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Does Import Competition Reduce Domestic Innovation? Evidence from the 'China Shock' and Firm-Level Data on Canadian Manufacturing

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Abstract

A key economic issue in Canada is the declining Business Enterprise Research and Development in manufacturing since the early 2000s. Accompanying this, the total factor productivity (TFP) growth in manufacturing slowed after 2000. However, there has not been a definitive explanation for these trends. To deepen our understanding of this phenomenon, we focus on the increasing Chinese import share in the total domestic absorption in Canadian manufacturing since the early 2000s, which appears to be driven by positive supply shocks within Chinese manufacturing. Based on a firm-level database covering all incorporated firms in Canadian manufacturing, we find that rising Chinese import competition led to declines in R&D expenditure and TFP growth within firms but reallocated employment towards more productive firms and induced less productive firms to exit. The negative within-effects were pronounced for firms that were initially smaller, less profitable, and less productive. These firms also experienced declines in their profit margins due to rising Chinese import competition while larger and better-performing firms did not. Our estimates imply that rising Chinese import competition can explain about 7 per cent of the total decline of $1.36 billion (2007 CAD) in R&D expenditure in Canadian manufacturing between 2005 and 2010. Although it led to declines in TFP within firms, the positive reallocation effects more than offset the negative within-effect. Had there been no increase in Chinese import competition between 2005 and 2010, TFP in Canadian manufacturing would have declined by 1.26 per cent per year instead of the actual 1.09 per cent per year over this period.

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Executive Summary

R&D is a key input to innovation and hence, a key determinant of productivity growth of firms. A key economic issue in Canada is the declining Business Enterprise Research and Development (BERD) since the early 2000s. Especially, in manufacturing, BERD started to decline after 2000 both in absolute and relative terms. The real BERD in manufacturing fell at 3.3 per cent per year over the 2000-2012 period and the manufacturing share of the total BERD in Canada fell from 68 per cent to 43 per cent between 2000 and 2012. Accompanying this, total factor productivity (TFP) growth in manufacturing slowed after 2000 and TFP declined between 2005 and 2009.

To deepen our understanding of this phenomenon, we examine the increasing Chinese import share in total domestic absorption (*i.e.* the import penetration ratio) in Canadian manufacturing since the early 2000s, which appears to be driven by positive supply shocks within Chinese manufacturing. After China joined WTO in 2001, the Chinese import penetration ratio in Canadian manufacturing rose rapidly over time. Increasing competitive pressure on domestic firms has implications for their decision to innovate and hence, their productivity growth. Some firms may choose to increase their innovative effort (*e.g.* performing R&D) to remain competitive in the market while others may not be able to do so as their profit margins are hurt. Also, increasing competition could induce less productive firm to exit and reallocate resources towards more productive firms. Hence, rising Chinese import competition may have distributional effects on innovation and productivity performance in Canadian manufacturing. The overall effect on R&D investment and TFP in Canadian manufacturing is *a priori* ambiguous

To examine these issues, we rely on firm-level data covering *all* incorporated firms including those that performed R&D in Canadian manufacturing for the 2000-2012 period. Using this comprehensive database, we assess the impact of rising Chinese import competition on R&D and productivity growth within manufacturing firms by initial conditions of firms (*e.g.* initial size, profitability or mark-up, and productivity level).

Exploiting the ‘natural experiment’ nature of the episode of rising Chinese exports to the world market since the early 2000s, we capture the common component of rising Chinese imports in Canada and other advanced economies, which presumably reflects rising Chinese exporting capacity driven by China’s rising competitiveness in their manufacturing and lower trade costs due to factors internal to China. We rely on this common component to estimate its impact on R&D expenditure and TFP growth in Canadian manufacturing.

We find that rising Chinese import competition reduced R&D and TFP growth within firms. However, the negative within-effects on R&D and TFP growth were most pronounced within initially smaller, less profitable, and less productive firms. It also appears that they scaled

back their R&D investment but did not resort to other productivity-enhancing activities (*e.g.* better management practices or inventory controls) to improve their TFP. In contrast, R&D investment within initially larger, more profitable, and more productive firms was not affected by rising Chinese import competition. We find evidence that, in response to rising Chinese import competition, some larger and better-performing firms engaged in productivity-enhancing activities other than R&D, and hence their TFP improved.

Importantly, the smaller and poorly-performing firms also experienced declining profit margins due to rising Chinese import competition. We did not find evidence that profit margins of larger and better-performing firms were affected by rising Chinese competition. Firms tend to finance innovation using internal cash flows as external financing would be costly due to uncertainty in its outcome. Thus, the declines in R&D and TFP within those firms may be explained by the shrinking room to finance R&D and other innovations.

We estimate that China can explain about 7 per cent of the total decline of $1.36 billion (2007 CAD) in R&D expenditure in Canadian manufacturing between 2005 and 2010. The impact is relatively small as most of the declines occurred within small firms who accounted for a small share of the total R&D expenditure in manufacturing.

However, rising Chinese import competition reallocated employment towards more productive firms and induced less productive firms to exit the domestic market. We estimate that the negative effect of rising Chinese competition on TFP growth within firms is potentially small as it was most pronounced within small firms who tend to be less productive initially. It is found that the positive effect of the reallocation of resources more than offset the negative effect on TFP growth within firms. Our estimates imply that had there been no increase in the share of Chinese imports in the total domestic absorption in manufacturing between 2005 and 2010, the aggregate TFP level in manufacturing would have declined by 1.26 per cent per year instead of the actual 1.09 per cent per year.

Does Import Competition Reduce Domestic Innovation? Evidence from the 'China Shock' and Firm-Level Data on Canadian Manufacturing[1]

I. Introduction

A key economic issue in Canada is the declining Business Enterprise Research and Development (BERD) – a key input to innovation – since the early 2000s. Especially, in manufacturing, BERD started to decline after 2000 both in levels and as a share of sales. Accompanying this, the total factor productivity (TFP) growth in manufacturing slowed after 2000. However, there has not been a definitive explanation for these trends.

Since the early 2000s, advanced economies including Canada had experienced a rapid increase in imports from China. A large literature has documented that increasing trade with low-wage countries such as China have an impact on domestic innovation although the evidence is mixed for the direction of the impact.[2] The implication of increasing trade is multi-dimensional: rising competition in the markets for final goods and intermediate goods; expanding export opportunities and access to imported intermediates. In this paper, we assess whether declining R&D and productivity performance in Canadian manufacturing can be linked to rising Chinese import competition in final product markets. As the competition in the domestic product market rises, surviving firms are likely to adjust their innovative effort as their rents after innovation relative to rents before innovation are affected. Less productive firms would exit and resources could be allocated towards more productive surviving firms.

