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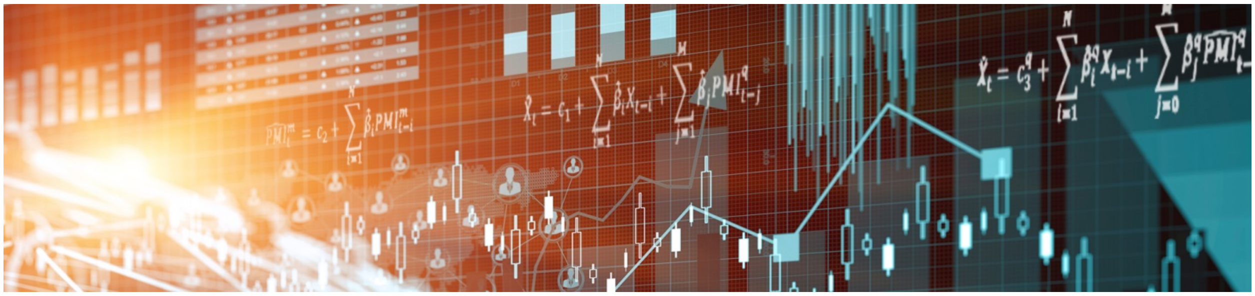

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Firm Dynamics and Multifactor Productivity: An Empirical Exploration

by

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Abstract

There are indications that business dynamism has declined in advanced economies. In particular, firm entry and exit rates have fallen, suggesting that the creative destruction process has lost some of its vitality. Meanwhile, productivity growth has slowed. Some believe that lower entry and exit rates partly explain the weaker productivity growth. However, the evidence supporting, or invalidating, this view is scarce. In the present paper, we use multi-horizon causality tests and dynamic simulations with Canadian and US data to examine the following question: Do changes to entry and exit rates provide information about, or Granger-cause, future productivity? We do not find significant evidence that entry rates Granger-cause productivity. But we do find evidence that productivity causes entry rates. Using small models with economy-wide data (but not at the sectoral level), we find some evidence that exit rates cause productivity in both countries. This suggests that the decline in productivity growth is partly caused by a decline in the productivity-based exit selection process. However, when other variables, such as measures of the business cycle and the real effective exchange rate, are controlled for, the significance of exit rates in explaining productivity tends to fall. Specifically, business-cycle measures appear to cause both productivity and the exit rate. This suggests that firm dynamics are an intermediate, not an ultimate, cause of productivity growth.

Bank topics: Firm dynamics; Productivity
JEL codes: M13, D24, O47

Résumé

Certaines indications donnent à penser que le dynamisme des entreprises a diminué dans les économies avancées. En particulier, les taux d’entrée et de sortie d’entreprises ont chuté, ce qui semble indiquer que le processus de destruction créatrice a perdu de sa vigueur. Parallèlement, la croissance de la productivité a ralenti. Certains croient que la baisse des taux d’entrée et de sortie explique en partie la décélération de la croissance de la productivité. Cependant, il y a peu d’éléments pour confirmer ou infirmer cette hypothèse. Dans la présente étude, nous employons des tests de causalité à divers horizons ainsi que des simulations dynamiques sur des données canadiennes et américaines afin de répondre à la question suivante : les variations des taux d’entrée et de sortie sont-elles des indicateurs, ou des causes au sens de Granger, de la productivité future? Les résultats obtenus ne nous permettent pas de conclure que les taux d’entrée causent au sens de Granger l’évolution de la productivité. En revanche, nous constatons que la productivité a une incidence sur les taux d’entrée. Les petits modèles dont nous nous servons, qui s’appuient sur des données (non sectorielles) pour l’ensemble de l’économie, nous amènent à relever que les taux de sortie influent sur la productivité dans les deux pays. La baisse de la croissance de la productivité serait donc causée en partie par une réduction du nombre de sorties d’entreprises affichant une faible productivité. Toutefois, lorsque d’autres variables sont prises en compte, par exemple les mesures du cycle économique et le taux de change effectif réel, l’incidence des taux de sortie sur la productivité a tendance à diminuer. En fait, les mesures du cycle économique semblent jouer un rôle déterminant tant pour la productivité que pour le taux de sortie : la dynamique des entreprises serait donc une cause intermédiaire, et non une cause première, de la croissance de la productivité.

Sujets : Dynamique des entreprises; Productivité
Codes JEL : M13, D24, O47

Non-technical summary

In this paper, the authors use multi-horizon causality tests to study the links between firm entry and exit rates and productivity. They find no evidence that entry rates cause productivity at short or longer horizons in Canada or the United States. This result could be consistent with the literature (e.g., Decker et al., 2017), pointing to technological developments that make entry more difficult but existing firms more productive. However, the authors find evidence that productivity causes entry rates, a result consistent with the model proposed by Gort and Klepper (1982). The evolution of entry rates may therefore partly reflect the evolution of productivity shocks in recent decades. In other words, positive technology developments stimulated entrepreneurship in the 1990s (high-tech boom), but slower technology progress contributed to weaker entry rates in the 2000s and thereafter. More research is needed on the causes of the decline in entry rates (see Decker et al., 2017, and Cao et al., 2015, for discussion of various explanations for the decline in entry rates in the United States and Canada, respectively).

The story concerning exit rates is different. In models that include productivity, entry rates and exit rates, the authors find statistically significant evidence that exit rates cause productivity. Dynamic simulations indicate that this relationship is positive, i.e., when exit rates rise, productivity tends to rise. This could be consistent with a productivity-based exit selection process, which is when the exit of weaker firms is positive for productivity because it facilitates the reallocation of resources toward more productive entrants or incumbents. Lower exit rates may therefore have contributed to weaker productivity growth in both Canada and the United States. When other variables, such as the output gap, corporate profits and the real effective exchange rate, are controlled for, however, the significance of exit rates in Granger-causing productivity tend disappear. This suggests that firm dynamics are an intermediate, not an ultimate, cause of productivity growth.

