which to draw cohort depreciation rates. Therefore, this study relies on the cohort depreciation rates used in different countries as a measure of uncertainty.

encouraging statistical agencies to develop internationally comparable data sources to estimate asset depreciation and retirement patterns, and to review these estimates regularly, including for assets that have been capitalized in national accounts for a long time (e.g. buildings, structures, machinery and equipment). The intention here is not to promote a complete standardization of asset depreciation and retirement patterns across countries, but to ensure that differences are well justified.

Another practical issue that statistical agencies face when estimating capital stocks and CFC is the estimation of initial capital stocks at a given date in the past in order to initialize the PIM. This article reviews two commonly used methods to estimate initial capital stocks. They assume either that investment growth rates or capital stock-to-output ratios are constant over time. By showing the limits of these methods, we aim at encouraging statistical agencies to use national sources and extend their investment series to the maximum extent before relying on any crude assumption on investment growth or capital stock-to-output ratios.

The national accounts produced by the US Bureau of Economic Analysis (BEA) are used as a laboratory to analyse the sensitivity of capital and MFP measurement in this paper. The reason is that the BEA produces the longest and most detailed investment series in OECD countries, which allows applying the assumptions of other countries and test their impact on US capital and MFP measurement.

This article focuses on produced assets that are included in the asset boundary of the 2008 System of National Accounts (SNA) and the US National Income and Product Accounts (NIPAs). This excludes some produced intangible assets such as brands, and firm-specific human and organizational capital, as well as non-produced assets such as land and subsoil assets. While such assets are important for MFP measurement (Corrado, Hulten and Sichel, 2009; Brandt, Schreyer and Zipperer 2017), they are either short lived (intangibles), not subject to an accumulation and depreciation process (land), or their depreciation (consumption) can be directly measured without resorting to imputed depreciation and retirement patterns (subsoil assets). Therefore, they are less relevant than assets in the SNA/NIPA asset boundary.

In theory, the sensitivity of capital and MFP measurement to alternative depreciation patterns and different methods to estimate initial capital stocks may depend on the composition of investment in each country. Nevertheless, it looks sufficiently similar across OECD countries to consider that the sensitivity of capital and MFP measurement in the United States is relevant for other advanced economies as well (OECD, 2023).

This paper extends a previous sensitivity analysis by Inklaar (2010), who focused on the sensitivity of capital services to the type of assets considered and to the measurement of capital user costs. First, it analyses the effect of changing depreciation/retirement patterns and/or initial capital stocks, which Inklaar (2010) did not consider but acknowledged as potentially important factors. Second, it discusses the sensitivity not only of capital services, but also of net capital stocks,[5] CFC and MFP. Third, it assesses the reliability of different methods to estimate initial capital stocks. Fourth, it compares cohort depreciation rates in Canada, France, Germany, Italy, the United Kingdom and the United States, and therefore extends a recent sensitivity analysis by Giandrea *et al.* (2021) which focused on Canada and the United States.

The rest of this article is organised as follows. Section 1 describes a synthetic way to compare combined asset depreciation and retirement patterns across countries, and the sensitivity of capital and MFP measurement to such patterns. Section 2 discusses two leading methods to estimate initial capital stocks and assesses their impact on capital and MFP measurement. Section 3 concludes. Figure 1 summarizes the organization of the sensitivity analysis and the article.

1. Impact of Changing Asset Depreciation and Retirement Patterns on Capital and MFP Measurement

1.1 Comparison of combined asset depreciation and retirement patterns across countries

Net capital stocks result from successive vintages of investment in productive assets and the combined effect of their depreciation and retirement over time. The depreciation pattern describes how the value of a single asset declines over time as the asset ages. The retirement pattern takes into account that not all assets purchased at the same time (i.e. belonging to the same cohort) are removed from the capital stock at the same age. For this purpose, non-degenerated probability distributions around average asset service lives are usually considered by statistical agencies.

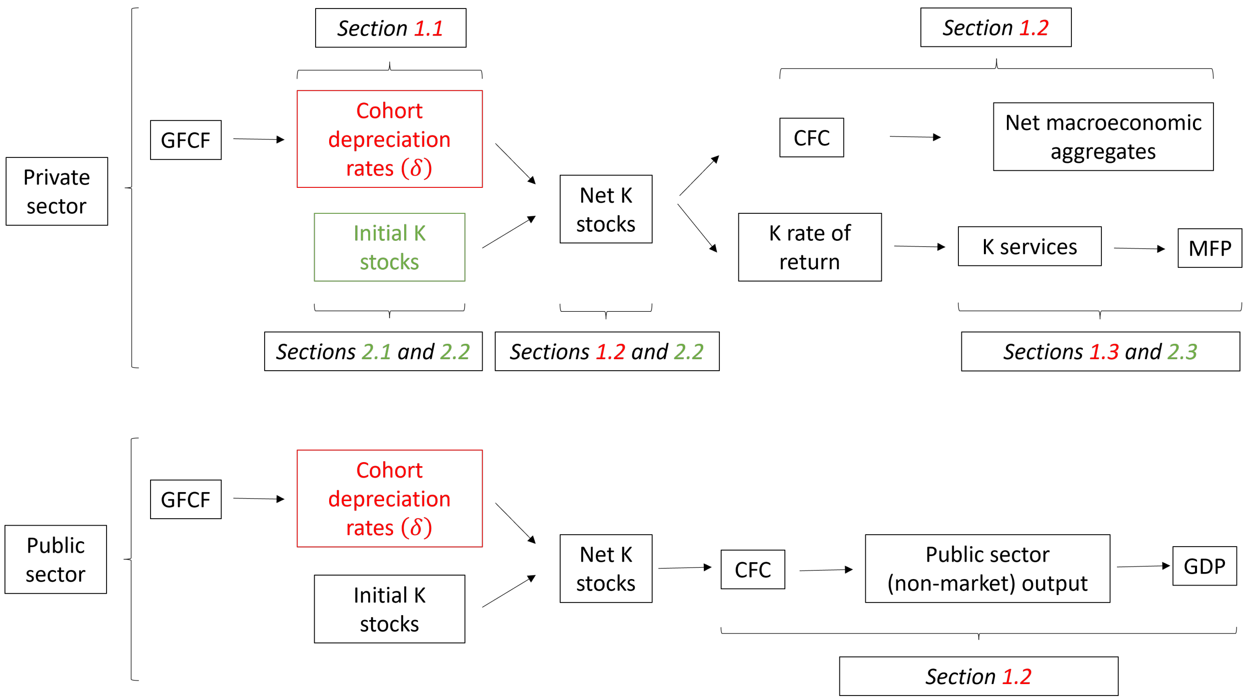
Hulten and Wykoff (1981a) showed how the combination of depreciation and retirement gives rise to convex age-price profiles for cohorts of assets, which can usually be approximated by geometric patterns.[6] The main advantage of geometric patterns is that they are characterized by a single and constant parameter (the geometric cohort depreciation rate). This simplicity led several statistical agencies such as the US BEA and Statistics Canada to rely on geometric patterns to estimate CFC for their national accounts (Fraumeni, 1997; Baldwin *et al.*, 2015).

However, not all countries rely on geometric patterns to summarize the combined effect of depreciation and retirement and estimate net capital stocks. For example, France relies on linear depreciation profiles for single assets and combines them with log-normal retirement patterns. Alternatively, the Netherlands and the United Kingdom estimate net wealth capital stocks using the combined depreci-

5 In this paper, the term “net capital stock” is used as synonymous for “net wealth capital stock”. The latter is only used when there is a need to distinguish net wealth and productive capital stocks.

6 Hulten (2008) later summarized this as follows: "The more assets are grouped together, the more the group experience tends to be a geometric-like pattern, regardless of the actual patterns of the individual assets in the group. If the individual patterns are themselves nearly geometric, the group effect is reinforced, but this is not a necessary condition."

Figure 1: Organization of the Sensitivity Analysis and the Article



Note: The red colour indicates a discussion related to cohort depreciation rates, and the green colour a discussion related to initial capital stocks.
Source: Authors' compilation

ation and retirement patterns that they derive from hyperbolic age-efficiency profiles combined with Weibull (for the Netherlands) or truncated normal (for the United Kingdom) retirement functions (Statistics Netherlands, 2019; Office for National Statistics, 2019).[7]

In order to compare countries that rely on different asset depreciation and retirement patterns, this sensitivity analysis follows Cabannes *et al.* (2013) who estimate geometric approximations of combined depreciation and retirement patterns for France. This method combines depreciation and retirement patterns analytically and estimates the geometric function that provides the best fit to the combined pattern in a least square sense.[8]

Table 1 provides average ratios of Canadian, French, German, Italian and UK cohort depreciation rates to the corresponding US parameters for aggregate asset categories. In nearly all cases, the cohort depreciation rates used in Canada, France, Germany and the United Kingdom are higher, or much higher, than those used in the United States. This is especially true for dwellings and non-residential buildings, as

7 The United Kingdom's Office for National Statistics applies this method to all assets except research and development, for which they combine a Weibull retirement distribution with a geometric age-efficiency function. See Appendix B in Pionnier *et al.* (2023) for additional information on the asset depreciation and retirement functions used in G7 countries. https://doi.org/10.1787/92498395-en.

8 Appendix B in the Working Paper version of this article (Pionnier *et al.*, 2023) discusses how these geometric approximations are obtained for France, Germany, Italy and the United Kingdom. https://doi.org/10.1787/92498395-en.

Table 1: Ratios of Cohort Depreciation Rates in Canada, France, Germany, Italy and the United Kingdom, relative to the United States

Asset label	Canada	France	Germany	Italy	United Kingdom
Dwellings	2.0	5.0	2.4	1.6	2.5
Buildings other than dwellings	3.0	2.8	2.1	1.4	3.1
Other structures	2.7	1.1	1.4	1.6	1.7
Transport equipment	1.5	1.5	1.4	1.1	1.3
Computer hardware	1.3	1.2	0.8	1.4	1.2
Telecom. equipment	2.1	1.4	1.6	2.8	1.2
Other machinery and equipment	1.8	1.1	1.5	1.4	1.1
R&D	1.8	1.0	1.0	1.3	1.8
Software & databases	1.0	0.7	0.9	0.9	0.7
Originals	6.3	2.6	2.7	1.4	1.5

Note: Ratios higher than 1.5 are colored in orange font, and ratios higher than 2.0 are colored in red font.
Source: The geometric cohort depreciation rates for Canada and the United States are sourced from Statistics Canada and Giandrea *et al.* (2021). Geometric approximations are used for France, Germany, Italy and the United Kingdom (Cabannes *et al.*, 2013 and Annex B in Pionnier *et al.*, 2023). Ratios are first calculated for detailed assets and then aggregated to the upper level of the asset classification using 2019 net capital stock shares in the US private sector as weights.

well as other (civil engineering) structures in Canada.[9] The Italian depreciation rates are closer to the US rates.

It is worth noting that this proposed comparison is better than relying on Declining Balance Rates (DBRs) to plug the depreciation and retirement patterns of other countries into the PIM used by the BEA. DBRs were first introduced by Hulten and Wykoff (1981b) to provide a simple inverse proportional relationship between geometric cohort depreciation rates (δ) and average asset services lives (T):

$$\delta = DBR/T$$

Nevertheless, DBRs do not have any obvious economic meaning. Pionnier *et al.* (2023): Appendix A[10] shows that they are not universal constants as they depend on the shape of the underlying depreciation and retirement functions used by national statistical agencies. Therefore, DBRs are country specific, and estimating geometric cohort depreciation rates for France, Germany, Italy and the United Kingdom based on the average asset service lives of these countries and the DBRs of the United States would be misleading. By contrast, the geometric approximations to asset depreciation and retirement in this article are only based on national assumptions and summarize all aspects of asset depreciation and retirement in each country.

1.2 Sensitivity of CFC and Net Capital Stocks to Changes in Cohort Depreciation Rates

1.2.1 US private sector

This section analyses the sensitivity of capital measurement to changes in cohort

9 The results for Canada and the United States are in line with Giandrea *et al.* (2021). The present article extends the comparison to France, Germany, Italy and the United Kingdom

10 https://doi.org/10.1787/92498395-en.

depreciation rates. In order to explore the range of possible depreciation patterns, the geometric cohort depreciation rates used by Canada, France, Germany, Italy and the United Kingdom are successively introduced into the US PIM along with the original US GFCF time series to recalculate the CFC and net capital stocks for all assets of the US private sector.[11]

Consistently with the evidence provided in Table 1, Chart 1 shows that the US ratio of CFC to gross value added (GVA) would be significantly higher if the BEA relied on the same cohort depreciation rates as Canada, France, Germany and the United Kingdom (15.9 percent, 15.5 percent, 15.2 percent and 15.2 percent against 14.2 percent, respectively). It would be only slightly higher if the BEA relied on the same cohort depreciation rates as Italy (14.6 percent against 14.2 percent). The main difference with the official US accounts relates to the CFC of residential and non-residential buildings.[12]

Accordingly, Chart 2 shows that the level of US net capital stock would be significantly lower, by up to one third, if the BEA relied on the same cohort depreciation rates as Canada, France, Germany and the United Kingdom, and only slightly lower if it relied on the same cohort depreciation rates as Italy. Here again, differences are mainly related to residential and non-residential buildings.

Nevertheless, the impact of switching to other countries' cohort depreciation rates is more limited on the growth rate of the US net capital stock (at constant prices) than on its level (at current prices). This is because an increase in the depreciation rate of an asset has two opposite effects on the growth rate of its net capital stock. Rewriting the generic capital accumulation equation $K_t = I_t + (1-\delta)K_{t-1}$ in terms of growth rate $\frac{\Delta K_t}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \delta$ shows that an increase in δ has a direct negative effect as well as an indirect positive effect on $\frac{\Delta K_t}{K_{t-1}}$ because it reduces K_{t-1}. This latter effect is more muted in a period of low investment ($I_t \rightarrow 0$). In this case, an increase in δ is more likely to reduce the growth rate of the net capital stock.

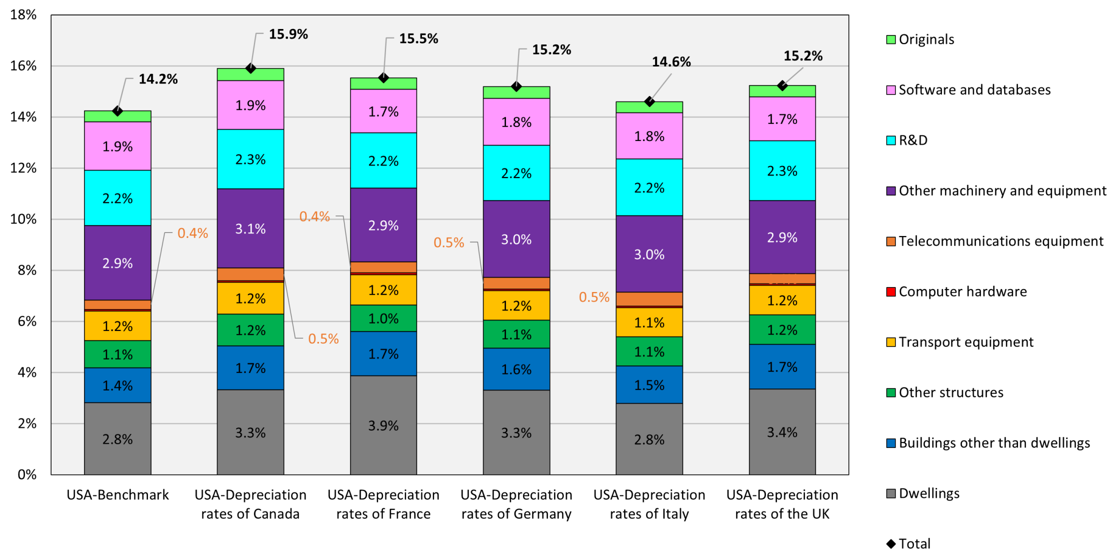
As expected, Chart 3 shows that the impact of switching to other countries' (larger) cohort depreciation rates on the growth rate of the US net capital stock has the largest (negative) impact in the period corresponding to the Great Recession and the immediately following years, which is a period of low investment. Nevertheless, on average between 1998 and 2019, the annual growth rate of the US net capital stock hardly changes when using Canadian, French or German cohort depreciation rates, and it is unaffected when using Italian or UK cohort depreciation rates.