There are some close antecedents to our study but their empirical evidence is mixed. Bloom, Draca, and Van Reenen (2016) use firm-level data from European countries to estimate the effect of increasing Chinese import competition on four indicators for technical change: patents, information technology intensity, R&D investment, and TFP growth. They find empirical evidence that increasing Chinese import competition had led to an increase in all four measures of technical change within firms and also reallocated employment towards more technologically-advanced firms.[3] Autor, Dorn, Hanson, Pisano, and Shu (2017) find conflicting

[1] This report was written by CSLS economist Myeongwan Kim for Innovation, Science, Economic Development Canada. The Centre for the Study of Living Standards would like to thank Innovation, Science, Economic Development Canada for financial support for this research. An earlier version of the report was presented at the CSLS session on "the Impact of China on the Canadian Economy" at the annual meeting of the Canadian Economic Association held in Banff, Canada, June 1, 2019. The author thanks the participants at the CEA session and Alex Murray (Finance Canada) for the discussion. The author also thanks Andrew Sharpe (CSLS), Bert Waslander, and Jianmin Tang (ISED) for useful comments. The analyses in this report are based on data from the Canadian Centre for Data Development and Economic Research at Statistics Canada. The opinions expressed in this report do not represent the views of the agency. More information on CDER is available at http://www.statcan.gc.ca/cder-cdre/index-eng.htm.
Email: kimyhtg@gmail.com.

[2] See Shu and Steinwender (2018) for a comprehensive review of the studies on the impact of trade liberalization on innovation and productivity.

[3] They also find that technologically-advanced firms are more likely to survive for a given increase in Chinese import competition than low-tech firms.

evidence using firm-level data for the United States. They find that, in response to increasing Chinese competition, firms scaled back their patent activity and R&D investment.[4]

Gong and Xu (2017) also studies the effect of rising Chinese import competition on R&D expenditure of the U.S. firms but focuses on the reallocation effect. They find that rising Chinese competition reallocated R&D expenditure towards more productive and profitable firms but find no evidence of any impact on R&D at the aggregate level. Using survey data[5], Keung, Li, and Yang (2016) find that Canadian manufacturing firms scaled back their innovate effort but process innovation more than product innovation in response to rising Chinese import competition between 1999 and 2005.[6]

Those conflicting empirical results are in line with the overall ambiguity in theoretical implications for the effect of rising competition on domestic innovation. In the literature, there are multiple theories underlying the relationship between competition and innovation. First, 'trapped inputs' for production implies that increased Chinese import competition fosters innovation as it reduces the relative profitability of low-tech products. Firms cannot get rid of their 'trapped' inputs easily, having more incentives to allocate them to inventing new products or technologies (*e.g.* Bloom, Romer, Terry and Van Reenen, 2010). Also, an increasing market size for Canadian firms due to expanding trade opportunity with China may encourage innovation as firms can spread the fixed costs of innovation over the larger market (*e.g.* Krugman, 1980; Acemoglu, 2008).

In contrast, in a standard oligopoly model, increased competition in product markets is likely to reduce incentives to innovate as profits decline (*e.g.* Dasgupta and Stiglitz, 1980). If we take into account differential degrees of competition faced by firms, the relationship between innovation and competition exhibits an inverted U-shape (*e.g.* Aghion, Bloom, Blundell, Griffith, and Howitt, 2005). That is, innovation is low when firms produce very similar products (close to perfect competition) – no room to capture rents; and when firms produce very differentiated products (close to oligopoly or monopoly) – hard for laggards to overtake leaders. At the intermediate level of competition, rents after innovation may exceed rents before innovation, resulting in relatively high innovation in such market segments. Similarly, Schmidt (1997) shows that increasing competition increases managerial effort to increase profit (so likely to increase innovation) but when competition becomes too intense, managerial effort may decline eventually.

Domestic innovation could decline as domestic firms are deterred from entering export markets. Innovation is a key factor that drives the level of competitiveness required to enter or remain in export markets. For example, Baldwin, Dar-Brodeur, and Yan (2016) find that Canadian manufacturing firms that entered export markets are more likely to have invested in R&D before entry and to invest more in R&D after entry. As the competitiveness of Chinese manufacturing in the world market increased significantly since the early 2000s, Canadian manufacturers might have been deterred from entry to or driven out of the world export market

[4] They do not assess the effect on TFP growth and the reallocation effect.
[5] The Workplace and Employee Survey (WES) by Statistics Canada.
[6] They also find that more differentiated firms along product space or geographic dimensions are more likely to exit but perform better if they survive.

by Chinese manufacturers, especially in clothing, textile, and electronics manufacturing.[7] As a result, Canadian firms could have had less incentive to perform R&D as it becomes more challenging to enter or remain in export markets.[8] Coupled with increasing Chinese competition in the domestic market, increasing competition in export markets may further decrease innovative activities such as R&D within Canadian manufacturing firms.

As emphasized in Melitz (2003) and Bloom *et al.* (2016), it is also important to consider an economy-wide innovation or technical change that occurs through the reallocation of resources towards more productive firms in response to an increase in Chinese import competition (*i.e.* between-firm effects). In theory, if we maintain the menu of products fixed in the economy, then increasing trade with low-wage countries like China would results in shrinking low-tech firms and growing high-tech firms (where Canada has comparative advantages). The opposite would occur in China.

Our study adds to the literature in two ways. First, to our knowledge, there is no empirical study that uses Canadian firm-level data to explore the impact of rising Chinese import competition on R&D which is a representative indicator of innovation activities or on the overall productivity performance in Canadian manufacturing. In this paper, we carry out a comprehensive assessment of trade-induced change in R&D and TFP within manufacturing firms. Especially, our data capture a broad R&D expenditure of firms covering in-house R&D, R&D contracted out, and the use of R&D performed by third-parties on a non-exclusive basis. We also explore whether technical changes occurring *between* firms are important in Canada by analyzing the effect on employment and survival of manufacturing firms, focusing on the differential effects stemming from different initial technology levels of firms.

Second, most empirical studies focus on very large firms (*e.g.* public firms in Compustat) or firms with patents among those large firms. Large firms, especially publically traded firms or firms with successful innovation outcomes (*i.e.* patents) could have different initial conditions and hence, their response could be quite different than the majority of smaller firms in manufacturing or firms that perform R&D whose outcome does not necessarily get patented. In our study, we use administrative firm-level data covering all incorporated firms in Canadian manufacturing. Also, the database is linked to the tax data covering all firms that claimed R&D expenditure credits in Canada. Using this comprehensive database, we explore potential heterogeneity in firm-level responses to rising import competition, providing a better understanding of trade-induced change in innovation and productivity. In particular, we assess the impact of rising import competition on R&D and TFP within firms by initial conditions of firms (*e.g.* initial size, profitability or mark-up, and productivity level).