1 Introduction

There is growing evidence that business dynamism has declined in advanced economies. For instance, entry rates (number of entries as a fraction of the total number of firms) have tended to fall (Decker et al., 2014; Macdonald, 2014; Cao et al., 2015; Criscuolo and Menon, 2016). Exit rates (number of exiting firms as a fraction of the total number of firms) have also been falling in Canada (Macdonald, 2014; Cao et al., 2015) and, to a lesser extent, in the United States (Decker et al., 2016).[1] These trends, illustrated in Charts A1 and A2 of Appendix A, are observed in most economic sectors in Canada (Macdonald, 2014; Cao et al., 2015) and in many sectors in the United States (Decker et al., 2014). These trends could mean that the creative destruction process,[2] often seen as key to productivity growth in a capitalist economy, has lost some of its vitality.[3]

Some analysts worry that these trends are negative for future economic growth. For example, in discussing economic prospects for the United States, Martin Wolf (2016) recently stated the following in the *Financial Times*:

"No less disturbing is a decline in economic dynamism. The rate of creation of new jobs has slowed markedly as have rates of internal migration. The rate of entry of new businesses into the marketplace has also been falling over an extended period, as has the share of ones less than five years old in both the total number of businesses and employment. Meanwhile, business fixed investment has been persistently weak."

Productivity growth has indeed also fallen in many countries (OECD, 2015). For instance, as is made clear in Charts B1 and B2 (Appendix B), after having accelerated in the 1990s, multifactor productivity (MFP) growth and labour productivity growth have both been relatively weak since the early 2000s in Canada and the United States.

In this paper, we assess the available time series evidence about the causality links between business dynamism and productivity. In particular, we test whether business dynamism, as measured by firm entry and exit rates, Granger-causes productivity growth at various horizons. Our specific objective is to answer the

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[1] The evidence concerning exit rates in other Organisation for Economic Co-operation and Development (OECD) countries is mixed (Criscuolo and Menon, 2016).

[2] Schumpeter (1942) is the classic reference on this concept.

[3] There are other indications that business dynamism is falling. For example, Davis and Haltiwanger (2014) show that the job reallocation process has slowed in several advanced economies. On their part, Decker et al. (2017) provide evidence that firms in the United States have become less responsive to shocks.

following question: Do changes to entry and exit rates provide information about, or Granger-cause, future productivity? The answer to this question should be useful to policy-makers interested in the implications for future productivity growth of trends in entry and exit rates. For instance, it should be of interest to central bankers trying to determine the implications of trends in entries and exits for future potential output growth; i.e. the level of real GDP that the economy can reach without generating inflationary pressures (potential output largely depends on trend productivity).

We are interested in multi-horizon causality because indicators of business dynamism may affect productivity differently at different time horizons. For instance, lower entry rates may not have significant effects on productivity in the short run because new firms tend to be small firms with little impact on aggregate productivity. However, lower entry rates could negatively affect productivity in the longer run if the smaller vintage of firms implies that fewer firms eventually become productivity champions. If this were the case, tests focusing on one-period causality could falsely conclude that entry rates do not cause productivity.

To test for multi-horizon causality, we use the approach developed by Dufour and Renault (1998) and Dufour, Pelletier and Renault (2006). These authors propose a generalization of the Granger (1969) approach, which tests for one-period causality. The concept of causality developed by Granger refers to whether X(t) can help predict Y(t) when the past values of Y(t) and, possibly, a vector Z(t) of auxiliary variables, are controlled for. Some authors (e.g. Lütkepohl, 1993) have noted that, in multivariate models where a vector of auxiliary variables Z(t) is used in addition to the variables of interest X(t) and Y(t), it is possible that Y does not cause X one period ahead but can still help predict X two or more periods ahead. For example, the values Y(t) up to time t may help predict X(t + 2), even though they are useless for predicting X(t + 1), because Y may help predict Z one period ahead, which in turn influences X in the following period. Such a generalization allows for distinguishing between short-run and longer-run causality and capturing causality links that may not be apparent in one-period causality tests.

A limitation of causality tests is that they do not provide indications about the sign of the relationships between variables. For instance, they do not indicate whether higher exit rates typically lead to stronger or weaker productivity growth. One could fail to reject the hypothesis that a change in the entry rate causes productivity, but this would not say whether the impact is positive or negative. To determine the sign of the relationship between the variables at various horizons, we simulate the effects on productivity of shocks to variables of interest.

In the rest of the paper, we proceed as follows. In Section 2 we briefly discuss the literature linking entry and exit rates with productivity. We discuss data sources in Section 3. We provide more details about our methodology in Section 4. We present our results in Section 5 and conclude in Section 6.

2 Linking productivity with entry and exit rates

Should we expect that firm entries and exits be linked with productivity? Some papers have addressed the issue. In particular, a number of studies have used firm-level data to analyze the contribution of firm dynamics to productivity growth. These analyses have typically been based on formulas decomposing productivity growth into contributions from entries and exits, changes in market shares and within firm effects. Results vary greatly depending on the time period and the sectors considered. For instance, Foster, Haltiwanger and Krizan (2006) decompose productivity into contributions from entries and exits, and find that most of the productivity growth experienced by the US retail trade sector in the 1990s could be accounted for by more-productive entering firms replacing less-productive exiting firms. Baldwin and Gu (2006) also use such decompositions to look into the Canadian manufacturing sector and find a substantial, but declining, contribution of firm entries and exits to productivity growth in that sector (from 25 percent for 1973-79 to 15-20 percent for 1988-97).