11 For France, this article relies on the geometric approximations provided by Cabannes *et al.* (2013). For Germany, Italy and the United Kingdom, it is based on geometric approximations of the combined depreciation/retirement profiles in each country. The asset classifications used in the five countries are mapped together using information from Cabannes *et al.* (2013), Giandrea *et al.* (2021) and the replies by Statistic Canada, ISTAT and the ONS to the 2019 Eurostat-OECD Questionnaire on the Methodology underlying Capital Stocks (See Appendix C in Pionnier *et al.* (2023)- https://doi.org/10.1787/92498395-en.)

12 Changes in CFC also affect the level of net investment. The impact of changes in cohort depreciation rates on the level of net investment is presented in Pionnier *et al.* (2023).

Chart 1: Sensitivity of Consumption of Fixed Capital to Changes in Cohort Depreciation Rates

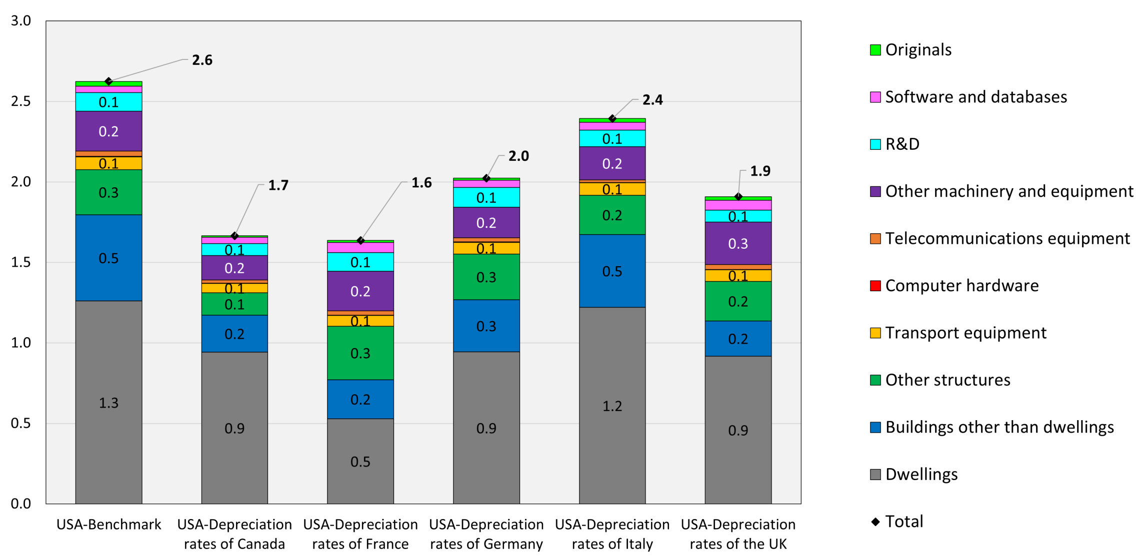
Ratio of consumption of fixed capital to gross value added, US private sector, 2019



Source: Authors' calculations, based on BEA depreciation rates, Cabannes *et al.* (2013), Giandrea *et al.* (2021), information shared by Statistics Canada, DESTATIS (Germany), ISTAT (Italy) and the ONS (United Kingdom). The USA-Benchmark is computed by the authors as described in Pionnier *et al.* (2023).

Chart 2 : Sensitivity of Net Capital Stock Levels to Changes in Cohort Depreciation Rates

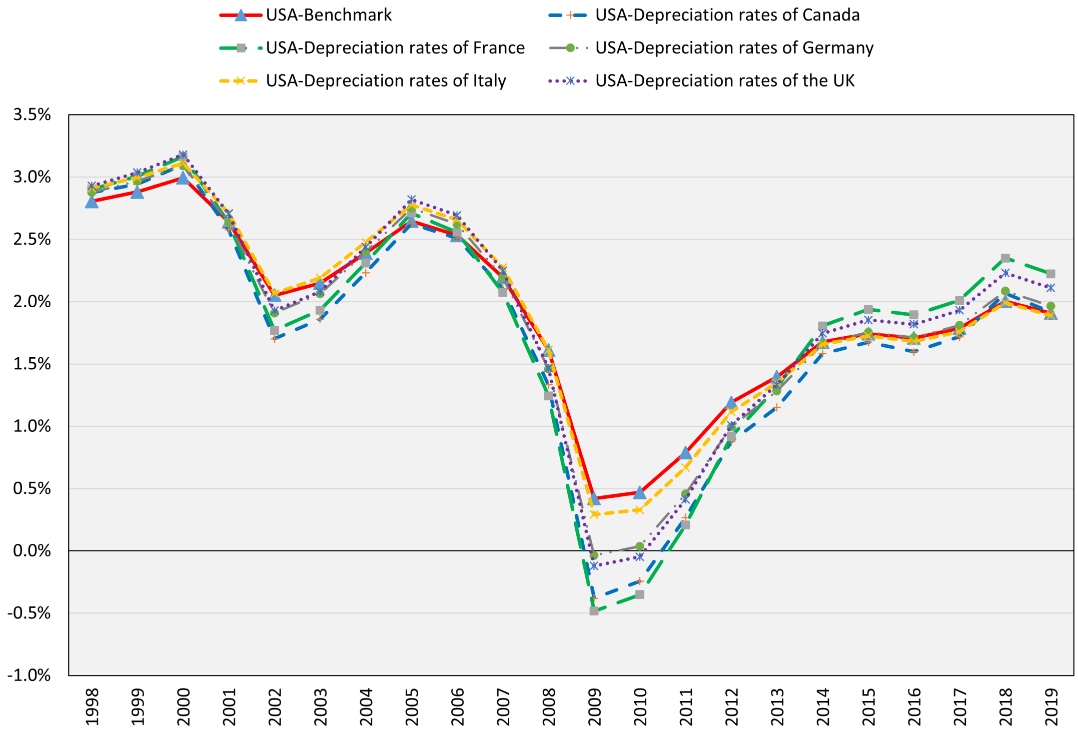
Ratio of net capital stock to gross value added, US private sector, 2019



Source: Authors' calculations, based on BEA depreciation rates, Cabannes *et al.* (2013), Giandrea *et al.* (2021), and information shared by Statistics Canada, DESTATIS (Germany), ISTAT (Italy) and the ONS (United Kingdom). The USA-Benchmark is computed by the authors as described in Pionnier *et al.* (2023).

Chart 3: Sensitivity of Net Capital Stock Growth to Changes in Cohort Depreciation Rates

Constant prices, US private sector, 1998-2019



Source: Authors' calculations, based on BEA depreciation rates, Cabannes *et al.* (2013), Giandrea *et al.* (2021), information shared by Statistics Canada, DESTATIS (Germany), ISTAT (Italy) and the ONS (United Kingdom). The USA-Benchmark is computed by the authors as described in Pionnier *et al.* (2023).

1.2.2 US Government Sector

This section extends the analysis of the previous section to the US government sector. The lack of publicly available detailed GFCF series only allows assessing how changes in cohort depreciation patterns affect the CFC of the government sector as a whole, but not for specific assets.[13] Since the gross output of the government sector is calculated as the sum of intermediate consumption, compensation of employees and CFC (BEA, 2021), any change in CFC affects the gross output and the value added of the government sector and, in turn, nominal GDP.

The level of the US government CFC in 2019 would increase by up to 19 percent if the BEA relied on the same cohort depreciation rates as Statistics Canada (Chart 4). Accordingly, the level of the US GDP in 2019 would be revised upwards by up to 0.5 per cent (Table 2).

13 Detailed GFCF series matching the granularity of depreciation rates used by the BEA would be required for this purpose. With this information, it would also be possible to assess how changes in cohort depreciation rates affect the stock, average age and remaining service life of specific government infrastructure assets such as roads, schools and hospitals.

Table 2: Sensitivity of Government Sector Value Added and GDP to Changes in Cohort Depreciation Rates

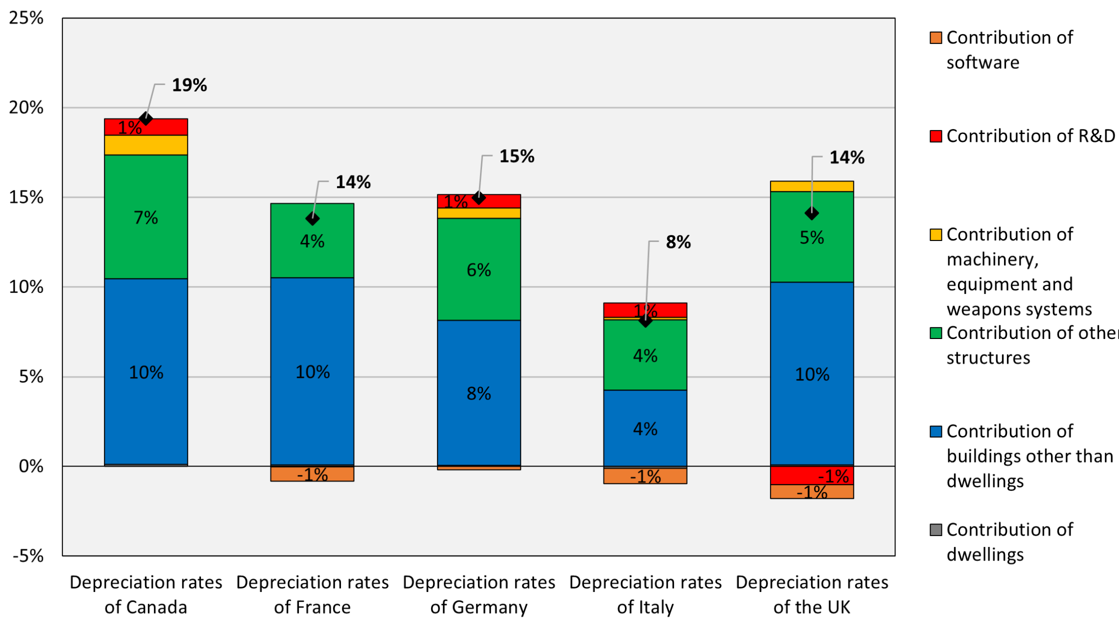
Increase in government sector value added and GDP, 2019

	Depreciation rates of Canada	Depreciation rates of France	Depreciation rates of Germany	Depreciation rates of Italy	Depreciation rates of the United Kingdom
Government sector value added	+4.7%	+3.4%	+3.6%	+2.0%	+3.4%
GDP	+0.5%	+0.4%	+0.4%	+0.2%	+0.4%

Source: Authors' calculations, based on BEA depreciation rates, Cabannes *et al.* (2013), Giandrea *et al.* (2021), information shared by Statistics Canada, DESTATIS (Germany), ISTAT (Italy) and the ONS (United Kingdom). For further info about authors' calculations, see Pionnier *et al.* (2023).

Chart 4: Sensitivity of Government Sector CFC to Changes in Cohort Depreciation Rates

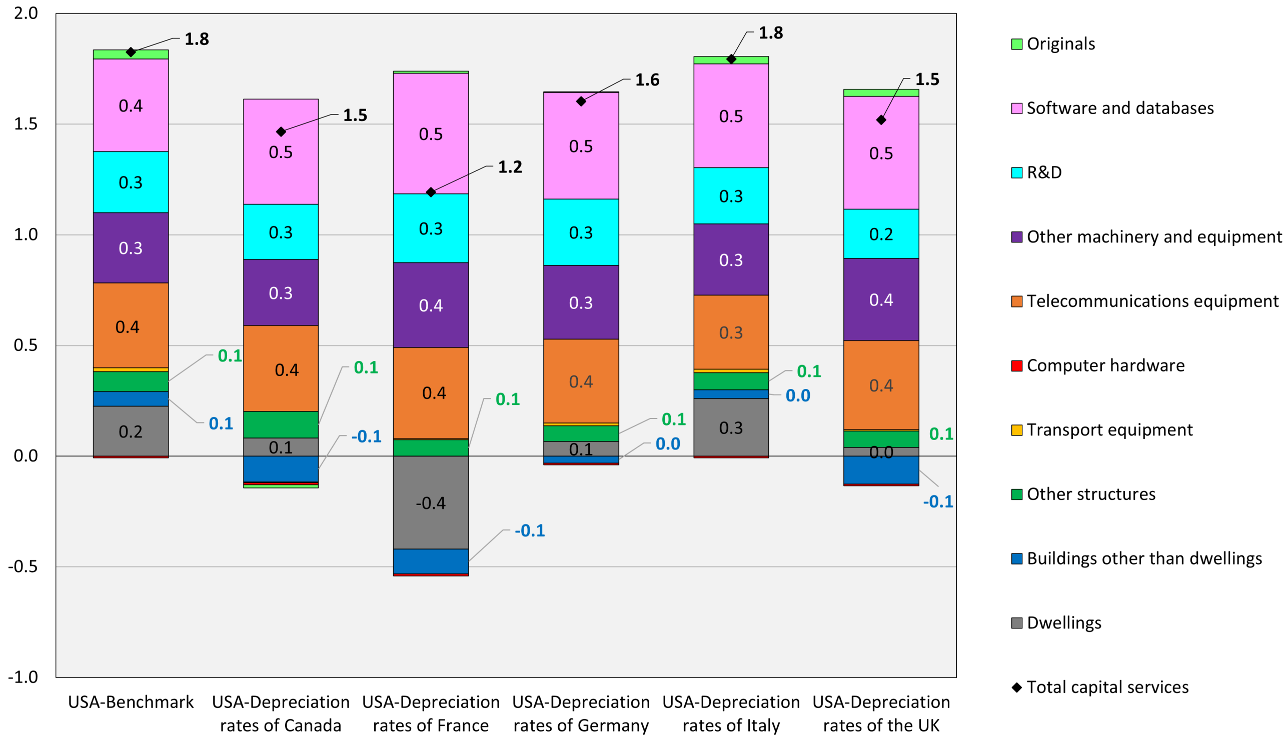
Percentage increase in CFC and contribution of underlying assets, US government sector, 2019



Note: The CFC of the US government sector would increase by 19 percent if the BEA relied on the same depreciation rates as Statistics Canada. Non-residential buildings would contribute to this increase by 10 percentage points.
Source: Authors' calculations, based on BEA depreciation rates, Cabannes *et al.* (2013), Giandrea *et al.* (2021), information shared by Statistics Canada, DESTATIS (Germany), ISTAT (Italy) and the ONS (United Kingdom). Additional information in available in Pionnier *et al.* (2023).

Chart 5: Sensitivity of Capital Services Growth to Changes in Cohort Depreciation Rates

Average annual percentage changes, US private sector, 2006-2012



Source: Authors' calculations.