We find that increasing Chinese import competition reduced R&D and TFP growth within firms but reallocated employment towards more productive firms and drove less productive firms out of the domestic market. The negative within-effects on R&D and TFP

[7] These are the sectors with the highest exposure to Chinese import competition in Canada. See Murray (2017) and Kim (2018a, b).
[8] This would be the case if Canadian manufacturing firms find no room to capture rents after innovation in export markets.

growth were pronounced within initially smaller, less profitable, and less productive firms.[9] It appears that they scaled back their R&D investment but did not resort to other productivity-enhancing activities (*e.g.* better management practices or inventory controls) when Chinese import competition rose in their product markets. Even if they did, they were not successful. R&D investment within initially larger, more profitable, and more productive firms was not affected by rising Chinese import competition. We find evidence that some larger and better-performing firms engaged in productivity-enhancing activities other than R&D when the Chinese presence increased in their product market, and hence their TFP improved. Very large firms (employees>500) do not appear to have adjusted their innovative effort or other effort to enhance their productivity.

We find that the smaller and poorly-performing firms experienced declining profit margins due to rising import competition while larger or their better-performing counterparts did not. A larger reduction in R&D and TFP may be explained by the shrinking room to finance R&D and other innovations. Firms tend to finance innovation using internal cash flows as external financing would be costly in this case. Or in a different perspective, these firms are likely to face greater product market competition with technology gaps initially. So, a further increase in competition may have made additional innovation unprofitable. In other words, the basic Schumpeterian effect dominates for these firms, reducing more the post-innovation rents than the pre-innovation rents.

Using the estimated marginal effects of rising Chinese import competition on relevant firm-level outcomes, we estimate that China can explain about 7 per cent of the total decline of $1.36 billion (2007 CAD) in R&D expenditure in Canadian manufacturing between 2005 and 2010. Our productivity decomposition exercise indicates that had there been no increase in the share of Chinese imports in the total domestic absorption in manufacturing between 2005 and 2010, the aggregate TFP level in manufacturing would have declined by 1.26 per cent per year instead of the actual 1.09 per cent per year. This implies that the positive between- and exit-effects more than offset the negative within-effects.

Our study can be related to the previous CSLS research report on the effect of Chinese import competition on manufacturing employment by skill level. In Kim (2018a), the author finds increasing Chinese import competition in Canadian manufacturing had a negative employment effect on low-skilled occupations while it had no effect on high-skilled occupations. This can be linked to our findings that Chinese import competition drove out low-tech firms; reallocated employment towards more technologically advanced firms; and increased technical progress within larger and more productive firms in manufacturing, which in turn, decreased the relative demand for low-skilled occupations.

The remainder of the report is organized as follows. The following section provides an overview of the trends in Chinese import competition, R&D expenditure, and productivity performance in Canadian manufacturing. Data sources are discussed in section III. Section IV introduces our empirical models and identification strategy, which is followed by the results in

[9] For R&D, we also find the declines were larger within foreign-controlled firms and firms receiving regular tax credits for R&D expenditure, compared to domestically-controlled firms and firms receiving enhanced tax credits, respectively.

section V and VI. In section VII, we contextualize our empirical findings by quantifying the role of rising Chinese import competition in driving the actual change in R&D investment and TFP growth in Canadian manufacturing. Section VIII concludes.

II. Chinese Imports, R&D Expenditure, and TFP Growth in Canadian Manufacturing

We provide an overview of the trends in Chinese import competition, R&D expenditure, and TFP in Canadian manufacturing. Note that, in this section, we mainly use the data from the Annual Survey of Research and Development in Canadian Industries (RDCI) and the Canadian Productivity Account (CPA) publicly available from Statistics Canada since our firm-level data on R&D and on the variables required to estimate firm-level TFP only cover the 2000-2012 period, preventing us from comparing the pre- and post-take-off in Chinese imports in Canada.[10] However, when possible, we discuss some key observations found in the T2-LEAP-SRED data for the post-2000 period. In general, we find that the aggregate-level and firm-level data show consistent stories for R&D expenditure and productivity performance in manufacturing for the post-2000 period.

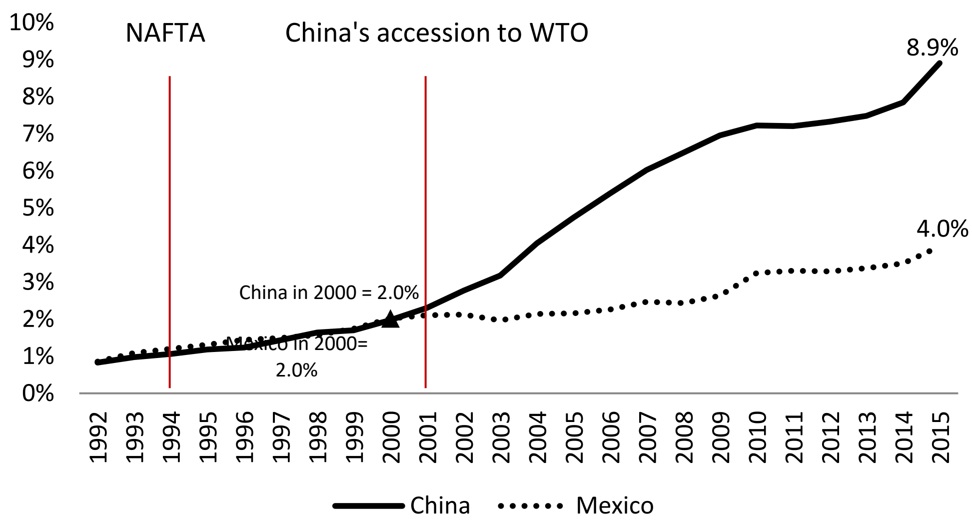
1. Chinese Imports

Imports from low-wage countries have implications for technical change in developed economies. A number of studies examine the impact of trade with low-wage countries on innovation across manufacturing sectors within advanced economies (*e.g.* Bartel *et al.*, 2007; Freeman and Kleiner, 2005; Bugamelli *et al.*, 2008). During the 2000s, two of the top ten importers to Canada were low-wage countries: China and Mexico. However, import penetration from China had been much more important in terms of both absolute levels and changes (see Chart 1). The import penetration ratio for Mexico remained below 4.0 per cent for most of the 1990s and 2000s. It increased from 2.0 per cent in 2000 to 4.0 per cent in 2015. The import penetration ratio for China surpassed that for Mexico during the early 2000s when China joined WTO, reaching 8.9 per cent in 2015. It grew by 6.9 percentage points between 2000 and 2015.

Moreover, increasing import competition from China is observed not only in Canada but also in other advanced economies around the world. Kim (2019a) shows that increasing Chinese import competition is observed in the United State and in other advanced economies such as Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland. This implies that rising Chinese import competition is not driven by demand shocks within Canada or individual advanced economies but likely to have been driven by rising exporting capacity of the Chinese manufacturing industry.