Such decompositions are helpful in understanding whether changes in productivity growth reflect resource reallocations or within-firm productivity changes, but they have limitations. In particular, they could not say whether changes to entry and exit rates signal productivity changes. This is the question we pose. Indeed, lower entry rates do not necessarily signal lower productivity growth since they could be caused by technological developments that are good for the incumbent's productivity and, therefore, for the economy's overall productivity, even if they make it difficult for new firms to enter. For instance, this may have been the case in the retail sector in recent years, with firms such as Walmart and Amazon exploiting scale and network economies that made them more productive, but also made it difficult for new firms to enter the market (i.e. lowering the entry rate). The positive effects on aggregate productivity from Walmart and Amazon's improved productivity could more than compensate for the negative effects resulting from lower entry rates.[4]

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[4] For discussion on the idea that lower entry rates may be consistent with rising productivity growth in retail trade sector, see, for example, Decker et al. (2017).

Also, some researchers argue that the decline in entry rates is compensated by an improvement in the quality of new entrants. For instance, Fazio et al. (2016) correct firm entry numbers with simple quality indicators and conclude that quality-adjusted dynamism has not declined in various regions of the United States. If this is right, the positive effects on productivity of better quality entrants could compensate for the negative implications of lower entry rates, and the latter may not signal lower productivity.

The implications of lower exit rates are also ambiguous. They could be bad for productivity if it is less efficient firms that survive for longer, possibly impeding the growth of firms with better potential.[5] But lower exit rates could also be good for productivity if it is firms with a potential to eventually become productivity champions that survive.

There is a time dimension to the contribution of firm entries to productivity. New firms tend to be small (Bartelsman, Haltiwanger and Scarpetta, 2004), and in the very short run, their contribution to aggregate output is also small. However, some of them survive and can eventually become substantial contributors. If, for some reason, fewer firms were created in a certain period, or if there were an increase in the exit rate, the economy could lose some of these substantial contributors and remain depressed for an extended period. This is the missing generation argument. Of course, this argument depends on the productivity of entering and exiting firms. A shock that reduces the entry of persistently unproductive firms, or that causes the exit of unproductive firms, would not have negative effects on productivity. The impact of such a shock on productivity could even be positive, especially if resources were redeployed towards more productive uses.

Gourio, Messer and Siemer (2016) discuss a simple model consistent with the missing generation argument. They present estimated impulse responses consistent with the hypothesis that weaker entry rates led to weaker real GDP and productivity growth in the United States. A limitation of their study is that in models with more than two variables, such as the one they use, statistically significant impulse responses do not necessarily imply Granger causality (Dufour and Tessier, 1993). Therefore, the impulse responses estimated by Gourio, Messer and Siemer do not necessarily imply causality. The present paper, by focusing explicitly on the Granger causality concept, is therefore not concerned with this problem.

Of course, factors other than changes to firm dynamics can cause changes to productivity growth. For instance, it has been argued that changes in investment

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[5] This is known as the zombie congestion effect. For discussion and for OECD evidence, see Adalet McGowan, Andrews and Millot (2017).

in information and communication technologies (ICT) have been an important factor behind the dynamics of productivity growth in advanced economies since the 1990s (Cette, Clerc and Bresson, 2015; Fernald, 2014; Sharpe, 2006). We therefore control for this variable in some of our models. We also control for related variables, such as R&D investment and investment in intellectual property products.

Also, official productivity statistics tend to be procyclical, as outputs tend to increase more than inputs, i.e. capacity use increases when the economy is strong (Bassu and Fernald, 2001; Rao, Tang and Wang, 2008).[6] Both labour productivity and MFP measures are affected by the phenomenon. Methods have been proposed to address the issue (Gu and Wang, 2013), but they are not yet used with official productivity data. We control for the effects of the business cycle on MFP by including measures of the business cycle in some of our models.

Some researchers argue that there is a link between the growth of labour input and that of productivity. For instance, De Michelis, Estevão and Wilson (2013) find that faster labour input growth negatively affects productivity. To control for this potential link, we have also included working-age population as a robustness check in some models.

We also control for corporate profits to reflect the possibility that stronger profits may lead to stronger investment with potentially positive effects on MFP.

Finally, some researchers have argued that exchange rate movements could affect productivity (Lafrance and Schembri, 2000; Tomlin, 2014). It has been argued, for instance, that low values of the Canadian dollar could affect Canadian productivity negatively by sheltering Canadian firms from international competitive pressures, allowing less-productive firms to survive. We therefore control for the effects of real effective exchange movements.

3 The data

Data on productivity and on firm dynamics are central to our exercise. To measure productivity we focus on the MFP data produced by Statistics Canada and by the US Bureau of Labor Statistics. We focus on MFP, instead of labour productivity, because statistical agencies control for factors, such as capital and the quality of

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[6] However, some papers (e.g. Wang, 2014) conclude that productivity has become less procyclical in the United States in recent years.

labour, that are thought to affect productivity when they calculate MFP.[7]

"Multifactor productivity measures at Statistics Canada are derived from a growth accounting framework that allows analysts to isolate the effects of increases in input intensity and skills upgrading on the growth in labour productivity." (Statistics Canada, 2016).

This means that in testing for causality between business dynamism indicators and productivity, we do not need to control for the changes in input intensity and skills that statistical agencies control for. However, business dynamism is not controlled for by statistical agencies in estimating MFP (except to the extent it contributes to the physical capital stock). For instance, the positive effects on productivity of replacing lower-productivity exiting firms with higher-productivity entrants (for a given capital stock) are not controlled for. The advantage of looking at MFP is that capital and quality of labour are controlled for, so we do not need to spend degrees of freedom controlling for these variables (we have short samples).[8]

To measure business dynamism in Canada, we use the entry and exit rates produced by Statistics Canada (Macdonald, 2014, discusses these data). The Canadian data are for enterprises. These data cover the period from 1984 to 2015. Our source for the United States is the US Census Bureau's Business Dynamics Statistics. The US data are for establishments.[9] These data start in 1981 and end in 2014. The data are annual for both countries.

Charts A1, A2, B1 and B2, in Appendices A and B, present the aggregate entry and exit rates and MFP data for both Canada and the United States.