1.3 Sensitivity of Capital Services and MFP Growth to Changes in Cohort Depreciation Rates

The subsequent analysis of how the capital services and MFP growth depends on cohort depreciation rates focuses on the US private sector. The user costs of capital underlying the calculation of capital services are based on exogenous and time-varying rates of return (Pionnier *et al.*, 2023).

Similarly to what is observed for the evolution of net capital stocks, the average evolution of capital services between 1998 and 2019 is not significantly affected by changes in cohort depreciation rates (Table 3).

The impact of changing cohort depreciation rates is more significant during the Great Recession and the immediately following years. Over 2006-2012, the average growth rate of capital services is 1.8 per cent per year with US and Italian depreciation rates, and declines up to 1.2 percent with French depreciation rates (Table 3, Chart 5). Dwellings and non-residential buildings are the main contributors to these differences, as expected since cross-country differences in depreciation patterns are larger for these assets.

An increase in the depreciation rate of a given asset impacts the growth rate of its capital services via three different channels: it increases the user cost of this asset, decreases the level of its net capital stock, and modifies the growth rate of its net capital stock. The first two channels have opposite effects on each asset's weight in aggregate capital services. Indeed, this weight is the share of each asset's capital services value (defined as the product of a user cost and a capital stock) in the total value of capital services. As already discussed above, an increase in the depreciation rate of an asset also has an ambiguous effect on the growth rate of its net capital stock, and a more negative impact on capital accumulation in a period of low investment. This is why the impact on capital services growth of switching to the higher depreciation rates of Canada, France, Germany and the United Kingdom is more visible in the low investment years following the Great Recession.

Consistently with the results obtained for capital services, US MFP growth rates are only marginally affected by changes in depreciation patterns (Table 3).

2. Impact of Initial Capital Stocks on Capital and MFP Measurement

2.1 Options for Estimating Initital Capital Stocks

In addition to specific assumptions on the depreciation and the retirement of assets, the estimation of capital stocks with the PIM requires investment time series and initial capital stocks to initiate the estimation process. Initial capital stocks matter all the more that the available investment series are short and the corresponding assets have long service lives. Unlike the United States, several OECD European countries, mostly in Central and Eastern Europe, only have investment series going back to the mid-1990s.

There are two main avenues for estimating initial capital stocks. The first possibility is to rely on national sources such as population censuses (giving information on the number of dwellings owned by households) and company accounts (giving information on the fixed assets owned by firms). Nevertheless, company accounts usually value assets at their book value (i.e. at their historical purchase price) and need to be supplemented with information on the date of purchase of all assets, depreciation patterns and price deflators to value the stock of assets at the price of a given year. The second possibility is to rely on stationarity assumptions to backcast investment time series and/or estimate initial capital stocks directly.[14]

Since the use of national sources to estimate initial capital stocks is country-specific and the lessons one may draw for the United States would be difficult to generalize to other countries, the present article focuses on the second possibility (stationarity assumptions). These assumptions may concern the growth rate of investment, in which case they are used to backcast investment time series, or capital stock-to-output ratios, in which case initial capital stocks are derived from the value of output (GDP) at the initial date.

14 In statistics, a (weakly) stationary time series has a mean and a standard deviation that does not vary with time. In the following, it will be assumed that either the growth rate of investment or the capital stock-to-output ratio is constant.

Table 3: Sensitivity of Capital Services and MFP Growth to Changes in Cohort Depreciation Rates

Average annual percentage changes, US private sector, 1998-2019

	USA - Benchmark	USA – Depreciation rates of Canada	USA – Depreciation rates of France	USA – Depreciation rates of Germany	USA – Depreciation rates of Italy	USA – Depreciation rates of the United Kingdom
Sensitivity of capital services Growth to changes in cohort depreciation rates						
1998-2019	**2.8**	**2.7**	**2.7**	**2.8**	**2.9**	**2.8**
1998-2006	3.6	3.4	3.9	3.8	3.7	3.7
2006-2012	1.8	1.5	1.2	1.6	1.8	1.5
2012-2019	2.7	2.8	2.7	2.8	2.8	2.8
Sensitivity of MFP Growth to changes in cohort depreciation rates						
1998-2019	**0.6**	**0.7**	**0.7**	**0.6**	**0.6**	**0.6**
1998-2006	0.7	0.8	0.6	0.7	0.7	0.7
2006-2012	1.5	1.7	1.8	1.6	1.6	1.7
2012-2019	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3

Source: Authors' calculations.

2.1.1 Assuming Constant Investment Growth Rates

A standard procedure to estimate initial capital stocks is to assume that investment in each asset type grows at a constant rate, usually taken equal to the average growth rate observed over a period where the data is available. In this case, denoting the average growth rate of investment in asset type i as g_i and its geometric cohort depreciation as δ_i, the capital stock of asset i at the end of period t can be calculated as follows:

$$K_{t,i} = \sum_{j=0}^{N}(1-\delta_i)^j I_{t-j,i} = I_{t,i}\sum_{j=0}^{N}\left(\frac{1-\delta_i}{1+g_i}\right)^j$$

Provided that $\left|\frac{1-\delta_i}{1+g_i}\right| < 1$ and letting N tend to infinity, the previous formula simplifies to:

$$K_{t,i} = \frac{1+g_i}{g_i+\delta_i} I_{t,i}$$

In this case, the initial capital stock at date t ($K_{t,i}$) can be estimated from investment at date t ($I_{t,i}$) and the two parameters g_i and δ_i.

2.1.2 Assuming Constant Capital Stock-to-output Ratios

Alternatively, it can be assumed that the capital stock-to-output ratio is constant over time. This assumption is based on the Solow (1957) growth model where, on a balanced growth path, capital and output grow at the same rate. Initial capital stocks in the Penn World Tables are estimated in this way (Inklaar and Timmer, 2013; Feenstra *et al.*, 2015).

2.2 Accuracy of Initial Capital Stock Estimates and Impact on Net Capital Stocks at Later Dates

In order to assess the accuracy of ini-

Table 4: Assumptions on Capital Stock-to-output Ratios to Estimate Initial Capital Stocks

Asset category	Capital stock-to-output ratio (total economy)
Structures (residential and non-residential)	2.2
Transport equipment	0.1
Other machinery and equipment	0.3
All other assets (i.e., IT equipment, software, and originals)	0

Note: Inklaar and Timmer (2013) did not cover R&D which, at the time, was considered intermediate consumption (not investment) in the System of National Accounts (SNA).
Source: Inklaar and Timmer (2013, Table 4).

tial capital stock estimates and their impact on net capital stocks at later dates, it is assumed that the US investment time series start in 1950, 1980 or 1995, instead of 1901 as in the BEA national accounts.[15] The above-described assumptions on investment growth rates and capital stock-to-output ratios for specific assets are then used in turn to estimate initial capital stocks.

In the first case, average investment growth rates are estimated for each aggregate asset and industry[16] over the first 20 years where investment series are available.[17] These average growth rates are then used to backcast investment series for each aggregate asset and industry.

In the second case, the asset-specific capital stock-to-output ratios calculated by Inklaar and Timmer (2013) are used. They are reported in Table 4. These are average capital stock-to-output ratios[18] estimated on a sample of 142 countries with asset series starting in 1970 or before. Output corresponds to GDP, and both capital and GDP are measured at current national prices.

For the purpose of this sensitivity analysis focusing on the US private sector, the three capital stock-to-output ratios given by Inklaar and Timmer (2013) have been multiplied by a factor 0.8, corresponding to

15 These cut-off dates are representative of the typical length of publicly available investment series across OECD countries. While according to the 2019 Eurostat-OECD Questionnaire on the Methodology underlying Capital Stocks, many OECD countries rely on unpublished historical investment series to implement their PIM. This is apparently not the case for Central and Eastern European countries, for which investment time series do not seem to available before 1995.

16 More precisely, average investment growth rates are estimated for dwellings, buildings other than dwellings, other structures, transport equipment, computer hardware, telecommunication equipment, other machinery and equipment, R&D, and software and originals, in each aggregate industry shown in Table D.1 of Appendix D in Pionnier *et al.* (2023)- https://doi.org/10.1787/92498395-en.

17 For example, for the scenario where investment series start in 1950, average investment growth rates are estimated over the period 1950-1969 for each aggregate asset industry.

18 Note that the adjustment advocated by Inklaar *et al.* (2019) to account for the slight increase in global capital stock-to-output ratios over time is not implemented in the present article. Since the US ratios in the BEA accounts do not show any trend (Charts 8 and 10), this adjustment would not improve the accuracy of national capital stock estimates for the United States. Similarly, their method to account for the fact that since the United States is close to the cross-country average, this correction is not implemented here. Because of the capital stock estimates for the United States across countries would not improve the accuracy.

19 This ratio is taken from the actual BEA accounts. Nevertheless, this operation does not bias our results because the actual stock-to-stock ratio for the US economy as a whole (0.75) is close to the cross-country average (0.76) calculated by Inklaar and Timmer (2013), which is the key reason why this method works well for the United States. That multiplication by 0.8 simply allows focusing on the US private sector rather than the US economy as a whole.

Table 5: Accuracy of Stationarity Assumptions to Estimate Initial Capital Stocks

Starting date of investment series (D)	Asset	Share of initial capital stock remaining in 2005(%)	Assuming constant investment growth rates		Assuming constant capital stock-to-output ratios	
			Ratio between estimated and BEA stocks at initial date (D)	Ratio between estimated and BEA stocks in 2005	Ratio between estimated and BEA stocks at initial date (D)	Ratio between estimated and BEA stocks in 2005
1950	All structures	23.5	2.0	1.0	1.0	1.0
	Of which: Dwellings	20.5	1.5	1.0	1.0	1.0
	Of which: Other buildings and structures	25.0	2.7	1.0	1.0	1.0
	Transport equipment	0.6	1.0	1.0	1.6	1.0
	Other machinery and equipment	0.8	1.1	1.0	1.1	1.0
	IT equipment, Software and Originals	0.1	0.9	1.0	0.0	1.0
	R&D	0.0	0.9	1.0	not estimated	not estimated
	Total		**1.8**	**1.0**	**1.0**	**1.0**
1980	All structures	48.4	1.3	1.1	1.0	0.9
	Of which: Dwellings	41.3	0.7	0.9	0.9	0.9
	Of which: Other buildings and structures	52.0	2.3	1.3	1.0	1.0
	Transport equipment	5.2	1.8	1.1	1.1	1.0
	Other machinery and equipment	6.5	1.0	1.0	0.8	1.0
	IT equipment, Software and Originals	2.4	1.2	1.0	0.0	1.0
	R&D	1.0	1.0	1.0	not estimated	not estimated
	Total		**1.3**	**1.0**	**0.9**	**0.9**
1995	All structures	72.5	26.1	15.8	1.2	1.0
	Of which: Dwellings	64.7	3.8	2.7	1.1	1.0
	Of which: Other buildings and structures	76.5	59.0	37.1	1.2	1.1
	Transport equipment	24.6	1.2	1.0	1.5	1.0
	Other machinery and equipment	28.2	1.1	1.0	1.0	1.0
	IT equipment, Software and Originals	15.9	1.2	1.1	0.0	0.9
	R&D	11.3	1.1	1.0	not estimated	not estimated
	Total		**20.5**	**13.0**	**1.1**	**1.0**

Note: The shares of initial capital stock remaining in 2005 are calculated as $(1-\delta_i)^{2005-D}$, where δ_i is the geometric cohort depreciation rate of asset i and D the starting date of investment series. These shares only depend on asset-specific cohort depreciation parameters, not on initial capital stock levels. In case depreciation rates are set at a more detailed level, an unweighted unweighted average of the corresponding shares is reported in Table 5. This unweighted average is only reported for homogeneous asset categories (e.g. transport equipment), but not for the whole economy.

private-sector share of the overall US capital stock.[19] Initial capital stocks are then further broken down into assets and industries based on their respective investment shares over the first 20 years where investment series are available. Finally, these initial capital stocks are used as starting points to apply the PIM and estimate net capital stocks at the same level of detail as the BEA.

Table 5 shows the accuracy of both methods to estimate initial capital stocks by comparing their results with the official capital stocks published by the BEA.[20] As expected, initial capital stocks have a long-lasting influence on future capital stock figures for structures and, to a lesser extent, for transport equipment and other machinery and equipment. For example out of the initial capital stocks of structures estimated in 1950, 1980 and 1995, 23.5 per cent, 48.4 per cent and 72.5 per cent, respectively, remain in use in 2005.[21] It is especially for long-lived assets that the accuracy of the method to estimate initial capital stocks is important.

The first conclusion that can be drawn from Table 5 is that the stationarity assumption on investment growth rates to estimate initial capital stocks can be very misleading, especially in the case of structures for which estimated capital stocks in 2005 with investment series starting in 1995 are 16 times higher than the official BEA estimates. This reflects the fact that the growth rate used to backcast investment series before 1995 is much below the actual average growth rate over the past, which leads to excessively large investment estimates before 1995, especially for buildings other than dwellings.

The US private sector exhibits large fluctuations and/or long-term trends in investment growth rates for dwellings and buildings other than dwellings, even when these growth rates are averaged over 20 years (Chart 6). Therefore, using investment growth rates that are based on a specific sample to backcast investment series over long periods in the past may lead to inaccurate results. This issue is magnified if available time series are short, like in the 1995 scenario. Nevertheless, given that more than half of the initial capital stock in structures remains in use after 25 years, a similar issue could have happened in the 1980 scenario. Therefore, relying on the assumption of constant investment growth rates to estimate initial capital stocks of long-lived assets such as structures should be avoided.

By comparison, capital-stock-to-output ratios for the US private sector are much more stable over time than investment growth rates (Chart 7). They are also rel-

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20 The BEA capital stock series start in 1947, or even 1925 for some assets, but these estimates are based on unpublished historical investment series. Based on publicly available investment series starting in before 1981, capital stocks for the published BEA assets (residential buildings) cannot be recalculated before 1981. Therefore, the longest-lived BEA capital stock series, rather than the ones that have long record histories, are used in the BEA code.

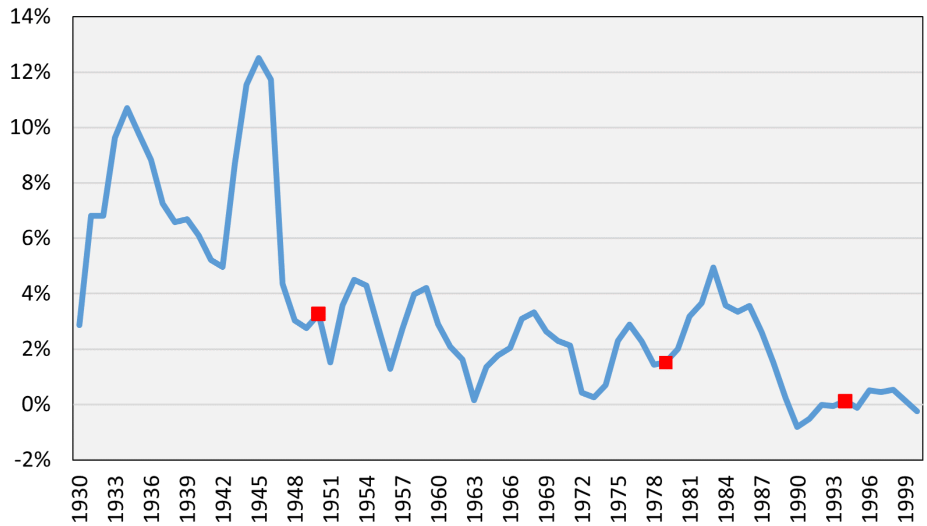
21 These numbers are implied by the BEA geometric cohort depreciation rates. See the note in Table 5.