[10] RDCI is a more comprehensive source of information for R&D spending than the tax data which covers only R&D performed or purchased in Canada by incorporated firms (*i.e.* T2-LEAP-SRED). The CPA data are based on establishment-level data.

Chart 1: Import Penetration Ratio in Canada, Low-wage Countries: China and Mexico, Manufacturing, 1992-2015



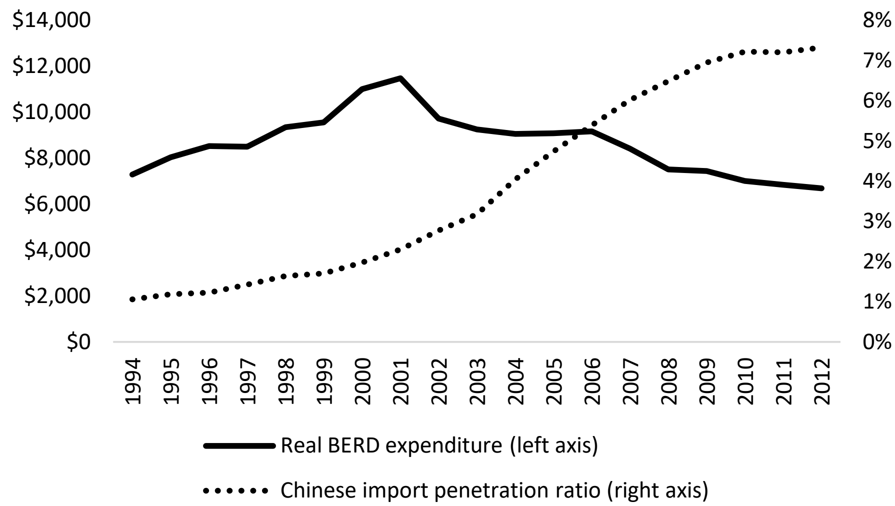
Note: The import penetration ratio is defined as the ratio of imports to domestic absorption (total industry shipment less exports plus imports). Mexico and China were low-wage countries among the top ten exporters to Canada during the 2000s. The top ten exporters to Canada were: United States, China, Mexico, Germany, Japan, South Korea, United Kingdom, Italy (including Vatican City State), France (including Monaco, French Antilles), and Taiwan.
Source: Authors' calculation based on trade data base maintained by Innovation, Science, and Economic Development Canada and Statistics Canada Table 16-10-0047-01.

2. R&D Expenditure in Canadian Manufacturing

According to the official data publicly available at Statistics Canada, between 1994 and 2000, the real BERD expenditure in Canadian manufacturing increased rapidly (see Chart 2).[11] However, it started to decline when Chinese imports surged in the early 2000s. Real R&D expenditure in manufacturing increased by 5.7 per cent per year on average during 1994-1999 but decreased by -0.58 per cent during 2000-2006. After 2006, real R&D expenditure fell year over year at a faster rate, -4.19 per cent over 2006-2012 period. We observe similar trends in the T2-LEAP-SRED database which covers only domestically performed R&D. The average annual growth rate in real R&D expenditure was -0.2 per cent in manufacturing for the 2000-2012 period.[12] The average annual growth rate was 4.1 per cent for the 2000-2005 period but fell to -3.2 per cent for the 2005-2012 period.[13]

[11] We use the GDP deflator for R&D expenditure. In our analysis using T2-LEAP-SRED, we use industry-specific deflator for R&D.
[12] The average annual growth was 1.3 per cent in non-manufacturing during the same period.
[13] A similar pattern is found in non-manufacturing: 5.9 per cent for the 2000/2001-2004/2005 period and -1.9 per cent for the 2005/2006-2011/2012 period.

Chart 2: Real R&D Investment in Canadian Manufacturing, Millions of 2007 CAD, 1994-2012



Source: Author's calculations based on Statistics Canada Table 27-10-0002-01, 27-01-0273-01, 16-10-0047-01, and Trade Data Online maintained by Innovation, Science, and Economic Development Canada.

BERD expenditure fell in relative terms as well. Manufacturing accounted for more than half of the total BERD expenditure in Canada.[14] However, the average share of manufacturing in the total BERD expenditure in Canada was lower in the post-2000 period than in the pre-2000 period. The manufacturing share was 64.5 per cent during the 1994-1999 period but it declined to 52.4 per cent during the 2000-2013 period. Over the 2000-2013 period, there was a gradual decline in the manufacturing share, falling from 68.4 per cent in 2000 to 42.0 per cent in 2013. We find a similar pattern in the T2-LEAP-SRED data for the post-2000 period. Panel A in Chart 3 shows the share of manufacturing in the total real R&D expenditure in Canada based on the T2-LEAP-SRED database. Consistent with the RDCI data, we observe that the manufacturing share declined from 42.8 per cent in 2000 to 39.2 per cent in 2012.[15] Over the same period, the Chinese import penetration ratio increased by 5.50 percentage points.

The R&D intensity in manufacturing also declined after 2000. Panel B in Chart 3 shows that BERD expenditure as a share of the total sales in manufacturing increased from 1.61 per cent to 1.92 per cent between 1994 and 2000. When the Chinese import penetration ratio started to take off in the early 2000s, the R&D expenditure ratio started to decline, dropping to 1.23 per cent by 2013. Again, we find a similar pattern in R&D intensity for manufacturing in the T2-LEAP-SRED data. The R&D intensity in both manufacturing and non-manufacturing gradually fell over the 2000-2012 period. The average R&D intensity in manufacturing was 3.2 per cent

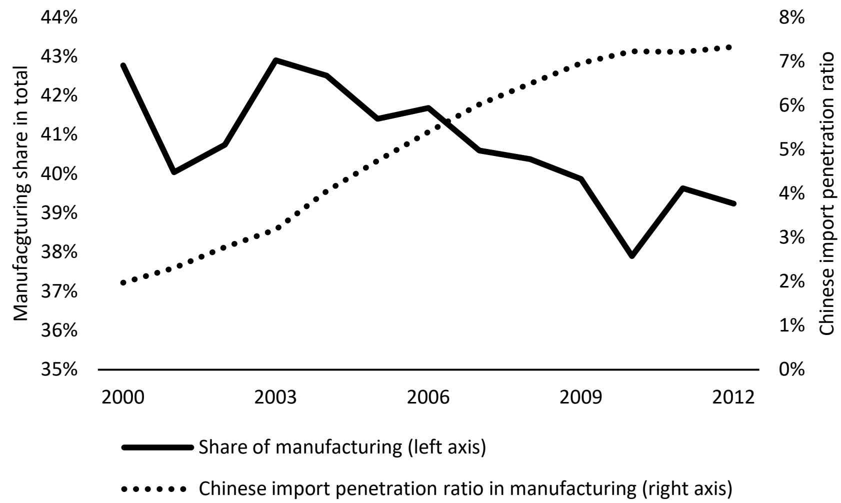
[14] According to the RDCI data, the average share of manufacturing in total BERD expenditure is 56.0 per cent over the 1994-2013 period.