We use data from Statistics Canada and the US Bureau of Labor Statistics to control for real investment in R&D and intellectual property products. Our ICT data are from Statistics Canada and the US Bureau of Economic Analysis. Our working-age population data are from Statistics Canada and from the US Census

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[7] Each statistical agency has a different approach to measuring productivity. However, these methodologies tend to converge, as they follow OECD guidelines. Also, these differences should mostly affect level comparisons and therefore should not have much impact on our results because we use growth rates and do not seek to compare the level of the two countries.

[8] We estimated models including labour productivity. The results are summarized at the end of Section 5.

[9] Although using establishment instead of enterprise data may have some effects on the results, we would expect the difference to be small because the dynamics of establishment and enterprise data should be similar. A business environment conducive to more entries and exits of enterprises should also, in general, be conducive to more entries and exits of establishments. For instance, following a positive shock to the demand for some product both the number of enterprises and the number of establishments should increase.

Bureau. Our Canadian operating profits data are also from Statistics Canada.[10] Our US pre-tax corporate profits data are from the database of the Federal Reserve Bank of St-Louis. We control for US and Canada exchange rates with the real effective exchange rate data collected by the Bank for International Settlements. We control for the effects of the business cycle on productivity by including output gaps in some of our models. These gaps are calculated by the Bank of Canada for Canada and by the Congressional Budget Office for the United States.

4 Methodology

In this section, we describe the statistical procedure proposed to test causality relationships at different horizons. To that end, we closely follow Dufour, Pelletier, and Renault (2006). Let us first describe the notion of "autoregression at horizon h" and the relevant notations. Consider a vector-autoregressive process (VAR(p)) of the form:

$$W(t) = \mu(t) + \sum_{k=1}^{p} \pi_k W(t-k) + a(t) \ , \quad t = 1, \ldots, T, \tag{1}$$

where $W(t) = \left(w_{1t}, w_{2t}, \ldots, w_{mt}\right)'$ is a random vector, $\mu(t)$ is a deterministic trend, and $a(t)$ is a white-noise process of order two with a non-singular variance-covariance matrix Ω. The most common specification for $\mu(t)$ consists in assuming that $\mu(t)$ is a constant vector, although other deterministic trends—such as seasonal dummies—could also be considered.

The $\mathrm{VAR}(p)$ is an autoregression at horizon 1. This autoregressive form can be generalized to allow for projection at any horizon h given the information available at time t. Hence, the observation at time $t+h$ can be computed recursively from equation (1) and is given by:

$$W(t+h) = \mu^{(h)}(t) + \sum_{k=1}^{p} \pi_k^{(h)} W(t+1-k) + \sum_{j=0}^{h-1} \psi_j a(t+h-j) \ , \tag{2}$$

where $\psi_0 = I_m$ and $h < T$. The appropriate formulas for the coefficients $\pi_k^{(h)}$ and $\mu^{(h)}(t)$ are given in Dufour and Renault (1998), and the ψ_j matrices are the

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[10] We use CANSIM Table 187-0002. However, these data start in 1988. To obtain the 1984-87 data, we backcast 187-0002 with 187-0003.

impulse-response coefficients of the process. The latter equation is called an "autoregression of order p at horizon h" or a "$(p,\, h)$-autoregression."

Let us consider equation (2) written under a more useful matrix form:[11]

$$W\left(t+h\right) = \overline{W}_p\left(h\right)\Pi^{(h)} + U\left(t+h\right)\,. \tag{3}$$

We can estimate this equation by ordinary least squares, which yields the estimator:

$$\hat{\Pi}^{(h)} = \left[\overline{W}_p\left(h\right)'\,\overline{W}_p\left(h\right)\right]^{-1}\overline{W}_p\left(h\right)'\,W\left(t+h\right)\,, \tag{4}$$

hence

$$\sqrt{T}\,[\hat{\Pi}^{(h)} - \Pi^{(h)}\,] = \left[\frac{1}{T}\overline{W}_p\left(h\right)'\,\overline{W}_p\left(h\right)\right]^{-1}\frac{1}{\sqrt{T}}\overline{W}_p\left(h\right)'\,U\left(t+h\right)\,. \tag{5}$$

Under usual regularity conditions, we can show that $\sqrt{T}\,vec\left[\hat{\Pi}^{(h)} - \Pi^{(h)}\right]$ converges to a normal distribution with a non-singular covariance matrix.

In this paper, we consider the hypothesis that a variable w_{jt} does not cause another one, w_{it}, at horizon h, and the restrictions related to that hypothesis take the form:

$$H_0^{(h)} : \pi_{ijk}^{(h)} = 0\,,\; k = 1,\,\ldots\,,\,p\,, \tag{6}$$

where $\pi_k^{(h)} = \left[\pi_{ijk}^{(h)}\right]_{i,\,j=1,\,\ldots\,,\,m}$ comes from the "$(p,\, h)$-autoregression" defined in equation (2). In other words, the null hypothesis takes the form of a set of zero restrictions on the coefficients of the matrix $\hat{\Pi}^{(h)}$. Under the hypothesis $H_0^{(h)}$ of non-causality at horizon h from w_{jt} to w_{it}, the asymptotic distribution of the Wald statistic $\mathcal{W}[H_0^{(h)}]$ is $\chi^2\left(p\right)$. In order to get an appropriate distribution, we have to take into account that the prediction error $\hat{u}\left(t+h\right)$ follows an MA$(h-1)$ process. To that end, we use the Newey-West procedure, which gives an automatically positive-semidefinite variance-covariance matrix.

The Gaussian asymptotic distribution provided may not be very reliable in finite samples, especially if we consider a VAR system with a large number of variables and/or lags.[12] Due to autocorrelation, a larger horizon may also affect the size and the power of the test. An alternative to using the asymptotic chi-square distribution of $\mathcal{W}[H_0^{(h)}]$ consists in using Monte Carlo test techniques or

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[11] For a more detailed description of these expressions, see Dufour, Pelletier, and Renault (2006).