22 As explained above, the capital stock-to-output ratios estimated by Inklaar and Timmer (2013) are multiplied by a factor 0.8 , in order to focus on the US private sector.

Chart 6: Investment Growth Rates

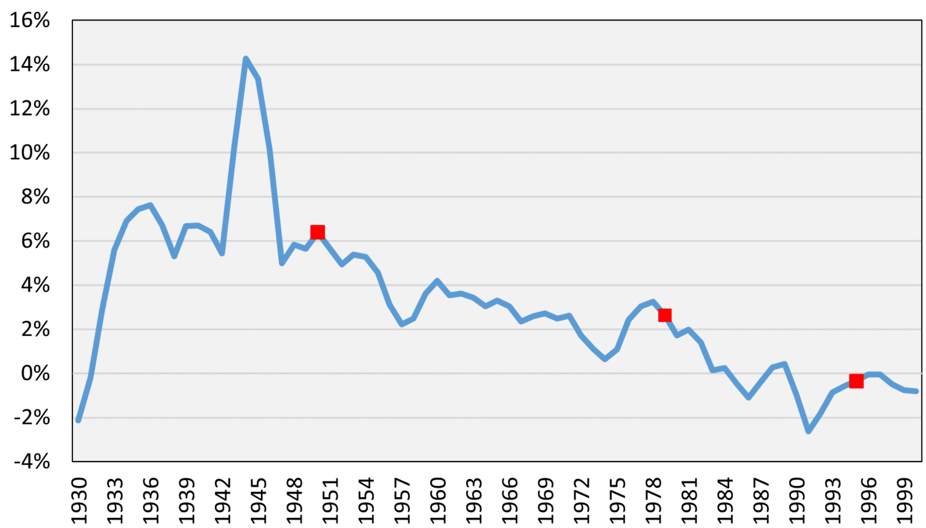
Panel A: Dwellings

20-year forward moving average, Constant prices, US private sector, 1930-2000



Panel B: Buildings Other than Dwellings

20-year forward moving average, Constant prices, US private sector, 1930-2000

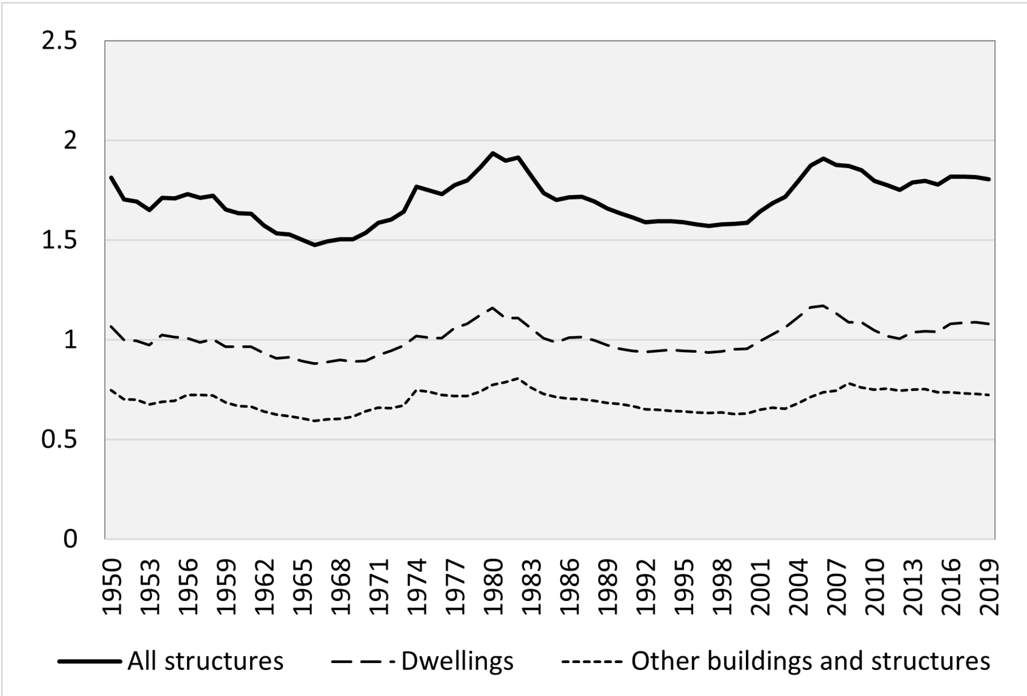


Note: The red dots indicate the 20-year forward moving average investment growth rates that are used to backcast investment time series from 1950, 1980 and 1995 backwards, respectively.
Source: Authors' calculations, based on BEA Fixed Assets Accounts.

Chart 7: Capital-stock-to-output Ratios

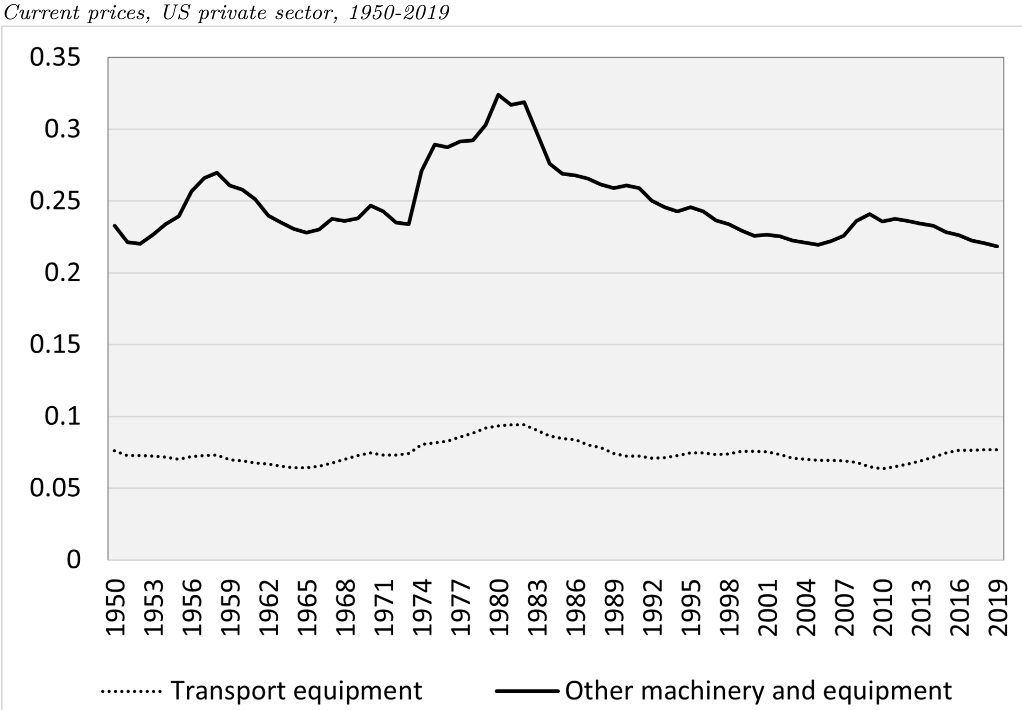
Panel A: For Structures

Current prices, US private sector, 1950-2019



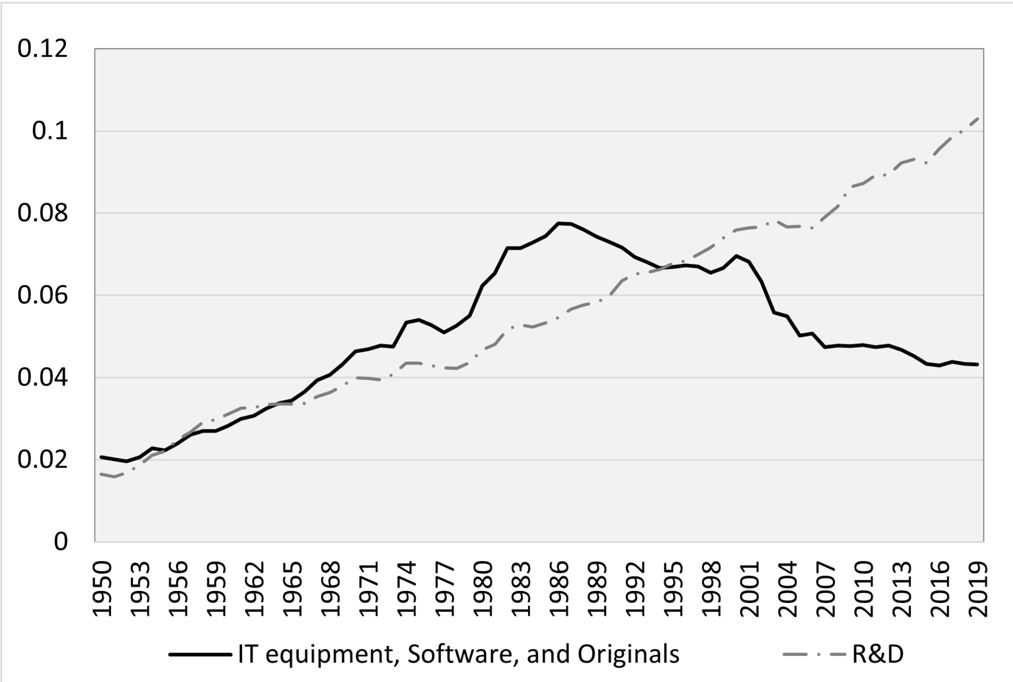
Panel B : For Transport Equipment, and Other Machinery and Equipment

Current prices, US private sector, 1950-2019



Panel C : For IT Equipment, Software, Originals and R&D

Current prices, US private sector, 1950-2019



Source: Authors' calculations, based on BEA Fixed Assets Accounts.

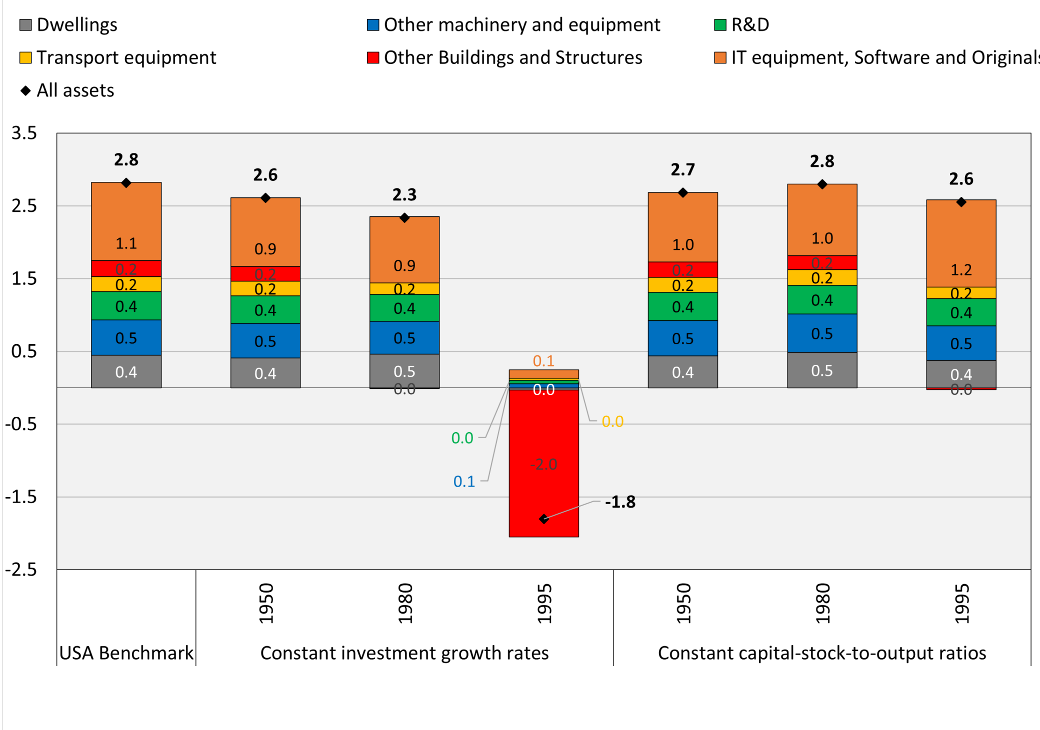
atively close to the cross-country averages estimated by Inklaar and Timmer (2013).[22] Assuming zero initial net capital stocks for IT equipment, software and originals as Inklaar and Timmer (2013) looks reasonable given the actual values for these ratios and the short service lives of these assets. Overall, estimates of net capital stocks in 2005 are in the +10/-10 per cent range around official values reported by the BEA for all main asset categories and under all scenarios (investment series starting in 1950, 1980 or 1995) when capital-stock-to-output ratios are used to estimate initial capital stocks. Nevertheless, given the dispersion of capital-stock-to-output ratios across countries (Inklaar and Timmer 2013, Figure 1), the same method may give less reliable results for other countries than the US. Exploring this issue is left for further research.

2.3 Sensitivity of Capital Services and MFP Growth to Initial Capital Stock Estimates

With short investment series, assuming constant investment growth to estimate initial capital stocks may lead to very inaccurate estimates of capital services growth (Chart 8). This reflects to a large extent the difficulty to estimate initial capital stocks for real-estate assets when assuming a constant investment growth rate. Long investment series are required to mitigate this problem. By contrast,estimating initial capital stocks by assuming constant capital-stock-to-output ratios gives rela-

Chart 8: Sensitivity of Capital Services Growth to Initial Capital Stocks

Average annual percentage changes, US private sector, 1998-2019



Note: This figure shows the sensitivity of capital services growth to initial capital stock estimates. Two different methods (relying on stationarity assumptions on investment growth rates or capital-stock-to-output ratios) and three possible starting dates for investment series (1950, 1980 and 1995) are considered.
Source: Authors' calculations.

Table 6: Sensitivity of MFP Growth to Initial Capital Stocks

Average annual percentage changes, US private sector, 1998-2019

	USA-Benchmark	Constant investment growth rates			Constant capital-stock -to-output ratios		
		1950	**1980**	**1995**	**1950**	**1980**	**1995**
1998-2019	**0.6**	**0.6**	**0.7**	**3.0**	**0.6**	**0.6**	**0.7**
1998-2006	0.7	0.8	0.8	3.3	0.7	0.7	0.7
2006-2012	1.5	1.6	1.6	3.4	1.6	1.6	1.6
2012-2019	-0.3	-0.3	-0.2	2.5	-0.3	-0.3	-0.3

Note: This table shows the sensitivity of MFP growth to changes in initial capital stock estimates. Two different methods (Assuming constant investment growth rates or capital-stock-to-output ratios) and three possible starting dates for investment series (1950, 1980 and 1995) are considered.
Source: Authors' calculations.

tively accurate estimates of US capital services growth, including when only short investment series are available. Nevertheless, the same caveat as for the estimation of net capital stocks holds. Indeed, the findings in this article are limited to the United States, for which the average capital-stock-to-output ratios estimated by Inklaar and Timmer (2013) on a large cross-section of countries work reasonably well. Considering the dispersion in capital-stock-to-output ratios across countries, this method may give less reliable results for other countries than the United States.

Similar results apply for MFP growth, but with attenuation due to the weighting of capital services growth (by roughly one third) in the calculation of MFP growth. MFP growth estimates only stand out as inaccurate when initial capital stocks are estimated in 1995, by assuming constant investment growth before that date (Table 6).