[15] The numbers are different from the shares measured based on the RDCI data. R&D expenditure in the T2-LEAP-SRED covers only incorporated firms and includes R&D performed domestically while RDCI includes unincorporated firms and R&D outsourced to non-residents.

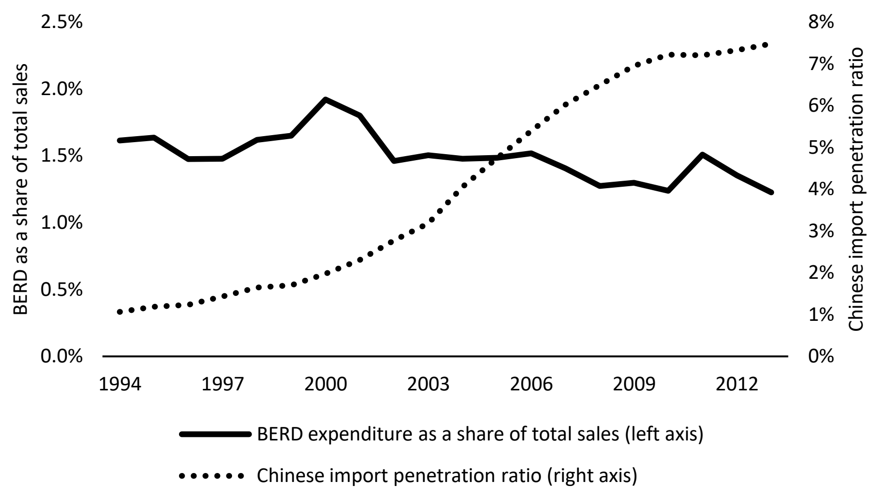
during the 2000-2006 period. The average intensity then fell to 1.9 per cent over the 2006-2012 period. On the other hand, the average R&D intensity for non-manufacturing did not fall as much: 2.1 per cent during the 2000-2006 period and 1.4 per cent during the 2006-2012 period.

Chart 3: R&D in Canadian manufacturing

Panel A: The Manufacturing Share in Total Real R&D Expenditure in Canada, Incorporated Firms, T2-LEAP-SRED, 2000-2012



Panel B: R&D Intensity in Canadian Manufacturing, RDCI data, 1994-2012



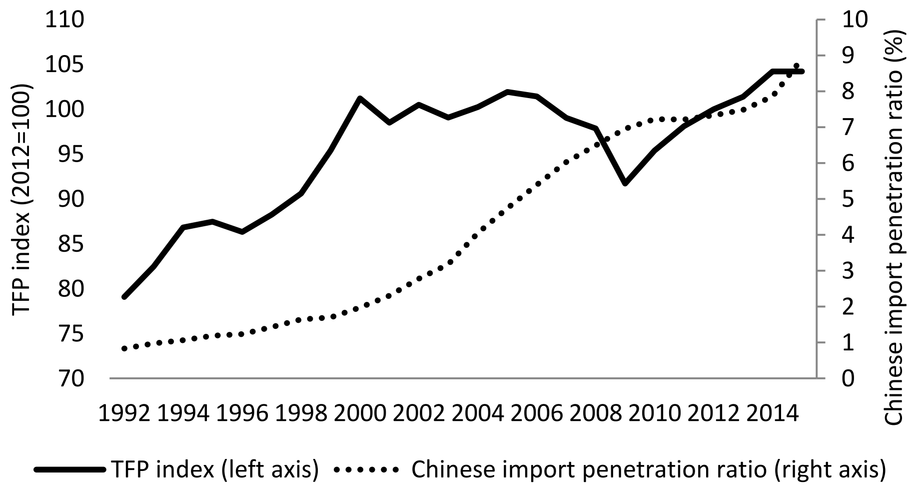
Note: Import penetration ratio is defined as the ratio of imports to domestic absorption (total industry shipment less exports plus imports).
Source: Panel A – Author's calculations based on the T2-LEAP-SRED database; Panel B- Author's calculations based on Statistics Canada Table 27-10-0002-01, 16-10-0047-01. Import penetration ratio is calculated based on Trade Data Online maintained by Innovation, Science, and Economic Development Canada and Statistics Canada Table 16-10-0047-01.

3. TFP in Canadian Manufacturing

TFP growth in manufacturing also slowed after 2000. Chart 4 shows time series for TFP index for Canadian manufacturing. TFP grew at a faster rate during the 1990s than during the 2000s. For instance, the annualized growth in TFP was 3.13 per cent over the 1992-2000 period. However, TFP declined at an annual rate of 1.09 per cent over the 2000-2009 period. After a rapid increase during the 1990s, TFP started to level off from the early 2000s. Then, it declined between 2006 and 2009. However, TFP started to recover after 2009 recovering to the levels observed in the early 2000s.

Again, due to the limited information in our T2-LEAP-SRED data, we examine TFP only for the 2000-2012 period.[16] We estimate TFP at the firm-level and aggregate using firms' shares in the total output in manufacturing. The TFP level in manufacturing based on T2-LEAP-SRED exhibits a pattern similar to that found in the CPA data. For the 2000-2006 period, TFP is relatively stable. Then, TFP fall between 2006 and 2009. TFP recovers after 2009.

Chart 4: TFP Index (2012=100) and Chinese Import Penetration Ratio in Canadian Manufacturing, 1992-2015



Source: Authors' calculation based Statistics Canada Table 36-10-0208-01 and on trade data base maintained by Innovation, Science, and Economic Development Canada and Statistics Canada Table 16-10-0047-01.

III. Data

Our sample period is restricted to 2000-2012. Data on R&D investment and some variables used to estimate firm-level TFP are not available for the 1990-1999 period. Ideally, we would like our sample period to cover some years in the 1990s so that we can assess pre-China shock estimates to support the plausibility of a causal interpretation of the effect of China on technical change. Nevertheless, we think this would not be a serious issue in our empirical assessment of the impact of the China shock since most of the increase in Chinese import competition in Canada occurred during the 2000s (see Chart 1).

[16] We do not have complete information for output in the data covering the 1990s preventing us from estimating a production function to retrieve TFP estimates based on our preferred estimation strategy.

Our sample for R&D analysis consists of firms that performed or purchased R&D at least once between 2000 and 2012. For the analysis on TFP, the sample consists of firms that have non-missing values for all the variables required to estimate firm-level TFP (see Appendix III). Hence, we have a larger number of firms in the TFP sample than in the R&D sample.