[12] Dufour, Pelletier, and Renault (2006) give some illustrations on the poor quality of the asymptotic approximation.

bootstrap methods. In view of the fact that the asymptotic distribution of $\mathcal{W}[H_0^{(h)}]$ is nuisance-parameter free, such methods yield asymptotically valid tests when applied to $\mathcal{W}[H_0^{(h)}]$ and typically provide a much better control of the test level in finite samples.

In the empirical study presented below, p-values are computed using a parametric bootstrap (i.e. an asymptotic Monte Carlo test based on a consistent point estimate). The number of replications is $N = 999$. The procedure can be described as follows:

1. an unrestricted VAR(p) model is fitted for the horizon one, yielding the estimates $\hat{\Pi}^{(1)}$ and $\hat{\Omega}$ for $\Pi^{(1)}$ and Ω ;
2. an unrestricted (p, h)-autoregression is fitted by ordinary least squares, yielding the estimate $\hat{\Pi}^{(h)}$ of $\Pi^{(h)}$;
3. the test statistic $\mathcal{W}$ for testing non-causality at the horizon h is computed;
4. N simulated samples are drawn by Monte Carlo methods, using $\Pi^{(h)} = \hat{\Pi}^{(h)}$ and $\Omega = \hat{\Omega}$ (and the hypothesis that $a(t)$ is Gaussian); we then imposed the constraints of non-causality to the matrix $\hat{\Pi}^{(h)}$;
5. the simulated p-value is obtained by calculating the rejection frequency.

5 Results

Before testing for causality relationships, it is necessary to determine whether our series are integrated. We therefore performed Augmented Dickey-Fuller (ADF) tests on the series in levels and in first difference. The number of lags included in the tests was determined by the Schwarz information criterion. We found that all our series were first-difference stationary. The only exception is the output gap, which is stationary in levels in both countries.

Given that our sample is small (about 30 years of annual data), we focus on parsimonious models. Our basic specification, for both Canada and the United States, includes three variables: the entry rate (*IN*), the exit rate (*EX*), and multifactor productivity (*MFP*). Causality test results for this specification are presented in Table 1 (Canada) and Table 5 (United States) of Appendix C. The p-values were computed with the parametric bootstrap procedure described in Section 4.

The discussion will emphasize the factors causing MFP (last two rows of Tables 1 and 5). It is immediately apparent (last row) that, in both countries, there is no statistically significant (at conventional levels) relationship between entry rates and MFP. We saw in Section 2 that entry rates could affect productivity through various channels. We also saw that there could be technology developments making entries more difficult but being positive for productivity. Our empirical findings suggest that, in the aggregate, these factors tend to cancel each other so that there is no statistically significant link between entries and productivity.

However, it is interesting to note that there is evidence that MFP causes entry rates in both countries (fourth rows of Tables 1 and 5). Such a link is consistent with the models, such as the one proposed by Gort and Klepper (1982), in which innovations are followed by a strong increase in the number of firms. Entry rates therefore seem to be more a consequence than a cause of developments affecting productivity.

Things are different for exit rates. We see in Table 1 (fifth row) that the exit rate significantly causes MFP at the one-year horizon in Canada (p-value = 4.20). There is also some, but weaker, evidence (fifth row of Table 5) that exit rates cause MFP in the United States at the 3-year horizon (p-value = 6.96).

Although the concept of Granger causality is a very useful tool to analyze the dynamic relationships between time series, it has the drawback of not giving the sign of the relations between the series. One cannot formally know what will be the sign of the impact of one variable on another. In order to overcome this deficiency, we perform a dynamic simulation in which we impose a change of one unit (1 percent) in the exit rate, and then simulate the dynamic impact over time on MFP. Chart 1 shows the effects of increasing the exit rate by 1 percent in Canada and in the United States on MFP. We see that stronger exit rates tend to increase productivity in both countries. This is consistent with the idea that higher exit rates can increase aggregate productivity by eliminating weaker (less-productive) firms and allowing for resources to flow to more productive firms, as discussed in Section 2.

It is well-known that causality tests results can be sensitive to the set of variables that are controlled for. This is why we also examined four-variable models (we keep the model small in recognition of our small sample), including other variables that have been associated with MFP growth (see Section 2 for some discussion and Section 3 for data description): ICT investment (*ICT*), investment in intellectual property products (*IPP*), R&D investment (*R&D*), working-age population (*POP*), the output gap (*GAP*), the real effective exchange rate (*RER*) and corporate profits (*Prof*).

We found that the first four control variables do not cause productivity. However, for both countries we found that the output gap plays an important role in determining MFP (reasons for this are discussed in Section 2). The implications of adding the output gap as a fourth control variable are shown in Tables 2 and 6 of Appendix C. In both countries, adding the output gap implies that we can no longer reject the hypothesis that exits do not cause productivity (tenth row). Entries still do not cause productivity (second to last row). But in the two countries the gap causes both productivity (last row) and exits (second row). It therefore appears that while the exit rate signals productivity changes (as we found in three-variable models), it is not an ultimate cause of productivity. Both MFP and exit rates are caused by business cycle fluctuations captured by our output gap variables.

Tables 3 and 7 show results for four-variable models, including the exit rate, the output gap and one of the other variables we consider in this study. This confirms that in both Canada and the United States, but particularly in Canada, the output gap tends to be significant in causing MFP.[13] In Canada, controlling for these variables makes the causality relationship running from the exit rates to MFP disappear entirely at conventional statistical levels. In the United States it makes it insignificant or weaker in most cases. Interestingly, the real effective exchange rate (RER) also appears to be significant in both countries (eleventh row of each table). This is consistent with previous studies cited in Section 2.