3. Conclusion

The measurement of capital stocks in an economy typically implies estimating initial capital stocks at a given date, and cumulating and depreciating investment flows over time. This article discussed the sensitivity of capital and MFP measurement to changes in the depreciation and retirement patterns of assets, and to the way initial capital stocks are estimated.

In order to capture differences in combined depreciation and retirement patterns across countries, this article focused on geometric approximations of cohort depreciation patterns. This allowed comparing the asset depreciation and retirement patterns used by national accountants in the United States and Canada, as well as France, Germany, Italy and the United Kingdom, where functional forms for asset depreciation and retirement differ from those used in Canada and the United States.

The sensitivity analysis in this article has two main characteristics. First, the distribution of cohort depreciation rates across countries for a given asset is used as a measure of uncertainty. This assumes that country-specific depreciation rates provide different estimates of the same unobserved depreciation rate, and that all differences across countries may be related to measurement errors. This extreme assumption ultimately provides a useful upper bound of the uncertainty on capital and MFP measurement.

Second, the US national accounts are used as a laboratory to analyse the sensitivity of capital and MFP measurement. Since the composition of investment is relatively similar across advanced economies, the sensitivity of capital and MFP measurement in the United States is relevant for other advanced economies as well.

Applying the same geometric cohort depreciation rates in the United States as in Canada, France, Germany or the United Kingdom would reduce the net capital stock of the US private sector by up to one third. Through an increase in the CFC of the government sector, this would also increase U.S. GDP by up to 0.5 per cent. This largely reflects the faster depreciation of buildings in the national accounts of Canada, France, Germany and the United Kingdom. Switching to Italian depreciation rates, which are closer to those used in the United States, would have a more limited impact.

Compared to the absolute levels of net capital stocks and CFC, the growth rates of net capital stocks, capital services and MFP are less sensitive to changes in depreciation and retirement patterns, no matter which country's depreciation rates are used.

This article also assessed the accuracy of two commonly used methods to estimate initial capital stocks and their impact on capital and MFP measurement. These methods involve stationarity assumptions on either investment growth rates or capital-stock-to-output ratios. While the estimation method of initial capital stocks is innocuous for rapidly depreciating assets, it has a more significant impact for long-lived assets. The US example shows that real-estate assets may exhibit large trends and fluctuations in investment growth. Since the same may be true in other countries, estimating initial capital stocks of real-estate assets by assuming constant investment growth rates over time should be avoided. On the contrary, relying on average capital-stock-to-output ratios in a large cross-section of countries works reasonably well to estimate initial capital stocks in the US private sector. Nevertheless, given the wide dispersion in capital-stock-to-output ratios across countries, this result may not be universally true and relying on the cross-country average of capital-stock-to-output ratios may give less reliable results for other countries than the United States.

Overall, the empirical evidence in this paper calls for a more frequent review of the methods used by statistical agencies to estimate asset depreciation and retirement patterns, including for assets that have been capitalised for a long time in national accounts (e.g. buildings, structures, machinery and equipment). The aim of this recommendation is not to standardize depreciation and retirement patterns across countries, but to ensure that differences reflect country-specific factors rather than statistical assumptions or measurement errors. The results also call for a careful use of stationarity assumptions to estimate initial capital stocks, especially for long-lived assets. Before relying on any stationarity assumption, statistical agencies should extend investment time series as much as possible based on historical vintages of national accounts, and use the information on capital stocks provided by population censuses, company accounts and administrative sources whenever possible.

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Capacity Utilization and Production Function Estimation: Implications for Productivity Analysis

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Abstract

During business cycles and disruptions of global value chains, capacity utilization has important implications for explaining variations in productivity and for evaluating the effectiveness of a certain investments such as R&D and ICTs. Unfortunately, data on capacity utilization is not easily available, especially at the firm level. This article develops and evaluates a methodology for measuring capacity utilization at the micro level. Unlike the literature using ad-hoc proxies (for example, the ratio of energy use to capital stock) or ex-post return to capital which is endogenous to productivity shocks, the new measure is practical and easily implemented. Importantly, it is based on the theory of the firm in terms of profit-maximizing and price-taking and is exogenous to productivity shocks. Using Canadian micro data, this article shows that the developed new measure under the assumption of capital being not adjustable in the short term explain well the variations in firm productivity. It also finds that controlling for capacity utilization may be essential in evaluating the economic impact of certain investments such as in ICT.

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A firm installs machines and hires workers to meet expected demand for its products. The maximum production level under normal economic conditions of the firm's operating practice with respect to the use of installed machines and the deployment of workers is the production capacity of the firm (Klein and Long, 1973). In reality, however, the operation of the firm may often not be at its capacity as the realized demand for its products may be lower/higher than expected or there is a shortage of necessary parts due to a disruption of global value chains. If actual demand is lower than expected or there is a shortage in necessary inputs, a firm may have to reduce its production. This leads to underutilization of production capacity as it is difficult or costly to adjust the installed capacity in a short-term. Similarly, if actual demand is higher than expected, the firm may want to increase production by operating overtime, resulting in capacity utilization higher than normal.

The variation in capacity utilization has important implications for production function estimation or measured productivity. If productivity is simply an indicator for how much output is produced by a unit of all inputs, including all workers and all installed capital, then measured productivity is not affected and capacity utilization is not an issue. However, if productivity is used as an indicator for technological change or production efficiency, which is often the case, then measured productivity under the full capacity utilization assumption may be misleading, particularly during shorter periods of time when the firm has not been able to adjust input levels to match demand. In this case, the appropriate measure should only include the actually-used inputs – the unutilized portion of production capacity should be excluded from the calculation. Thus, it has become important to adjust for capacity utilization in estimating productivity function.

Capacity utilization may also indirectly affect the estimation of the economic performance of policy programs or certain investments such as R&D and ICTs. Without controlling for capacity utilization, econometric analyses may incorrectly estimate the economic impact of policy programs or investments. Thus, controlling for capacity utilization is also important for evaluation and development of industrial policies.

Capacity utilization is commonly measured as a ratio of the actual level of output to a sustainable maximum level of output (Corrado and Mattey, 1997). Unfortunately, despite several decades of research and a well defined definition, how to actually measure capacity utilization is still debated. Importantly, data on capacity utilization is not readily available for economic analysis and research at the firm level or at the industry level for service industries. This opens the door for various proxies for capacity utilization. Measures based on both inputs and output have been put forward. For input-based measures, the proxies includes uses unemployment rates by Solow (1957), an index of electric motor utilization by Jorgenson and Griliches (1967), the ratio of energy costs to capital stock by Burnside *et al.* (1995), the growth of materials by Basu (1996), and hours worked per worker by Basu and Fernald (2001) and Basu *et al.* (2006). For output-based measures, the most popular and traditional one is actual output divided by potential/capacity output (Berndt and Fuss, 1989; Statistics Canada, 2022 for non-manufacturing goods industries). Following Berndt and Fuss (1986) and Hulten (1986), more recently, Baldwin *et al.* (2013) and Gu and Wang (2013) suggest a measure based on ex-post return to capital, and propose capacity utilization as the ratio of the ex-post return to the ex-ante expected return on capital.

However, these measures have limitations. The input-based proxies are unsatisfactory due to lacks a theoretical framework (Berndt and Fuss, 1986). They tend to capture the utilization of labour/energy utilization rather than capital utilization, which is the most difficult to adjust in the short term. Also, these proxies can be different across different groups of firms or industries, and can change over time even in normal economic conditions (for example, from input substitution effect due to relative price changes). These measures are found to be poor indicators for capacity utilization in Canada, and are unable to significantly remove the cyclical fluctuations in productivity growth (Baldwin *et al.* 2013).

Output-based measures are also questionable as the ex-post return to capital is endogenous to productivity. Ex-post income to capital is measured as output net of labour and intermediate inputs costs. Firms are often price takers for labour and intermediate inputs. Most of the gains (or loss) from positive (or negative) productivity improvements accrue to capital, which leads to over estimation (under estimation) of capacity utilization. An over- or under-estimation may be problematic if the measure is used to adjust variation in productivity or for assessing the economic performance of some economic policy instruments. The practice will also lead to the endogeneity problem in estimating production functions when capacity utilization enters regressions as an explanatory variable.

The objective of this article is to use the theory of the firm, which assumes that firms are profit maximizing and price-taking in both output and input markets, to develop a practical methodology under the Cobb-Douglas production function for estimating capacity utilization.[2] Unlike output-based measures in the literature, the theory-based measure is also exogenous to productivity shocks. Using econometric analyses, we validate the new methodology by its effectiveness in explaining variations in productivity performance of firms over business cycles. We also provide evidence on the importance of controlling for capacity utilization in assessing the economic performance of investments in R&D and ICTs during business cycles.

It is important to note that the main objective of this study is not to replace the valuable data development programs on capacity utilization at statistical agencies around world. Instead, it is to provide a practical way for researchers to estimate capacity utilization at the firm level or at

2 The project also contributes to the data development at Statistics Canada by estimating capacity utilization at the micro level.

the industry level for services industries, which currently have no capacity utilization estimates at least in Canada.

Following the introduction section, this article develops a methodology to estimate capacity utilization at the firm level, together with two hypotheses. In the data section, it briefly describes the micro data, which is used to evaluate the developed methodology. This is followed by a discussion of the measured capacity utilization under two different hypotheses. It then tests and evaluates the two hypotheses, by associating the measured capacity utilization with output, labour, investments, and official capacity utilization at the sector or industry level. It also shows whether or not controlling for capacity utilization is important in measuring productivity and in evaluating the economic impact of investments in R&D and ICTs. Finally, it concludes.

Methodology

We assume that a firm uses two inputs for its production: one input is fully adjustable (for example, combined labour and intermediate inputs) and the other is not adjustable in the short term (for example, capital). In formulation, firm i at time t maximizes profit from its production as follows:

$$\begin{cases} \max \pi_{it} = P_{it}^{Y} Y_{it} - P_{it}^{C} C_{it} - P_{it}^{F} V_{it} \\ \text{s.t. } Y_{it} = A C_{it}^{\alpha} V_{it}^{\beta} \end{cases} \tag{1}$$

Where π, Y, C, and V denote profit, output, un-adjustable input, and adjustable input, respectively; P^Y, P^C, and P^V are the prices corresponding to Y, C, and V. Note that A is a production efficiency parameter, and α and β are the output elasticities with respect to inputs C and V.

Assume that the firm is a price taker in both output and in inputs markets. From the first order conditions of the maximization problem of equation (1), we obtain

$$\frac{V_{it}^{*}}{C_{it}^{*}} = \frac{\beta P_t^C}{\alpha P_t^V} \tag{2}$$

where V_{it}^{*} and C_{it}^{*} represent the optimal levels of the adjustable and un-adjustable inputs for a given output Y_{it} for firm i at time t.

Equation (2) is the input ratio of the adjustable input to the un-adjustable input. It captures the substitution effect between the two inputs due to a relative change in input prices.

We define capacity utilization as the extent to which a firm uses its installed productive capacity. Thus, for firm i at time t, it equals

$$U_{it} = \frac{C_{it}^{*}}{C_{it}} \tag{3}$$

where C_{it} is the total installed production capacity for firm i at time t.

By this definition, we implicitly assume that a firm will install production capacity to meet expected demand in the medium- or long-term while actual use of the installed capacity is based on the short term (or yearly) demand.

This is an input-based measure of capacity utilization. The optimal level of C_{it}^{*} for a realized demand can be smaller or larger than the installed C_{it}. If actual demand is lower than expected, a firm may have to adjust its operation, leading to under-utilization of installed production capacity.

In contrast, if actual demand is higher than expected, the firm may want to increase production by operating overtime, resulting in capacity utilization higher than normal. Substituting (2) into (3), we derive capacity utilization as:

$$U_{it} = \frac{\alpha}{\beta}\frac{P_{it}^{V}V_{it}^{*}}{P_{it}^{C}C_{it}} \tag{4}$$

The measure has a desirable property. It is exogenous as it is not influenced by the production efficiency parameter (A), which is affected by productivity shocks, in equation (1).[3] During normal business operation under the Cobb-Douglas production function, the capacity utilization measure equals 1. When there is a negative (positive) shock to the demand condition, the capacity utilization measure is below (above) 1 as C_{it} is larger (smaller) than C_{it}^{*}.

It is important to note that in the context of this study, the price of the installed capacity, C_{it}, should not be determined endogenously, that is, the compensation for C_{it} should not be equal to the output value $P_{it}^{V}Y_{it}$ minus the cost of the adjustable input $P_{it}^{V}V_{it}^{*}$. It should be exogenously determined, which will be discussed further when we introduce our hypotheses.

For an empirical analysis, the output elasticity parameters α and β can be obtained by estimating the production function. Alternatively, they can be estimated by income shares as they are equivalent to income shares when inputs are paid the value of their marginal products (Hulten, 2009). Accordingly, we derive the firm-specific ratio of the two elasticity parameters for firm i as the firm sample average, that is,

$$\begin{aligned}\frac{\alpha_i}{\beta_i} &\approx \frac{1}{T_i}\sum_{t=1}^{T_i}\frac{\alpha_{it}}{\beta_{it}}\\ &= \frac{1}{T_i}\sum_{t=1}^{T_i}\frac{\left(P_{it}^{Y}Y_{it}-P_{it}^{V}V_{it}^{*}\right)/P_{it}^{Y}Y_{it}}{P_{it}^{V}V_{it}^{*}/P_{it}^{Y}Y_{it}}\\ &= \frac{1}{T_i}\sum_{t=1}^{T_i}\frac{P_{it}^{Y}Y_{it}-P_{it}^{V}V_{it}^{*}}{P_{it}^{V}V_{it}^{*}} \quad (5)\end{aligned}$$

where T_i is the total number of yearly observations for firm i.

Under this model, the average capacity utilization over time will be one. The model is then used to test two hypotheses.

Hypothesis 1: Labour and intermediate inputs are fully adjustable, and capital cannot be adjusted in the short term.

In this case, like intermediate inputs, employment can be adjusted in the short term and labour hoarding is insignificant.[4] Under this hypothesis, the adjustable input F is both labour and intermediate inputs and the un-adjustable input is capital, that is, in formulation:

$$U_{it}^{K} = \frac{\alpha^{K}}{\beta^{LM}}\frac{P_{it}^{LM}V_{it}^{LM*}}{P_{it}^{K}C_{it}^{K}} \tag{5}$$

The combined labour-intermediate input for firm i at time t is calculated as a weighted sum of labour and real interme-

3 Note also that firms are price-taking in labour and intermediate inputs and the price of capital is determined by the long-term return to capital, which will be discussed later.

4 To reflect the full adjustment in labour input, employment here should ideally be measured in hours worked. In the empirical analysis of this study, we have only data on the number of employees."

diate inputs in the Törnqvist index as follows:

$$\Delta \ln(V_{it}^{LM*}) = \overline{\phi}_{it} \Delta \ln(L_{it}^{*}) + (1 - \overline{\phi}_{it}) \Delta \ln(M_{it}^{*}) \tag{6}$$

where $\overline{\phi}_{it}$ is the average share of labour cost in the total cost of labour and intermediate inputs between t and $t-1$.