1. T2-LEAP-SRED

The main data source for our analysis is corporate income tax (T2) files linked to Statistics Canada's Longitudinal Employment Analysis Program (LEAP) data file. In order to have information on R&D expenditure for each firm, the database has been linked to the Canada Revenue Agency (CRA) form T661 filed by firms to claim their tax credits for expenditure on scientific research and experimental development (SRED).[17]

The T2-LEAP-SRED file follows the statistical enterprise concept. The data include all legal entities controlled by the same corporation as the basis for its panel structure. Hence, it is possible that a firm consists of more than one legal entity filing a corporate income tax return with CRA. Also, the data are adjusted to remove spurious entries and exits resulting from mergers and acquisitions and legal restructurings. For example, when two firms merge, the new entity is synthetically created and assumed to have existed since the birth of the oldest of the two firms.

Statistics Canada produces new version of T2-LEAP over time as new data become available, reflecting new organizational structures among other things. The underlying organizational structure in a given T2-LEAP is represented by a vintage. We rely on the 2016 vintage for our T2-LEAP-SRED database that covers the period 2000-2012. However, certain variables not originally available in the T2-LEAP-SRED database are constructed based on the 2019 vintage and merged with our main data.[18]

1-1. Research and Development (R&D)

In CRA form T661, firms report expenditure on scientific research and experimental development. Specifically, they report expenditure on wages and salaries, materials costs, equipment leasing, equipment purchase, contracts and "third-party payments" for R&D.[19] However, firms do not report investment in structures used to perform R&D. Following Kim and Lester (2019), adjustments are made to obtain a comprehensive measure of R&D expenditure. Our measure includes R&D performed in-house for internal use; R&D performed under contract by other Canadian firms that the firm can exploit on an exclusive basis; and R&D performed by

[17] The T2-LEAP-SRED database was developed by John Lester, Ryan MacDonald, Javad Sadeghzadeh and Weimen Wang at the Centre for Data Development and Economic Research at Statistics Canada.
[18] Note that the organizational structure is defined at the BN level, a lower level of aggregation than the LBRID level which is our unit of analysis.
[19] Contracts and third-party payments are distinguished by the degree of control over the performance of the R&D and the right to use the R&D. In a contract, the payer has full control and exclusive use of the R&D. In a third-party payment, the performer has full control over the performance of the R&D and the payer has non-exclusive rights to use the outcomes of the R&D.

third parties in Canada that the firm can exploit on a non-exclusive basis. However, our data do not capture spending on R&D outsourced to non-residents.

We deflate nominal values of R&D spending by industry-specific implicit deflators developed by Statistics Canada. These deflators are constructed based on input costs for R&D such as wages and salaries for R&D personnel and the cost of intermediate materials. The deflator for wages and salaries is based on hourly compensation in occupations likely to perform R&D. The deflator for materials is a weighted average of the KLEMS price indices for the materials used in performing R&D.

In our analysis on the effect of rising Chinese import competition on the employment and survival of manufacturing firms, we rely on R&D capital stock to measure the initial technology level of a given firm.[20] We follow the methodology developed in Kim and Lester (2019) to estimate initial R&D capital stock at the firm level. The methodology is described in Appendix I.

1-2. Output and Inputs of Production

In T2-LEAP-SRED, we also have information on firm-level output and conventional factors of production to estimate TFP. These variables are constructed based on information from financial statements submitted by firms with their income tax return (*i.e.* the General Index of Financial Information or GIFI). The files include information on items such as the value of sales, tangible investment, depreciation expenses, and the capital stock.

We adopt value-added as our measure of output[21] and deflate it using industry-specific implicit deflators from the KLEMS database. Value added is calculated as the sum of payroll from the LEAP file and capital income constructed based on information available in the GIFI file. Ideally, we would calculate the two components from the same data source. However, data on employment levels (*i.e.* labour input) is only available from the LEAP file. Favouring consistency between employment levels and labour income, we choose the LEAP file as the source for labour income.

Capital income is calculated as operating revenue minus operating expenses. We make three adjustments for operating expenses. First, we adjust them to exclude user costs (*i.e.* depreciation and interests) and taxes. Second, we exclude expenses associated with R&D not capitalized by firms to avoid the "expensing bias" – understatement of capital income by excluding the items in a balance sheet (see Hall, Mairesse, and Mohnen, 2010). Third, following Moussaly and Wang (2014), we make adjustments to attribute income generated by leased tangible capital to the firm using the capital not the owner of the capital.[22]

[20] We also use TFP level (relative to industry average) as a measure of the technology level of a firm.
[21] It is also common to use sales as a measure of (gross) output in the literature. Hall, Mairesse, and Mohnen (2010) state that although theory suggests gross output is the preferred measure, in empirical works, value-added appears to be the better choice. For example, differences in the degree of vertical integration among firms lead to variations in the materials-output ratio. It is difficult to reflect them in an empirical model.
[22] In the GIFI files, payments for capital lease are recorded as income by the owner of the capital while the leased capital is recorded in the balance sheet of the user. Hence, we remove capital lease income from the owner's file and treat capital lease payments as capital income of the user. Note that for an operating lease, the owner takes

We rely on balance sheet items from the GIFI files to calculate the net stock of tangible capital for firms.[23] Firms report the book value of tangible capital in use and the accumulated depreciation expenses. Deflating net capital stock is challenging since book values of the capital stock and accumulated depreciation expenses consists of different historical dollars. Due to the lack of completely satisfactory way of deflating, we resort to the industry-specific implicit deflator for capital stock from the industry productivity database.

Since firm-level data on hours worked are not readily available, we instead use an estimate of the number of employees developed for the LEAP data. We rely on average labour unit (ALU) which is constructed by taking the ratio of total payroll to average annual earnings of a typical worker in the firm's 4-digit NAICS industry, province and firm size class.

2. Trade data

We use the Trade Data Online by Innovation, Science, and Economics Development Canada and the UN Comtrade database to construct our measure of Chinese import competition for Canada and other advanced economies required for our identification strategy. The UN Comtrade database follows the Harmonized Item Description and Coding System (HS). We therefore implement a mapping between HS and NAICS following the algorithm developed by Pierce and Schott (2012).[24] Refer to Murray (2017) and Kim (2018a, b) for more detailed description of the data.

IV. Empirical Models and Identification Strategy

1. Technical changes within firms

Our empirical models assess the effect of Chinese import competition on technical change within firms in manufacturing. To do so, we analyze two indicators of technical change: R&D expenditure and TFP growth. Following Bloom *et al.* (2016), we estimate the following two equations:

$$(1)\quad \Delta\ln\,(R\&D)_{i,j,\tau} = \beta^{R\&D}\Delta IP_{j,\tau} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau}$$

$$(2)\quad \Delta\ln\,(TFP)_{i,j,\tau} = \beta^{TFP}\Delta IP_{j,\tau} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau}$$

where i denotes firms and j denotes sectors in manufacturing. Δ represents the operator for long differences (*e.g.* 5-year long differences) for a given variable. $X_{i,j,\tau}$ includes all other controls for

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responsibilities for repair and maintenance. Hence, both ownership and rental incomes are attributed to the owner. We make adjustments accordingly.