Table 4 shows the results for Canada of a model including *EX*, *GAP*, *RER* and *MFP*. Again, *GAP* appears to cause productivity (last row) at conventional levels of significance at the one (*p*-value: 0.08) and two-year horizon (*p*-value: 4.27). *RER* also appears to cause productivity (second to last row) at the two-year horizon (*p*-value: 1.67). Once more, in this model *EX* does not appear to cause productivity (ninth row). But *GAP* causes exits at the one-year horizon (second row; *p*-value: 2.79). Table 8 shows similar results for the United States.

An interesting fact of Table 7 is that profits appear to cause MFP at the two-year horizon in the United States (second to last row). Table 3 shows a similar (but weaker) result for Canada. The link between profits and productivity could be an interesting topic for future research.

We estimated three-variable models for the manufacturing and retail trade sectors of the two countries but did not find significant causality relationships with

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[13] This link between output gaps and MFP should not surprise given that MFP is the residual from the growth accounting framework and, as a result, picks up cyclical variations in output that are not captured by capital and labour services. To the extent the output gap captures these cyclical variations its significance was to be expected.

these data. This could be due to the greater volatility of sectoral data.

Finally, we also estimated models with labour productivity, instead of MFP, and did not find statistically significant results linking firm entry or exit rates with productivity. For firm entry rates, this is the same result we found with MFP. For exit rates, this is different, as we found some indications that the exit rates cause MFP. The difference could be due to the fact that MFP controls for capital deepening and labour quality, making it easier to capture the link between exit rates and productivity.

6 Conclusions

In this paper, we use multi-horizon causality tests to study the links between firm entry and exit rates and productivity. We find no evidence that entry rates cause productivity at short or longer horizons in Canada or the United States. This result could be consistent with the literature (discussed in Section 2), pointing to technological developments making entries more difficult but incumbents more productive. It could also be consistent with the findings, by some authors, that the quality of new entrants has improved, which would compensate, in terms of impact on aggregate productivity, for the negative effects of lower entry rates.

However, we find evidence that productivity causes entry rates, a result consistent with the model proposed by Gort and Klepper (1982). The evolution of entry rates may therefore partly reflect the evolution of productivity shocks in recent decades, with positive technology developments stimulating entrepreneurship in the 1990s (high-tech boom), but slower technology progress contributing to weaker entry rates in the 2000s and thereafter. More research is needed on the causes of the decline in entry rates (see Decker et al., 2017 and Cao et al., 2015 for discussion of various explanations for the United States and Canada, respectively).

The story concerning exit rates is different. In models including productivity, entry rates and exit rates, we find statistically significant evidence that exit rates cause productivity. Dynamic simulations indicate that this relationship is positive, i.e. when exit rates rise, productivity tends to rise. This could be consistent with a productivity-based exit selection process and with the idea that the exit of weaker firms is positive for productivity because it facilitates reallocation of resources towards more productive entrants or incumbents (Section 2). Weaker exit rates may therefore have contributed to weaker productivity growth in both Canada and the United States.

However, when other variables, such as the output gap, corporate profits and the real effective exchange rate, are controlled for, the significance of exit rates in Granger-causing productivity tends disappear. This suggests that firm dynamics are an intermediate, not an ultimate, cause of productivity growth.

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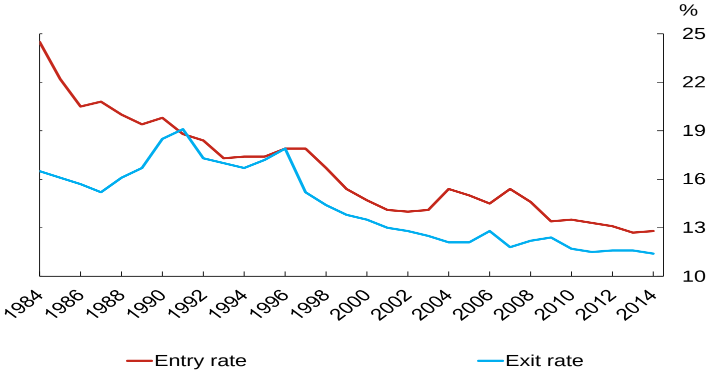
Appendix A