Firm-level price data are not easily available. Fortunately, for our estimation of capacity utilization, we do not have to obtain firm-level price data for all inputs. According to equation (6), $P_{it}^{LM} Y_{it}^{LM*}$ is equal to the sum of the labour compensation $P_{it}^{L} L_{it}^{*}$ and the nominal value of intermediate inputs $P_{it}^{M} M_{it}^{*}$, that is,

$$P_{it}^{LM} Y_{it}^{LM*} = P_{it}^{L} L_{it}^{*} + P_{it}^{M} M_{it}^{*}$$

and

$$P_{it}^{K} C_{it}^{K} = P_{it}^{K} K_{it}$$

is the cost of installed capital. To estimate the cost of installed capital, we need to estimate the price of capital, P_{it}^{K}. As capital investment is in the long term and also to avoid the volatility in return to the investments in the short term we approximate P_{it}^{K} by the average return to capital over the whole sample period. [5]

$$P_{it}^{K} \approx P_{i}^{K} = \frac{1}{T_i} \sum_{s=1}^{T_i} \frac{P_{is}^{Y} Y_{is} - P_{is}^{L} L_{is} - P_{is}^{M} M_{is}}{K_{is}}. \tag{7}$$

The ratio of the output elasticity of the adjustable input to the output elasticity of the un-adjustable input can also be estimated by

$$\frac{\alpha_i^K}{\beta_i^{LM}} \approx \frac{1}{T_i} \sum_{t=1}^{T_i} \frac{P_{it}^{Y} Y_{it} - P_{it}^{L} L_{it} - P_{it}^{M} M_{it}}{P_{it}^{L} L_{it} + P_{it}^{M} M_{it}} \tag{8}$$

Hypothesis 1 has been developed under the assumption that both labour and intermediate inputs are fully adjusted in the short term. If the assumption that labour is fully adjustable in the short term is violated and there is labour hoarding when demand is lower than expected is significant, then installed capacity should also include labour. Although it will be rejected later on, we develop our second hypothesis by going to extremes and assuming that like capital, labour is not adjustable.

Hypothesis 2: Intermediate inputs are fully adjustable and both labour and capital are not adjustable in the short-term.

Thus, in this case, installed capital cannot be adjusted in the short term and labour hording is significant. They together form the installed capacity, C^{LK}. In contrast, intermediate inputs are fully adjustable, and $V^* = M^*$.

Under this hypothesis, the capacity utilization firm i at time t is:

$$U_{it}^{LK} = \left(\frac{\alpha^{LK}}{\beta^{M}}\right) \left(\frac{P_{it}^{M} V_{it}^{M^*}}{P_{it}^{LK} C_{it}^{LK}}\right) \tag{9}$$

The combined labour-capital input for firm i at time t can be calculated as a

5 The micro data we have are for 2000-2017. Also, the measure is firm-specific. Alternatively, for a general ex-ante user cost of capital, we can use a standard rate of return to capital for all firms. For example, Diewert (2001) suggests that a constant real interest rate of 4% per year plus the actual rate of consumer price inflation may be used for the user cost of capital.

weighted sum of labour and capital input in the Törnqvist index as follows:

$$\Delta \ln \left(C_{it}^{LK}\right) = \bar{w}_{it} \Delta \ln \left(L_{it}\right) + (1 - \bar{w}_{it}) \Delta \ln \left(K_{it}\right) \tag{10}$$

where $\bar{w}_{it}$ is the average share of labour cost in the total cost of labour and capital at time $t-1$ and $t.\Delta \ln \left(C_{it}^{LK}\right), \Delta \ln \left(L_{it}\right)$, and $\Delta \ln \left(K_{it}\right)$ are log difference of C^{LK}, L, and K between t and $t-1$, respectively.

For this hypothesis, $P_{it}^{M} V_{it}^{M^*} = P_{it}^{M} M_{it}^{*}$ and $P_{it}^{LK} C_{it}^{LK} = P_{it}^{L} L_{it} + P_{it}^{K} K_{it}.P_{it}^{LK}$ is the price of installed capacity. As capacity investments are in the long term and also to avoid the volatility in return to the investments in the short term, in this article, we approximate P_{it}^{LK} by the average return to installed capacity over the whole sample period: [6]

$$P_{it}^{LK} \approx P_{i}^{LK} = \frac{1}{T_i} \sum_{s=1}^{T_i} \frac{P_{is}^{Y} Y_{is} - P_{is}^{M} M_{is}}{C_{is}^{LK}} \tag{11}$$

$$\frac{\alpha_i^{LK}}{\beta_i^{M}} \approx \frac{1}{T_i} \sum_{t=1}^{T_i} \frac{P_{it}^{Y} Y_{it} - P_{it}^{M} M_{it}}{P_{it}^{M} M_{it}} \tag{12}$$

Thus the new method in estimating capacity utilization is an input-based measure, which utilizes all information on labour, capital and intermediate inputs. As such, it is exogenous to output and productivity shocks.

Micro Data

The empirical analysis for evaluating the proposed measure of capacity utilization is based on micro data in Canada, covering total business sector from 2000-2017. The micro data file is from National Accounts Longitudinal Microdata File (NALMF), which is an administrative data file created by the Economic Analysis Division at Statistics Canada. The NALMF makes use of administrative tax records (T2 and PD7), T4 data, and information from the Business Register (BR), and the Survey of Employment, Payrolls and Hours (SEPH).[7] The T2 data includes corporations that file a T2 tax return with the Canada Revenue Agency (CRA). The T4 data, PD7 and SEPH include corporations and unincorporated firm that hire employees.

From the NALMF dataset, we extract for each firm, gross output, physical capital stock, intermediate inputs, R&D stock, and ICT capital stock. R&D stock is derived using the perpetual inventory method (PIM).

NALMF also has data on foreign ownership and firm birth year. These data are originally from Business Register (BR). BR is the central repository of information on businesses in Canada. Used as the principal frame for the economic statistics program at Statistics Canada, it maintains a complete, up-to-date and unduplicated list

6 The micro data we have are for 2000-2017. Also, the measure is firm-specific. Alternatively, for a general ex-ante user cost of capital, we can use a standard rate of return to capital for all firms. For example, Diewert (2001) suggests that a constant real interest rate of 4 per cent per year plus the actual rate of consumer price inflation may be used for the user cost of capital.

7 When a firm files its tax return, PD7 is the statement of account for payroll deduction containing the total number of employees and the gross payrolls. For an employee, T4 is the statement of remuneration paid by an employer, containing employment earnings.

on all active businesses in Canada that have a corporate income tax (T2) account, are an employer or have a goods and services tax account. The BR information on foreign ownership is combined with an updated foreign ownership information from Industrial Organization and Finance division (IOFD) at Statistics Canada.

Output and intermediate inputs in the NALMF database are in nominal dollars. To ensure comparison over time, it is necessary to deflate the nominal variables. Deflators at the firm level are not available so detailed industry deflators based on the KLEMS database are used.[8]

We end up with 12.3 million observations for the whole sample period (Table 1). The number of observations gradually increased for most of the non-manufacturing industries from 2000 to 2017, and it decreased for most of the manufacturing industries. This reflects the general change in the industrial structure of the Canadian economy, moving into a more service oriented economy.

Measured Capacity Utilization

Using the micro data, we estimate capacity utilization using our developed methodology under the two hypotheses. To reflect the importance of each firm in an industry group, capacity utilization for the industry is the average of capacity utilization of all firms in the industry, weighted by their output. Table 2 is the measured capacity utilization under hypothesis 1 (or CU1) for selected years, which assumes that only capital input is not adjustable in the short term. The years are the beginning and the ending points of our data, or they are associated with the two significant economic downturns in Canada.[9] In general, the measured capacity utilization is consistent with the movement in real GDP, that is, capacity utilization was high when the Canadian economy was performing well while it was low in economic downturns, especially in the 2008-2009 global financial crisis. Over the data period, the annual correlation between the measured capacity utilization (level) and real GDP growth for the business sector was highly significant at 0.49.

Chart 1 illustrates the movement of capacity utilization for industry groups for the analysis period. In general, capacity utilization decreased over time, mainly driven by non-manufacturing industries. The capacity utilization of the non-manufacturing goods-producing industry group is more volatile than manufacturing and services, with standard deviation being 0.18, 0.09 and 0.10, respectively. The high volatility in capacity utilization in the non-manufacturing goods-producing industry group can be partly explained by the high volatility of commodity price and economic activities in the mining sector.

The measured capacity utilization also captures well the change in economic condi-

8 For a description of the KLEMS database for Canada, see Baldwin *et al.* (2007).

9 Over the sample period 2000-2017, Canada only experienced one recession due to the great financial crisis, with real GDP declining 2.9 percent in 2009. Unlike the United States, Canada did not enter recession in 2001. However, due to our export industries heavily depending on the U.S. economy, Canada's real GDP growth slowed significantly from an average of 2.9 percent per year in 1990-2000 to 1.8 percent in 2001, with many manufacturing and information related services industries being hit hard.

Table 1: Number of Firms (Observations by Industry in Sample, between 2000-2017)

Industry	2000	2009	2017	**Total 2000-2017**
Forestry and logging	5855	4449	3709	86221
Fishing, hunting and trapping	1836	2137	2311	38237
Support activities for agriculture and forestry	2642	2827	3016	51081
Crop and animal production	4944	5124	4675	89940
Oil and gas extraction	1071	1616	1235	26005
Mining and quarrying	725	676	605	12145
Support activities for mining and oil and gas extraction	3820	6523	5473	101892
Utilities	445	588	545	10124
Construction	73654	104003	122712	1807629
Total manufacturing	48985	46042	42890	834814
Food	4657	4285	4568	80049
Beverage and tobacco	433	531	1106	10862
Textile and product mills	1524	1088	858	20641
Clothing, leather and allied product	3178	1818	1303	37665
Wood product	3269	3000	2709	54477
Paper	604	498	362	8990
Printing	4450	3859	3096	69113
Petroleum and coal	188	134	161	2680
Chemical	1616	1548	1528	28271
Plastics and rubber	2036	1896	1781	34499
Non-metallic mineral	1688	1651	1475	29194
Primary metal	543	552	467	9444
Fabricated metal	7386	7335	6800	131063
Machinery	4710	4615	4212	82774
Computer and electronics	2066	1796	1529	32167
Electrical equipment	1018	1017	1004	18275
Transportation equipment	2011	1800	1621	32747
Furniture	3342	3672	3352	64037
Miscellaneous manufacturing	4266	4947	4958	87866
Wholesale trade	44964	47292	42383	823391
Retail trade	77681	84197	85365	1512108
Transportation and warehousing	29958	42657	59588	775239
Information and cultural industries	8674	10434	10894	185604
Finance, insurance, real estate, and company management	58225	68136	62587	1154877
Professional, scientific and technical services	70947	106856	122517	1833234
Administrative, waste management	26892	37186	38999	635512
Arts, entertainment and recreation	10145	13698	13302	234670
Accommodation and food services	44444	53697	62411	973437
Other services except public administration	43452	62825	60446	1072343
Total business sector	559359	700963	745663	12258503

Source: Authors' own compilations based on the micro dataset for this study.

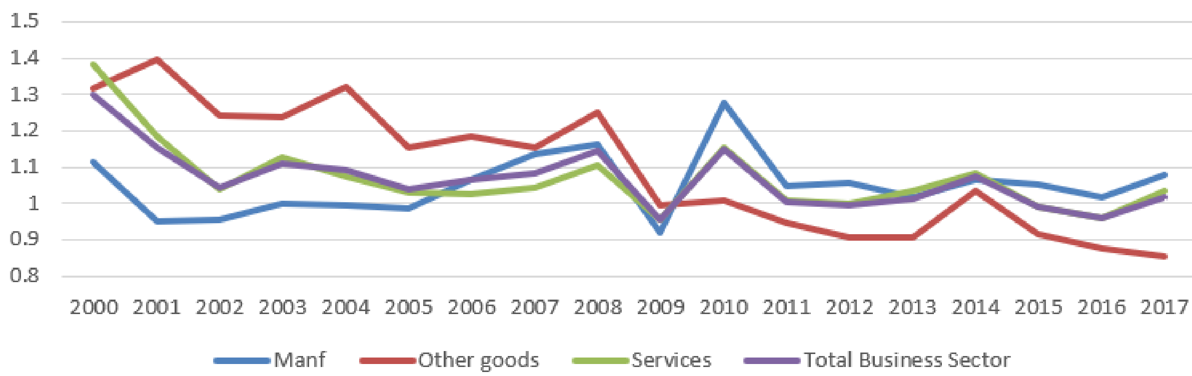
Table 2: Capacity Utilization When Only Capital Cannot Be Adjustable in the Short Term (Hypothesis 1, CU1)

Industry	2000	2001	2009	2017	**Average 2000-2017**
Forestry and logging	1.44	1.23	0.90	0.91	1.06
Fishing, hunting and trapping	1.63	1.40	0.89	1.03	1.09
Support activities for agriculture and forestry	1.48	1.33	1.00	0.97	1.08
Crop and animal production	1.42	1.26	2.36	1.01	1.18
Oil and gas extraction	0.79	1.49	1.08	0.79	1.12
Mining and quarrying	0.96	0.88	1.25	0.68	1.05
Support activities for mining and oil and gas extraction	1.42	1.28	0.91	0.88	1.07
Utilities	1.69	1.64	0.58	0.48	0.91
Construction	1.49	1.28	1.02	0.97	1.11
Total manufacturing	1.11	0.95	0.92	1.08	1.05
Food	1.24	1.14	1.00	0.94	1.01
Beverage and tobacco	1.18	0.92	0.68	0.96	0.97
Textile and product mills	1.19	1.04	1.01	0.91	1.01
Clothing, leather and allied product	1.34	1.25	1.02	0.91	1.05
Wood product	1.15	1.10	0.79	1.01	0.99
Paper	0.90	0.78	0.73	1.09	1.07
Printing	1.07	0.99	1.09	1.02	0.97
Petroleum and coal	1.11	0.92	0.84	0.97	1.12
Chemical	0.97	0.84	0.86	1.46	1.03
Plastics and rubber	1.35	0.96	0.89	0.91	0.96
Non-metallic mineral	1.09	1.14	0.91	0.95	1.02
Primary metal	1.06	0.96	1.00	0.85	1.05
Fabricated metal	1.31	1.08	0.96	0.93	1.03
Machinery	1.19	1.17	1.00	0.92	1.04
Computer and electronics	1.48	0.85	1.57	1.04	1.06
Electrical equipment	1.52	0.88	1.05	1.11	1.08
Transportation equipment	0.90	0.83	0.75	1.14	1.02
Furniture	1.28	1.30	0.84	0.92	0.99
Miscellaneous manufacturing	1.29	1.13	1.04	0.92	1.07
Wholesale trade	1.35	1.16	0.98	1.00	1.06
Retail trade	1.18	1.10	0.94	1.07	1.02
Transportation and warehousing	2.13	1.66	0.90	0.92	1.09
Information and cultural industries	0.96	0.90	0.97	0.74	1.05
Finance, insurance, real estate, and company management	1.48	1.18	0.92	1.09	1.08
Professional, scientific and technical services	1.28	1.20	1.00	1.06	1.16
Administrative, waste management	1.35	1.26	1.03	1.07	1.09
Arts, entertainment and recreation	1.43	1.18	0.79	0.93	1.10
Accommodation and food services	1.21	1.09	1.05	0.97	1.02
Other services except public administration	1.51	1.31	0.96	1.05	1.06
Total business sector	1.30	1.15	0.96	1.02	1.07

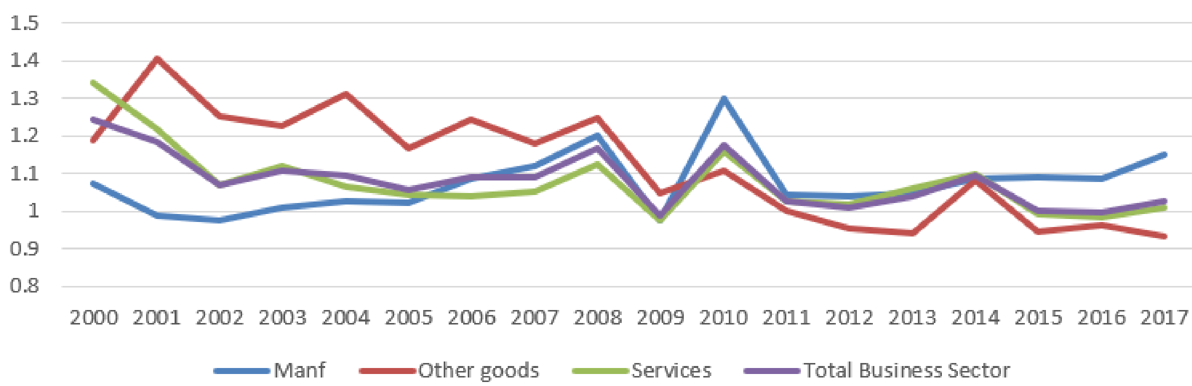
Note: The years selected are the peaks and troughs of real GDP line in Canada. The capacity utilization at the industry level is aggregated from the firm level, weighted by gross output.
Source: Authors' own compilations based on the micro dataset for this study.