[23]Tangible capital includes assets with a physical form such as buildings, land, and machinery and equipment.

[24] Note that there is no mapping between HS and NAICS 3328 (Coating, engraving, cold and heat treating and allied activities). As a result, we drop all firms in this sector. This is not likely to pose a serious problem as the value of Chinese imports in this sector in Canada is very close to zero, if not missing, for several years in our sample period.

non-trade related factors specific to firms and to sectors in manufacturing. α_τ represents period fixed effects. $\Delta IP_{j,\tau}$ is a measure of Chinese import penetration which is constructed as follows:

$$(3) \quad \Delta IP_{j,\tau} \equiv \frac{\Delta M_{j,\tau}^{China}}{Y_{j,\tau_0}+M_{j,\tau_0}-E_{j,\tau_0}}$$

where the numerator $\Delta M_{j,\tau}^{China}$ denotes the change in import in sector j from China over period τ. The denominator $(Y_{j,\tau_0} + M_{j,\tau_0} - E_{j,\tau_0})$ represents the domestic absorption in sector j in the initial period τ_0.

2.Technical changes between firms: reallocation of employment and survival

To assess between-firm effects of Chinese import competition, we estimate the following equation:

$$(4) \quad \Delta\ln(N)_{i,j,\tau} = \beta^N \Delta IP_{j,\tau} + \lambda^N\left(TECH_{i,j,\tau_0} * \Delta IP_{j,\tau}\right) + \varphi TECH_{i,j,\tau_0} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau}$$

where N is a measure of employment. $TECH_{i,j,\tau_0}$ is a measure of technology level for firm i in sector j in the initial period τ_0.

Increasing import competition from China could affect the probability of survival. Thus, we estimate the effect of trade on survival of firms in our data as follows:

$$(5) \quad S_{i,j,\tau} = \beta^S \Delta IP_{j,\tau} + \lambda^S\left(TECH_{i,j,\tau_0} * \Delta IP_{j,\tau}\right) + \varphi TECH_{i,j,\tau_0} + \gamma X_{i,j,\tau} + \alpha_\tau + \varepsilon_{i,j,\tau}$$

where $S_{i,j,\tau} = 1$ if firm i in sector j survives over period τ and zero otherwise. Equation (5) is estimated on a cohort of firms that exist in the sample in a given base period.[25] We follow those firms over period τ to assess their value for $S_{i,j,\tau}$.

The main parameter of interest is λ in equation 4 and 5 as it reflects whether the size of the effect of Chinese import competition on employment growth or survival varies with the initial level of technology. If low-tech firms are affected more negatively by China then we expect $\lambda > 0$.[26] In other words, $\lambda > 0$ indicates that employment tends to shift towards high-tech firms and low-tech firms tend to exit in response to increasing Chinese import competition.

3. Identification strategy

To identify shocks exogenously driven by rising Chinese exporting capacity, we exploit the fact that growth in Chinese exports to developed economies like Canada since the early 2000s were mostly driven by factors internal to China (*e.g.* urbanization, opening to foreign

[25] Unlike the firm-level data used in Bloom *et al.* (2016) and Autor *et al*. (2017), T2-LEAP-SRED is adjusted for mergers and acquisitions and legal restructuring. Therefore, we do not have to worry about whether a disappearance of firms is a true exit.

[26] We expect β<0 in both Equation (4) and (5).

investment, rising competitiveness in manufacturing, and accession to the WTO) rather than by positive demand shocks within developed economies.

We capture the common within-industry factors of rising Chinese exporting capacity, which stemmed from rising Chinese comparative advantage in manufacturing and lower trade costs due to factors internal to China. Thus, following Autor, Dorn, and Hanson (2013), we instrument for changes in the Chinese share of the domestic absorption in Canada using the changes in Chinese imports in the following eight advanced economies: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.[27]

The first-stage regression is given by the following:

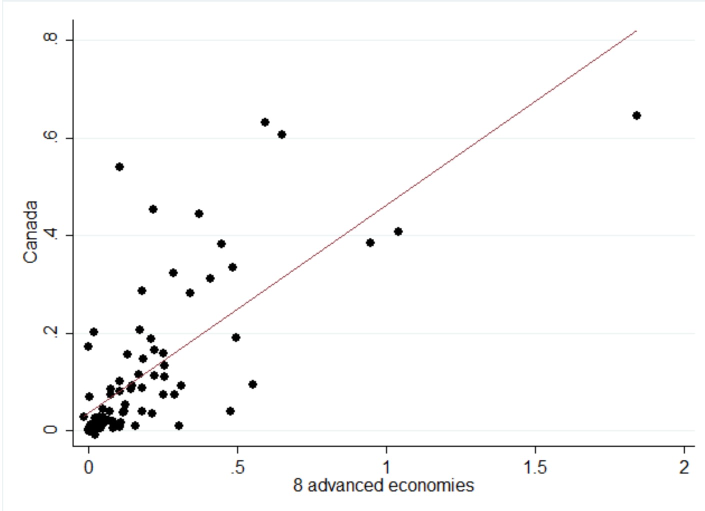
$$(6)\ \ \Delta IP_{j,\tau} = \delta \Delta IPE_{j,\tau} + \tilde{\gamma} X_{j,\tau} + \widetilde{\alpha_\tau} + \widetilde{\eta_j} + \mu_{j,\tau}$$

where $\Delta IPE_{j,\tau}$ represents changes in the Chinese import penetration ratio in the eight comparison countries.

The above strategy has the following key identifying assumptions: 1. industry-specific shocks are uncorrelated across Canada and the eight countries; and 2. there are no strong increasing returns to scale in Chinese manufacturing such that Canadian shocks increase efficiency within relevant Chinese manufacturing industries and lead them to export more to the eight other economies. The former may be a concern in our analysis. We are particularly concerned with the possibility of correlated shocks related to the innovation in the use of ICT technologies, which were observed in most of the advanced economies around the world, increasing demand for ICT-related goods from China. We provide some robustness checks on this issue in section V. The second is not of serious concern since Canada is a small open economy. Shocks within 4-digit NAICS in Canada are not likely to have a substantial impact on the efficiency within relevant Chinese industries.

[27] We exclude the United States because its economy is highly integrated with Canada and is likely to have experienced similar demand shocks.