Chart A1: Entry and exit rates are trending down in Canada

Annual data

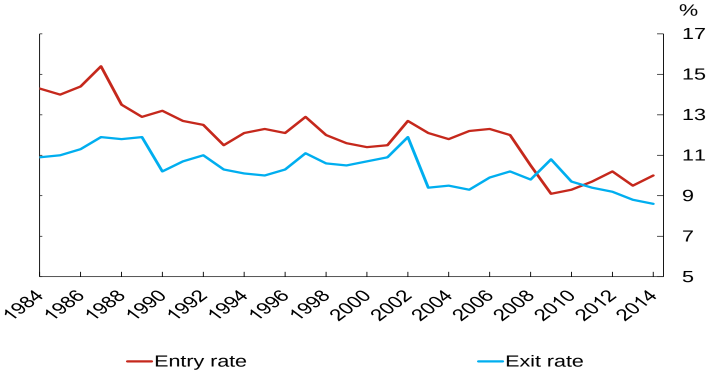


Source: Statistics Canada

Last observation: 2014

Chart A2: Entry and exit rates are trending down in the United States

Annual data



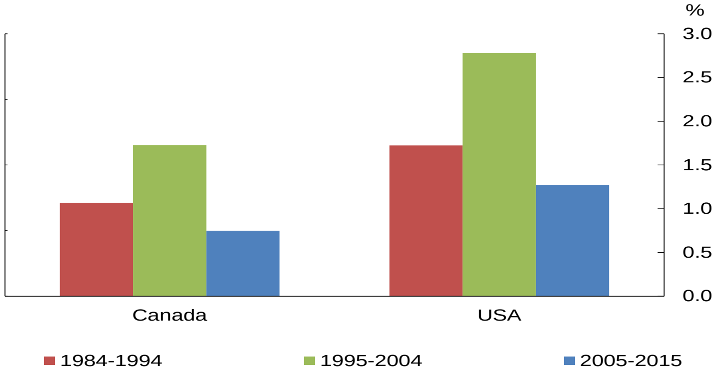
Source: Business Dynamics Statistics

Last observation: 2014

Appendix B

Chart B1: Labour productivity growth has slowed

Annual data

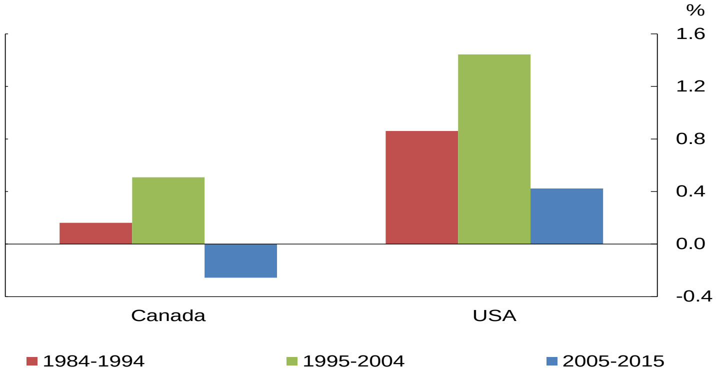


Source: Statistics Canada

Last observation: 2015

Chart B2: Multifactor productivity growth has also slowed

Annual data



Source: Statistics Canada

Last observation: 2015

Appendix C

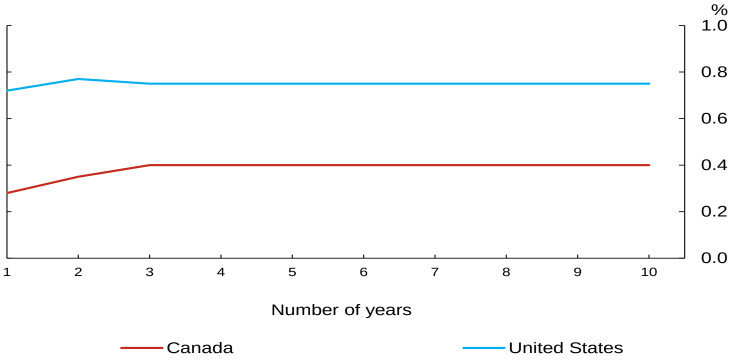
Table 1: Causality tests at horizons 1 to 4; Canada, 3-variable model [ΔIN,ΔEX,ΔMFP]; 1984-2015; 1 lag.

h			1	2	3	4
IN	$\nrightarrow$	EX	43.19	59.30	10.13	70.72
MFP	$\nrightarrow$	EX	20.59	91.65	56.14	17.42
EX	$\nrightarrow$	IN	25.24	8.16	18.44	40.06
MFP	$\nrightarrow$	IN	93.13	3.84	88.10	73.01
EX	$\nrightarrow$	MFP	4.20	16.81	33.95	13.27
IN	$\nrightarrow$	MFP	17.74	15.75	54.99	70.92

Table 2: Causality tests at horizons 1 to 4; Canada, 4-variable model [ΔEX,ΔIN,GAP,ΔMFP]; 1984-2015; 1 lag.

	h		1	2	3	4
IN	$\nrightarrow$	EX	47.21	52.64	11.13	72.03
GAP	$\nrightarrow$	EX	4.12	23.96	86.20	96.14
MFP	$\nrightarrow$	EX	49.33	83.53	60.46	20.63
EX	$\nrightarrow$	IN	4.65	7.67	20.95	44.44
GAP	$\nrightarrow$	IN	14.18	52.25	85.50	93.21
MFP	$\nrightarrow$	IN	89.39	2.89	85.56	73.39
EX	$\nrightarrow$	GAP	17.68	31.64	10.44	86.38
IN	$\nrightarrow$	GAP	35.23	15.41	48.99	72.34
MFP	$\nrightarrow$	GAP	79.60	83.39	49.59	66.33
EX	$\nrightarrow$	MFP	45.93	59.75	63.41	13.19
IN	$\nrightarrow$	MFP	14.38	13.27	53.59	68.15
GAP	$\nrightarrow$	MFP	0.07	4.14	50.39	46.00

Chart C1: **Impact on multifactor productivity of a one per cent increase in the exit rate**



Source: Bank of Canada calculations

Table 3: Causality tests at horizons 1 to 4; Canada, 4-variable model [ΔEX,ΔXX,GAP, ΔMFP]; 1984-2015; 1 lag.

	h		1	2	3	4
EX	$\nrightarrow$	MFP	72.82	79.35	57.71	30.26
ICT	$\nrightarrow$	MFP	16.54	87.20	76.15	53.76
GAP	$\nrightarrow$	MFP	0.07	11.01	82.11	94.20
EX	$\nrightarrow$	MFP	59.66	66.75	64.48	17.58
IPP	$\nrightarrow$	MFP	5.77	56.34	78.66	52.83
GAP	$\nrightarrow$	MFP	0.09	3.21	63.12	46.15
EX	$\nrightarrow$	MFP	65.15	42.75	55.13	13.94
$R\&D$	$\nrightarrow$	MFP	51.65	9.54	69.36	83.69
GAP	$\nrightarrow$	MFP	0.11	1.26	60.25	63.99
EX	$\nrightarrow$	MFP	65.69	72.41	65.17	16.86
RER	$\nrightarrow$	MFP	45.49	1.88	58.88	72.34
GAP	$\nrightarrow$	MFP	0.12	4.51	65.37	60.04
EX	$\nrightarrow$	MFP	75.24	74.06	48.96	20.16
POP	$\nrightarrow$	MFP	74.42	86.48	67.65	61.39
GAP	$\nrightarrow$	MFP	0.09	3.49	57.26	49.34
EX	$\nrightarrow$	MFP	82.40	85.65	64.96	17.80
$Prof$	$\nrightarrow$	MFP	17.93	7.64	89.73	64.06
GAP	$\nrightarrow$	MFP	0.17	5.88	60.57	58.10