Chart 1 : Capacity Utilization

Panel A: When Only Capital Cannot Be Adjustable in the Short Term (Hypothesis 1, CU1) for Aggregated Industry Groups



Panel B: When Both Labour and Capital Input Cannot Be Adjustable in the Short Term (Hypothesis 2, CU2) for Aggregated Industry Groups



tion at the industry level, although the general annual correlation between real GDP growth and the measured capacity utilization was 0.13 at the industry level, as shown later on in Table 5.[10] For the 2001 U.S. recession, which was mainly due to the collapse of the dotcom bubble and the 9/11 attacks, Canada's export-orientated manufacturing sector, especially computer and electronics and electrical equipment, was significantly affected (Table 2). We observe that the capacity utilization for total manufacturing declined 15 percent, from 1.11 in 2000 to 0.95 in 2001. The decline was more

10 The lower correlation at the industry level than at the aggregate business sector may be due to the fact that the variation in real GDP growth across industries was mainly driven by other industry-specific factors other than capacity utilization.

dramatic for the computer and electronics and electrical equipment manufacturing industry, from 1.48 to 0.85. For the great financial crisis, the negative economic impact was deeper and widespread across industries. Consistent with the development, we observe that 33 out of the 38 industries experienced a significant decline in capacity utilization. In 2009, The industries with the largest decline in capacity utilization were oil and gas extraction, petroleum and coal, primary metal, machinery, and finance, insurance and real estate.

Table 3 and Chart 1 is the measured capacity utilization under hypothesis 2 (or CU2), which assumes that both labour and capital input are not adjustable in the short term. The industry variation and movement pattern of CU2 is generally similar to that of CU1, with a correlation of 0.94 at the industry level and 0.98 for the total business sector.

The Evaluation of the Measured Capacity Utilization

How well does our estimated capacity utilization capture the actual capacity utilization? In this section, we assess them by correlating our measures with the official measure of capacity utilization and with economic growth.

Against Official Capacity Utilization for the Goods Producing Industries

Statistics Canada regularly releases capacity utilization statistics for the non-agriculture goods producing industries. In its recent practices, two approaches are followed for estimating capacity utilization rates at Statistics Canada (Statistics Canada, 2022). For manufacturing industries, the rates are directly calculated using survey data from the Monthly Survey of Manufacturing (MSM). In the survey, a plant is asked at what percentage of its capacity it has been operating, with capacity being defined as maximum production attainable under normal conditions. For other non-agriculture goods producing industries, the rates are calculated as the actual output-to-capital ratio divided by the potential output-to-capital ratio. The latter is the de-trended output-to-capital ratio, derived from actual output-to-capital ratio using the Hodrick-Prescott filter (HP filter). As discussed before, the capacity utilization estimates using output-to-capital ratio are endogenous to productivity shocks as they reflect the change in productivity.

The official rates are reported in Table 4. For a comparison between our measured capacity utilization and the official one, the official capacity utilization is normalized to the average of CU1 and CU2 for manufacturing over 2000-2017.

The movement pattern of the official capacity utilization is in general similar to that of our measures, although the correlation between our measures and the official measure at the industry level for 2000-2017 is only modest at 0.18 for CU1 and 0.17 for CU2. In consistent with CU1 and CU2, the largest decline in 2001 were computer and electronics and electrical equipment. For the Great Financial Crisis, in 2009, the decline was widespread across all industries.

Chart 2 illustrates the movement of the official measure and our measured capacity utilization for the total manufacturing

Table 3: Capacity Utilization When Both Labour and Capital Input Cannot Be Adjustable in the Short Term (Hypothesis 2, CU2)

Industry	2000	2001	2009	2017	**Average 2000-2017**
Forestry and logging	1.15	1.09	1.02	0.97	1.06
Fishing, hunting and trapping	1.31	1.17	0.99	0.98	1.07
Support activities for agriculture and forestry	1.18	1.20	1.05	1.01	1.11
Crop and animal production	1.44	1.29	2.38	1.07	1.21
Oil and gas extraction	0.77	1.60	1.05	0.98	1.17
Mining and quarrying	0.86	0.98	1.07	0.76	1.08
Support activities for mining and oil and gas extraction	1.27	1.18	1.27	1.02	1.11
Utilities	1.66	1.65	0.82	0.68	1.04
Construction	1.26	1.22	1.05	0.98	1.09
Total manufacturing	1.07	0.99	0.97	1.15	1.07
Food	1.10	1.10	1.01	1.02	1.02
Beverage and tobacco	1.01	1.04	0.86	1.15	1.02
Textile and product mills	1.07	1.02	1.05	1.05	1.02
Clothing, leather and allied product	1.17	1.13	1.03	0.93	1.03
Wood product	1.06	1.09	0.90	1.10	1.02
Paper	0.93	0.79	0.75	1.12	1.12
Printing	1.28	1.36	0.94	1.02	1.04
Petroleum and coal	1.40	1.10	0.95	0.96	1.18
Chemical	0.91	0.88	0.93	1.58	1.09
Plastics and rubber	1.10	1.11	0.96	1.02	1.02
Non-metallic mineral	1.00	1.08	0.96	0.98	1.03
Primary metal	0.91	0.96	1.04	0.93	1.07
Fabricated metal	1.15	1.01	1.00	0.98	1.02
Machinery	1.06	1.08	1.07	1.02	1.05
Computer and electronics	1.61	0.88	1.62	1.18	1.12
Electrical equipment	1.17	0.92	1.07	1.06	1.07
Transportation equipment	0.90	0.91	0.80	1.20	1.02
Furniture	1.09	1.24	0.92	0.98	1.00
Miscellaneous manufacturing	1.17	1.06	1.10	0.98	1.06
Wholesale trade	1.27	1.16	1.01	1.04	1.07
Retail trade	1.14	1.15	0.97	1.05	1.03
Transportation and warehousing	2.18	1.75	0.94	0.97	1.11
Information and cultural industries	1.00	1.03	1.01	0.74	1.07
Finance, insurance, real estate, and company management	1.45	1.24	0.95	1.00	1.08
Professional, scientific and technical services	1.23	1.15	0.99	1.01	1.16
Administrative, waste management	1.21	1.19	1.04	1.10	1.07
Arts, entertainment and recreation	1.34	1.14	0.83	0.97	1.11
Accommodation and food services	1.16	1.13	0.99	0.96	1.02
Other services except public administration	1.29	1.21	0.98	1.04	1.05
Total business sector	1.24	1.18	0.99	1.02	1.08

Note: The years selected are the peaks and troughs of real GDP line in Canada. The capacity utilization at the industry level is aggregated from the firm level, weighted by gross output.
Source: Authors' own compilations based on the micro dataset for this study.

Table 4: Official Capacity Utilization for the Non-Agriculture Goods Producing Industries

Industry	2000	2001	2009	2017	**Average 2000-2017**
Forestry and logging	1.11	1.11	0.88	1.11	1.13
Oil and gas extraction	1.13	1.08	0.98	1.04	1.06
Mining and quarrying	1.13	1.13	0.83	1.01	1.06
Construction	1.15	1.17	1.07	1.16	1.17
Food	1.08	1.08	1.09	1.05	1.06
Beverage and tobacco	1.05	1.05	0.96	1.00	0.99
Textile and product mills	1.10	1.04	0.86	1.02	0.99
Clothing, leather and allied product	1.09	1.04	0.87	1.10	0.99
Wood product	1.13	1.09	0.81	1.10	1.09
Paper	1.22	1.18	1.09	1.16	1.18
Printing	1.06	1.02	0.97	0.99	0.97
Petroleum and coal	1.23	1.26	1.04	1.19	1.14
Chemical	1.06	1.07	0.94	1.05	1.05
Plastics and rubber	1.12	1.11	0.90	1.01	1.07
Non-metallic mineral	1.06	1.07	0.90	0.87	1.03
Primary metal	1.21	1.15	1.01	1.06	1.13
Fabricated metal	1.12	1.06	0.86	0.94	1.04
Machinery	1.11	1.04	0.93	1.01	1.06
Computer and electronics	1.29	0.96	1.11	1.05	1.10
Electrical equipment	1.23	1.01	0.99	1.01	1.03
Transportation equipment	1.18	1.14	0.89	1.12	1.12
Furniture	1.13	1.07	0.92	1.01	1.06
Miscellaneous manufacturing	1.11	1.07	1.01	0.99	1.07
Total Manufacturing	1.14	1.09	0.96	1.04	1.07

Source: Statistics Canada Table 16-10-0109-01.
Note: Official capacity utilization is normalized to the average of CU1 and CU2 for manufacturing over 2000-2017.

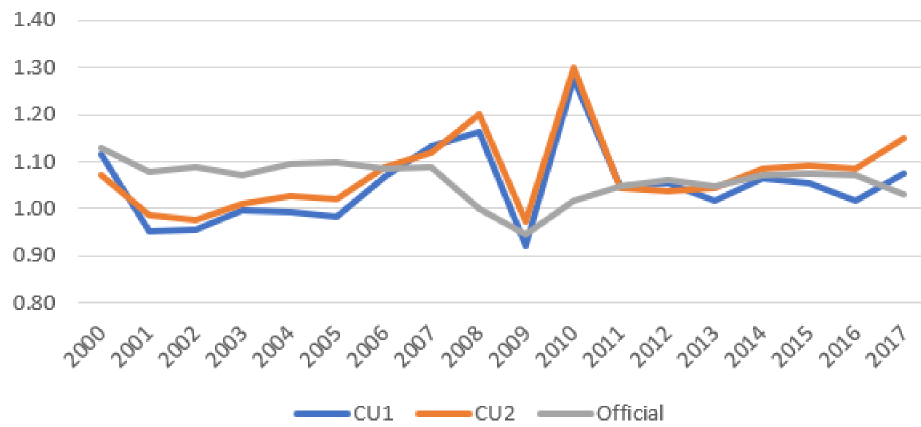
sector. The three measures are broadly similar. For example, during the economic downs in 2001 and 2008-2009, all measures fell substantially. However, our measures are more volatile than the official measure.

Correlation with Output, Employment, and Investment Growth

Measured capacity utilization should generally reflect the change in business conditions. To provide some evidence, we also associate the measured capacity utilization indicators with growth in output (value added), employment (number of employees and hours worked), and investment (total investment and investment in machinery & equipment), which is done at the industry level.

In Table 5, we report the correlations for 38 goods and services industries. All correlations are positive. In general, the associations of CU1 with output, employment and investment growth are better than with CU2 at the manufacturing or the business sector level. This suggests that CU1 may be a better measure for capacity utilization than CU2. It should be noted, however, that a higher correlation of a CU measure with output may not necessarily indicate that the CU measure is a better measure of true capacity utilization as output is determined by many factors besides the use of installed capacity. On the other hand, a higher correlation of a CU measure with inputs directly related to installed capacity may indicate that the CU measure a better measure. This is case for CU1 for

Chart 2: Comparison to the Official Capacity Utilization Manufacturing



Note: Official capacity utilization is normalized to the average of CU1 and CU2 for manufacturing over 2000-2017.

the manufacturing sector as its correlations with growth in total investment and investment in M&E are significantly higher than for CU2. However, at the detailed industry level, we do not observe large differences between CU1 and CU2 as the correlations with output growth, employment growth, and investment growth are generally similar for CU1 and CU2.

In Table 5, we also include the correlations for official CU, which are only available for 22 goods producing industries. The correlation results are mixed for the CU measures. Despite a similar broad trend as shown in Chart 2, the correlations between our CU measures and the official CU is negative, especially for CU2. The correlation of capacity utilization with growth in output and employment/hours worked is higher for official CU than for CU1 or CU2. But, for the manufacturing sector, the correlations with growth in total investment and investment in M&E are significantly higher for CU1 than official CU or CU2.

Correlation is a simple indicator for possible relationship between two variables, without controlling for the effects from other factors. To validate our CU measures related to productivity estimation and the role in evaluation of policy instruments, we need to isolate the effects of other factors. To this end, in the remaining two sections, we conduct an econometric analysis.

Capacity Utilization and Measured Multifactor Productivity

In this section, we assess the role of controlling for capacity utilization in explaining variations of measured productivity. To this end, we compare the smoothness of measured productivity with and without controlling for capacity utilization. We use the mean square error to measure smoothness. The basic production regression model with capacity utilization is:

$$\ln(Y_{i,t}) = \alpha_0 + \alpha_L \ln L_{i,t} + \alpha_K \ln K_{i,t} + \alpha_M \ln M_{i,t} + \beta_1 \ln U_{i,t} + \sum_{j=2}^{s} \beta_j Z_{i,j,t} + \varepsilon_{i,t} \tag{14}$$

where $Y_{i,t}$ is gross output; $L_{i,t}$, $K_{i,t}$, and

Table 5: Industry-Year Correlation between Measured Capacity Utilization and Economic Performance Indicators, 2000-2017

Aggregate Manufacturing Sector

	CU1	CU2	OCU	VA	L	H	I	ME
CU Under Hypothesis 1 (CU1)	1.00							
CU Under Hypothesis 2 (CU2)	0.94	1.00						
Official CU (OCU)	-0.08	-0.24	1.00					
Value Added Growth (VA)	0.38	0.25	0.65	1.00				
Employment Growth (L)	0.17	0.09	0.63	0.89	1.00			
Hours Worked Growth (H)	0.30	0.21	0.62	0.91	0.98	1.00		
Total Investment Growth (I)	0.52	0.38	0.31	0.69	0.59	0.63	1.00	
M&E Investment Growth (ME)	0.44	0.36	0.37	0.60	0.55	0.59	0.93	1.00

Aggregate Business Sector

	CU1	CU2		VA	L	H	I	ME
CU Under Hypothesis 1 (CU1)	1.00							
CU Under Hypothesis 2 (CU2)	0.98	1.00						
Value Added Growth (VA)	0.49	0.44		1.00				
Employment Growth (L)	0.40	0.36		0.84	1.00			
Hours Worked Growth (H)	0.37	0.32		0.82	0.95	1.00		
Total Investment Growth (I)	0.52	0.53		0.70	0.65	0.68	1.00	
M&E Investment Growth (ME)	0.44	0.40		0.72	0.71	0.71	0.94	1.00

Goods and Service Industries (38 industries)

	CU1	CU2		VA	L	H	I	ME
CU Under Hypothesis 1 (CU1)	1.00							
CU Under Hypothesis 2 (CU2)	0.94	1.00						
Value Added Growth (VA)	0.13	0.10		1.00				
Employment Growth (L)	0.11	0.12		0.63	1.00			
Hours Worked Growth (H)	0.11	0.12		0.66	0.97	1.00		
Total Investment Growth (I)	0.08	0.10		0.22	0.22	0.22	1.00	
M&E Investment Growth (ME)	0.04	0.06		0.22	0.23	0.23	0.80	1.00

Non-Agriculture Goods Industries (22 industries)

	CU1	CU2	OCU	VA	L	H	I	ME
CU Under Hypothesis 1 (CU1)	1.00							
CU Under Hypothesis 2 (CU2)	0.94	1.00						
Official CU (OCU)	0.18	0.17	1.00					
Value Added Growth (VA)	0.15	0.12	0.40	1.00				
Employment Growth (L)	0.12	0.14	0.32	0.63	1.00			
Hours Worked Growth (H)	0.12	0.14	0.33	0.64	0.98	1.00		
Total Investment Growth (I)	0.10	0.14	0.20	0.06	0.10	0.11	1.00	
M&E Investment Growth (ME)	0.03	0.07	0.21	0.03	0.09	0.09	0.79	1.00

Note: There is no official capacity utilization estimates for service industries.
Source: Authors' own compilations based on Statistics Canada Table 16-10-0109-01 and the micro dataset for this study.

$M_{i,t}$ are the inputs representing labour, capital and intermediate inputs, respectively ; U_{it} is capacity utilization; Z_i is a set of control variables such as foreign ownership, firm age, and industry-year specifics; and $\varepsilon_{i,t}$ is an error term.

In the regression, we control for firm age as it takes time for new entrants young firms to learn their markets, establish supplier and distribution networks and develop scale. Thus, they are generally less efficient than established firms. To reflect this, we introduce a dummy for young firms, which takes 1 for firms being not more than 5 years and 0 otherwise. This is based on Liu and Tang (2017). They show that entrants take about 5 years to become as productive as incumbents.

We also control for foreign ownership as it is well established that foreign controlled firms in Canada are on average more productive than Canadian controlled firms in Canada. Finally, we introduce industry-year dummies to capture any effect at the industry level, including technological progress and changes in competition.

Estimation and Discussion

To ensure robust results, each regression model is estimated by two different methodologies. First, we assume robust standard error when ordinary least square estimation (OLS) is used. Robust standard error is a common and effective way to deal with heteroscedasticity, minor problems associated with the lack of normality, or some observations that exhibit large influence. Second, we estimate the model with firm fixed effects, which concerns only within-firm variation and ignores between-firm changes. The design aims to control for individual firm fixed effects. It also corrects potential miss-specifications of the regression model due to missing time-invariant variables, and addresses the endogeneity problem when a component of the productivity shock is fixed over time at the firm level. To ensure robust results, each regression model is estimated by two different methodologies.

Our sample contains many small firms. The data for small firms tend to be noisy. So we limit our estimation to firms with average number of employees being 10 or more.[11]

The regression results based on the whole sample for firms with average number of employees being 10 or more are reported in Table 6. In general, the results based on OLS assuming robust standard error and those with firm fixed effects are fairly similar. As expected, labour, capital, intermediate inputs, and foreign ownership are found to be positive and statistically significant while young firms are found to be less productive.

Important for this article are the estimates related to capacity utilization. For CU1, the coefficients are positive and sta-

11 The possibility that the effect of capacity utilization in economic downturns differs from that in normal times as production capacity is mostly underutilized. To capture this, we divide our sample into two groups: normal times and downturn times. The down times contains two economic downturns: the dotcom bust 2001-2002 and the Great Financial Crisis 2008-2009. The normal times is the rest years in our sample 2000, 2003-2007, and 2010-2017. However, the estimation results with the two sub-samples are fairly similar to those with the whole sample.

Table 6: The Estimation of the Production Function With and Without CU

	Robust standard error			Firm Fixed effects		
	Without CU	With CU1	With CU2	Without CU	With CU1	With CU2
Labour (in log)	0.249***	0.247***	0.241***	0.265***	0.250***	0.241***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangible Capital (in log)	0.049***	0.055***	0.042***	0.040***	0.112***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intermediate inputs (in log)	0.706***	0.701***	0.717***	0.605***	0.564***	0.644***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Foreign ownership dummy	0.100***	0.098***	0.095***	0.217***	0.213***	0.200***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Young firm dummy	-0.033***	-0.033***	-0.031***	-0.034***	-0.036***	-0.032***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capacity utilization		0.034***	-0.071***		0.088***	-0.062***
		(0.000)	(0.000)		(0.000)	(0.000)
Industry-year dummies	Yes	Yes	Yes			
Year dummies				Yes	Yes	Yes
Firm-fixed effects				Yes	Yes	Yes
Number of observations	2978996	2978996	2978996	2978996	2978996	2978996
R-square	0.95	0.95	0.95			
R-square, within				0.85	0.86	0.85
R-square, between				0.94	0.94	0.94

Note: P-values are in parenthesis. "***" denotes significance at the 1% level.

tistically highly significant, indicating that firm production and capacity utilization are positively correlated, that is, higher capacity utilization means higher production. We also observe that with CU1, the relationship between output and capital stock becomes stronger. This suggests that after controlling for capacity utilization, output is more sensitive to capital stock. So, CU1 serves the purpose.

In contrast, the results on CU2 are surprising. First, the coefficient is negative. Second, after controlling for CU2, the relationship between output and capital (or labour) becomes weaker. Thus, after controlling for the effects of other factors, CU2 has a negative relationship with output, which cannot be explained in an economic sense. For those reasons, we reject hypothesis 2.

In the remaining of this paper, we continue to validate the importance of controlling for capacity utilization for CU1.

Productivity Dispersion Before and After Controlling for Capacity Utilization

Firms with lower capacity utilization are likely to be less productive when the measured productivity is estimated with all installed capacity. Controlling for capacity utilization reduce productivity dispersion and the productivity gap between frontier firms and laggards. In Table 6, we report the mean square error (MSE) of multifactor productivity (MFP) by industry, with or without controlling for capacity utilization (CU1).

According to Table 7, without controlling for capacity utilization, productivity dispersion varies significantly across indus-

Table 7: Mean Squared Error of Measured MFP With and Without Capacity Utilization

Industry	2000-2017			2001-2002, 2008-2009		
	Capacity U		A/B	Capacity U		C/D
	No	Yes		No	Yes	
	A	B		C	D	
Forestry and logging	1.08	1.00	1.07	1.12	1.06	1.05
Fishing, hunting and trapping	1.94	1.87	1.04	1.21	1.15	1.05
Support activities for agriculture and forestry	1.14	1.10	1.04	0.91	0.86	1.06
Crop and animal production	4.24	4.15	1.02	3.41	3.41	1.00
Oil and gas extraction	5.06	4.95	1.02	5.16	5.11	1.01
Mining and quarrying	2.52	2.52	1.00	2.10	1.91	1.10
Support activities for mining and oil and gas extraction	2.14	2.12	1.01	2.53	2.52	1.01
Utilities	4.03	3.94	1.02	4.71	4.89	0.96
Construction	1.22	1.16	1.05	1.24	1.19	1.04
Food	0.75	0.74	1.01	0.59	0.57	1.03
Beverage and tobacco	1.06	1.00	1.07	0.45	0.44	1.03
Textile and product mills	0.70	0.67	1.04	1.62	1.52	1.06
Clothing, leather and allied product	0.76	0.74	1.04	1.14	1.08	1.05
Wood product	0.49	0.48	1.02	0.54	0.54	1.00
Paper	0.35	0.33	1.04	0.09	0.09	1.00
Printing	0.63	0.62	1.01	0.54	0.56	0.96
Petroleum and coal	1.09	1.13	0.96	1.53	1.64	0.93
Chemical	1.04	1.02	1.02	0.53	0.52	1.01
Plastics and rubber	0.64	0.61	1.05	0.42	0.42	1.01
Non-metallic mineral	0.47	0.44	1.06	0.31	0.31	1.02
Primary metal	0.48	0.46	1.05	0.20	0.20	0.99
Fabricated metal	0.78	0.75	1.04	0.98	0.93	1.05
Machinery	1.01	0.97	1.03	1.04	1.02	1.01
Computer and electronics	1.28	1.21	1.06	1.45	1.39	1.04
Electrical equipment	0.82	0.77	1.06	0.44	0.45	0.98
Transportation equipment	1.43	1.34	1.07	0.35	0.34	1.01
Furniture	0.48	0.46	1.05	0.24	0.24	1.01
Miscellaneous manufacturing	0.66	0.65	1.02	0.74	0.73	1.02
Wholesale trade	1.00	0.96	1.04	0.93	0.92	1.02
Retail trade	0.51	0.48	1.05	0.43	0.41	1.04
Transportation and warehousing	0.92	0.90	1.02	0.91	0.90	1.00
Information and cultural industries	2.70	2.59	1.04	2.78	2.64	1.05
Finance, insurance, real estate, and company management	8.82	8.47	1.04	7.82	7.58	1.03
Professional, scientific and technical services	3.77	3.59	1.05	3.70	3.52	1.05
Administrative, waste management	3.06	2.94	1.04	2.96	2.85	1.04
Arts, entertainment and recreation	1.68	1.62	1.03	1.44	1.40	1.03
Accommodation and food services	0.58	0.55	1.06	0.62	0.60	1.03
Other services except public administration	1.18	1.14	1.04	1.19	1.14	1.04
Total	2.28	2.18	1.04	2.16	2.09	1.04

Source: Authors' own compilation based on results from columns (1) and (2) in Table 5 with robust standard error and under CU1 tries from 0.35 in the paper manufacturing industry to 8.82 in finance, insurance, real estate and company management. After, controlling for capacity utilization, the dispersion was significantly reduced, about 4 per cent on average. The reduction is mostly significant in forestry and logging, beverage and tobacco, and transportation equipment.

In Table 7, we also single out productivity dispersion in economic downturns 2001-2002 and 2008-2009. Interestingly, the productivity dispersion during downturns is very similar to average for the whole sample period. We also observe that the reduction in dispersion after controlling for capacity utilization in downturns is very similar to that for the whole sample period. Notably, the largest reduction during downturns is in mining and quarrying.

Capacity Utilization and the Economic Performance of Investments in R&D and ICTs

In this section, we use the micro database to demonstrate whether or not controlling capacity utilization is important in evaluating the economic impact of investments in R&D and ICTs. Our basic regression model is following:

$$\ln (Y_{i,t}) = \alpha_0 + \alpha_L \ln L_{i,t} + \alpha_K \ln K_{i,t} + \alpha_M \ln M_{i,t} + \beta_1 \ln U_{i,t} + \sum_{j=2}^{s} \beta_j Z_{i,j,t} + \varepsilon_{i,t}, \tag{15}$$

The regression model above extends regression model (14) by adding two variables: R&D intensity and ICT intensity, which are defined as the ratios of R&D stock to capital and ICT stock to capital, respectively. Basically, here we would like to see if firms with high R&D and ICT investments are doing better in productivity than firms with lower R&D and ICT investments.

The estimation results with or without controlling for capacity utilization (CU1) is reported in Table 8. The estimation shows that controlling for capacity utilization substantially improves the significance of ICT on firm performance. Under the OLS estimation, ICT being insignificant in the absence of capacity utilization becomes highly significant with the presence of the capacity utilization. Under the estimation with fixed effects, the estimated coefficient on ICT doubles after introducing the capacity utilization variable. The effect of R&D on firm performance is highly significant. However, the size of the effect is not influenced by the presence of capacity utilization. This may be because ICT investments are more related to installed capacity than R&D investments.

Conclusions

Firms invest production capacity to meet expected long-term demand. This is often a long process as design, equipment purchase, and installation take time. In other words, capacity cannot be changed in a short time. However, in reality, production in a particular year often deviates from expected, and thus the use of production capacity may not be at the capacity level. When actual demand is more than expected, firms may choose to use overtime

Table 8: The Estimation of the Production Function With and Without CU

	Robust standard error		Firm Fixed effects	
	Without CU	With CU1	Without CU	With CU1
Labour (in log)	0.248***	0.246***	0.266***	0.251***
	(0.000)	(0.000)	(0.000)	(0.000)
Tangible Capital (in log)	0.047***	0.054***	0.039***	0.112***
	(0.000)	(0.000)	(0.000)	(0.000)
Intermediate inputs (in log)	0.705***	0.700***	0.604***	0.562***
	(0.000)	(0.000)	(0.000)	(0.000)
Foreign ownership dummy	0.103***	0.101***	0.217***	0.213***
	(0.000)	(0.000)	(0.000)	(0.000)
Young firm dummy	-0.033***	-0.033***	-0.034***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
Capacity utilization		0.034***		0.090***
		(0.000)		(0.000)
R&D Intensity (in log)	0.009***	0.009***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
ICT intensity (in log)	-5.8e-5	1.9e-4***	0.002***	0.004***
	(0.316)	(0.001)	(0.000)	(0.000)
Industry-year dummies	Yes	Yes		
Year dummies			Yes	Yes
Firm-fixed effects			Yes	Yes
Number of observations	2978996	2978996	2978996	2978996
R-square	0.95	0.95		
R-square, within			0.85	0.86
R-square, between			0.94	0.94

Note: P-values are in parenthesis. "***" denotes significance at the 1% level.

and the use of capacity will be above the normal. Similarly, when demand is lower than expected or when necessary parts are in shortage due to disruptions of global value chains, say, caused by such as the current COVID-19 pandemic, production will be reduced, leading to under utilization of production capacity.

The issue is that productivity is often estimated under the assumption of full production capacity, that is, installed capacity is always used for whatever level of production. Given inputs are not actual used fractions, this leads to under- or overestimation of productivity. To produce a reliable productivity measures, we need to control for capacity utilization in estimating productivity. Unfortunately, capacity utilization is not available at the firm level. To bridge the data gap, this study developed a methodology in estimation capacity utilization at the firm level. The methodology is based on the theory of the firm in terms of profit-maximizing and price-taking. Unlike some proxies used in the literature, it is exogenous to productivity shocks. Importantly, it is fairly practical to estimate.

We tested two hypotheses, and showed that the hypothesis that labour and intermediate inputs are fully adjustable in the short term and capital cannot be adjusted in the short term is more appropriate. Controlling for capacity utilization based on the hypothesis increased the relationship between capital and output. It also reduced variation in measured productivity across firms, lessened the divergence in productivity between frontiers and laggards. Finally, we found that ICT investments that are insignificant in firm performance before controlling for capacity utilization became highly significant after controlling for capacity utilization.

With micro data being increasingly available, research using micro data to measure productivity or to evaluate policy programs has become increasingly common. The approach to analysis often relies on the estimation of a production function. This study showed that to produce a more reliable estimate, it is important to controlling for capacity utilization in estimation. It leads to more reliable productivity estimates or correct conclusion about the effect of some investments on firm performance, which has important implications for policy developments.

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