Table 4: Causality tests at horizons 1 to 4; Canada, 4-variable model [ΔEX,ΔRER,GAP, ΔMFP]; 1984-2015; 1 lag.

h			1	2	3	4
RER	$\nrightarrow$	EX	94.70	45.62	63.89	76.20
GAP	$\nrightarrow$	EX	2.79	31.30	69.52	99.83
MFP	$\nrightarrow$	EX	52.47	94.81	66.09	22.18
EX	$\nrightarrow$	RER	29.08	48.52	16.15	55.49
GAP	$\nrightarrow$	RER	80.75	60.15	47.20	93.97
MFP	$\nrightarrow$	RER	95.22	57.30	87.71	89.96
EX	$\nrightarrow$	GAP	23.70	50.69	16.01	69.11
RER	$\nrightarrow$	GAP	22.93	83.46	62.64	42.83
MFP	$\nrightarrow$	GAP	69.87	89.15	51.08	62.97
EX	$\nrightarrow$	MFP	66.84	72.10	65.39	17.80
RER	$\nrightarrow$	MFP	46.46	1.67	59.75	72.45
GAP	$\nrightarrow$	MFP	0.08	4.27	65.00	59.09

Table 5: Causality tests at horizons 1 to 4; United-States, 3-variable model [ΔEX,ΔIN,ΔMFP]; 1981-2014; 1 lag.

h			1	2	3	4
IN	$\nrightarrow$	EX	67.27	25.30	43.54	65.23
MFP	$\nrightarrow$	EX	47.08	7.22	48.42	95.94
EX	$\nrightarrow$	IN	36.59	2.35	65.04	38.05
MFP	$\nrightarrow$	IN	3.85	96.27	93.98	24.74
EX	$\nrightarrow$	MFP	99.63	14.32	6.96	68.47
IN	$\nrightarrow$	MFP	63.61	40.51	93.82	73.19

Table 6: Causality tests at horizons 1 to 4; United-States, 4-variable mode l[ΔEX,ΔIN,GAP, ΔMFP]; 1981-2014; 1 lag.

	h		1	2	3	4
IN	$\nrightarrow$	EX	52.51	35.81	47.91	72.72
GAP	$\nrightarrow$	EX	5.25	15.95	80.39	30.59
MFP	$\nrightarrow$	EX	20.46	13.41	43.95	77.68
EX	$\nrightarrow$	IN	28.21	2.08	34.08	49.26
GAP	$\nrightarrow$	IN	34.31	34.36	16.53	66.51
MFP	$\nrightarrow$	IN	4.20	82.77	70.51	25.96
EX	$\nrightarrow$	GAP	54.59	65.46	99.14	43.34
IN	$\nrightarrow$	GAP	86.23	22.82	6.57	29.07
MFP	$\nrightarrow$	GAP	21.34	17.34	30.11	32.96
EX	$\nrightarrow$	MFP	67.59	14.17	13.58	37.04
IN	$\nrightarrow$	MFP	62.30	42.88	99.82	56.95
GAP	$\nrightarrow$	MFP	7.01	76.71	35.26	7.15

Table 7: Causality tests at horizons 1 to 4; United-States, 4-variable model [ΔEX,ΔXX,GAP, ΔMFP]; 1981-2014; 1 lag.

	h		1	2	3	4
EX	$\nrightarrow$	MFP	95.45	2.75	11.48	60.23
ICT	$\nrightarrow$	MFP	23.26	21.45	77.75	6.80
GAP	$\nrightarrow$	MFP	34.71	18.49	63.25	90.07
EX	$\nrightarrow$	MFP	57.68	9.20	9.11	37.58
IPP	$\nrightarrow$	MFP	35.52	79.17	67.91	91.40
GAP	$\nrightarrow$	MFP	3.52	67.73	66.18	12.90
EX	$\nrightarrow$	MFP	65.85	10.45	12.07	38.97
$R\&D$	$\nrightarrow$	MFP	93.31	54.83	95.74	81.93
GAP	$\nrightarrow$	MFP	9.44	50.50	42.75	11.00
EX	$\nrightarrow$	MFP	67.75	9.84	11.51	22.67
RER	$\nrightarrow$	MFP	7.25	18.87	4.92	20.23
GAP	$\nrightarrow$	MFP	5.76	64.18	26.24	3.32
EX	$\nrightarrow$	MFP	87.52	9.84	20.57	7.78
POP	$\nrightarrow$	MFP	11.06	55.81	77.09	11.44
GAP	$\nrightarrow$	MFP	2.96	89.44	49.20	12.45
EX	$\nrightarrow$	MFP	66.40	13.49	9.73	36.24
$Prof$	$\nrightarrow$	MFP	76.31	3.93	24.40	54.95
GAP	$\nrightarrow$	MFP	7.48	82.99	64.01	8.15

Table 8: Causality tests at horizons 1 to 4; United-States, 4-variable model [ΔEX,ΔRER,GAP, ΔMFP]; 1981-2014; 1 lag.

h			1	2	3	4
RER	$\nrightarrow$	EX	30.98	76.64	55.60	14.28
GAP	$\nrightarrow$	EX	5.19	7.49	81.54	39.35
MFP	$\nrightarrow$	EX	15.04	14.42	33.42	37.93
EX	$\nrightarrow$	RER	51.58	40.01	37.69	14.49
GAP	$\nrightarrow$	RER	62.19	88.05	73.35	66.00
MFP	$\nrightarrow$	RER	93.55	46.27	15.35	74.80
EX	$\nrightarrow$	GAP	51.68	54.52	81.21	37.21
RER	$\nrightarrow$	GAP	68.20	81.02	72.19	14.91
MFP	$\nrightarrow$	GAP	19.72	21.71	33.88	25.51
EX	$\nrightarrow$	MFP	67.53	9.82	12.19	21.58
RER	$\nrightarrow$	MFP	6.89	18.71	4.64	20.49
GAP	$\nrightarrow$	MFP	5.98	64.29	26.76	3.20