Chart 5: Changes (long-differences) in the Chinese Import Penetration Ratio, Canada and the Other Advanced Economies (ΔIP and ΔIPE), 2000-2012, Percentage Point



Note: The comparison countries include: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland.
Source: Author's calculation based on Statistics Canada Table 16-10-0047-01 and the United Nations Comtrade database after mapping CPI products to HS commodities following the algorithm developed by Pierce and Schott (2012).

It appears that the change in trade exposure to China in the eight advanced economies has good predictive power for the change in Canada (see Chart 5). Approximately 52.5 per cent of the variation in the import penetration ratio in Canada is presumably driven by exogenous supply shocks for the 2000-2012 period. In our regression analysis, we use rolling 5-year sub-periods covering the 2000-2012 period. R-squared varies across the 5-year sub-periods but is greater than 80 per cent in most cases.

4. Descriptive Statistics

We report summary statistics for some key variables used in our analysis by initial employment size in Table A2 and A3 in Appendix IV. Firms in the R&D sample (Table A2) tended to be larger in terms of employment and had a larger increase in their productivity over time, compared to the firms in the TFP sample (Table A3) which is a larger sample including the R&D-performing firms. Both in the R&D and the TFP sample, we find that the initial level of profitability (a proxy for the initial competition level) and the initial productivity level were lower for smaller firms than for larger firms. In other words, firms with initially smaller employment are more likely to operate in more competitive markets with technology gaps in the initial period.

Both in theoretical and empirical works, it is suggested that the initial level of profitability (or product market competition) and productivity of a firm have important implications for the firm's innovative effort in response to an increase in competition.[28] It is

[28] See, for example, Aghion, Bloom, Blundell, Griffith, and Howitt (2005) and Autor *et al.* (2017). They suggest firms that are facing more competitive product markets with technology gaps in the initial period are more likely to reduce innovation in response to an increase in product market competition.

observed that, on average, smaller firms spent a smaller amount on R&D and experienced a larger increase in the Chinese import competition; a larger decrease in profitability; and a smaller increase in their productivity level. In the table, we report only the mean values for the variables due to confidentiality requirements but the median values follow similar patterns.

V. Regression results: R&D equation

1. Baseline results

In Table 1, we report the regression results for estimating our R&D equation. We use rolling long-differenced samples of a 5-year period (*i.e.* 2000-2005; 2001-2006; 2002-2007; and so on) to maximize the number of observations in our sample.[29] Using first-differenced samples (*i.e.* change from one year to another) may lead to attenuation bias. It may not capture any meaningful adjustment in the innovation effort in response to increasing Chinese import competition, which is likely to occur over the medium- or long-term.

In column 1 and 2, we estimate the same R&D equation but using different estimation methods. The OLS estimate in column 1 indicates that there is no significant effect of the China shock on the R&D expenditure growth within manufacturing firms. However, using exogenously-driven variation in ΔIP (*i.e.* 2SLS), we find a negative and statistically significant effect on R&D in column 2. Our estimate indicates that, on average, R&D expenditure growth within firms falls by 1.027 percentage points in response to a one-percentage-point increase in the Chinese import share in the total domestic absorption.

Table 1: R&D Equation, 2SLS, Manufacturing, 2000-2012

	1	2	3	4	5
ΔIP	-0.461 (0.285)	-1.027*** (0.395)	-0.857* (0.448)	-2.181** (1.051)	-0.805** (0.398)
No. firm x period	118,427	116,683	116,683	109,871	101,485
No. firms	17,314	17,066	17,066	16,867	15,529
Estimation method	OLS	2SLS	2SLS	2SLS	2SLS

Note: The dependent variable is Δln(R&D expenditure). All columns include period fixed effects. Standard errors are in parenthesis. Δ denotes a 5-year difference. The number of observations is smaller for the columns based on our IV approach than column 1 since there is no HS-NAICS mapping for NAICS 3328. The number of observations for column 4 (alternative instrument) is smaller than the columns based on our preferred instrument since some industries have missing values for imports from China in some years in the early 1990s – see the main text for detail. *** $p< 0.01$; ** $p<0 .05$; * $p< 0.10$.

However, there could be unobserved industry-specific shocks that are correlated with both R&D investment and the Chinese import penetration ratio despite our effort to identify exogenous shocks. Hence, as our first robustness check, in column 3, we report the results for controlling for industry trends in our sample. Here, we include 3-digit NAICS industry dummies,

[29]Similar results are found when we use different lengths of rolling sub-periods (*e.g.* 3-year; 6-year). We also tried using one or two long-differenced sub-periods (*e.g.* 2000-2007 or 2000-2005 and 2005-2010). Again, we found that the coefficients for ΔIP remain very similar to the ones reported in Table 1.

which is equivalent to including 3-digit NAICS industry trends in the equation in levels.[30] This is a quite tough test on the robustness of our estimate since we are essentially switching off some important variation used to identify the parameter of interest. We continue to obtain a negative and statistically significant coefficient on ΔIP although the coefficient is slightly smaller due potentially to attenuation bias.

In column 4, we use an alternative instrument as proposed in Bloom *et al.* (2016), which is similar in nature to the instrument used in Card (2001).[31] Using the same argument for our baseline IV strategy (*i.e.* the rapid increase in Chinese imports is driven by positive supply factors internal to China), we argue that Chinese manufacturing sectors with comparative advantages are likely to have exported more strongly than other sectors even before the take-off in Chinese exports in the early 2000s. In other words, we can argue that sectors that already had very strong exports in the initial period (*e.g.* during the late 1990s) are likely to be the sectors in which China had a comparative advantage. Moreover, these sectors tend to have strong export growth over the following years as well.[32] Therefore, we use the Chinese import penetration ratio measured in the initial period as instrument for its subsequent increases. Specifically, we use ($IP_{j,t-6}^{China} * \Delta M_t^{China}$) as an instrument for $\Delta IP_{j,t}^{China}$. $IP_{j,t-6}^{China}$ is the initial Chinese import penetration ratio (*e.g.* the ratio in 1999 for the 2000-2005 period). ΔM_t^{China} is the exogenous growth in Chinese imports in Canadian manufacturing at time t.

We find that the alternative instrument has strong predictive power for the Chinese import penetration ratio for Canada. The alternative instrument can explain roughly 62 per cent to 86 per cent of the change in Chinese import competition in Canada in each of the 5-year sub-periods covering the 2000-2012 period. Using this alternative instrument, we continue to obtain a negative and statistically significant coefficient for ΔIP although the magnitude of the coefficient is roughly twice as large as that reported in column (2).

In column 5, we include different firm-level controls to account for potential confounding factors. Some observations have missing values for some of the control variables we consider. Hence, the number of observations is slightly smaller than in the other columns. Here, we include five different control variables. First, we include R&D intensity (R&D stock divided by value added) and tangible capital-to-value added ratio, both measured in the initial period (*e.g.* the 2000 value for the 2000-2005 sub-period). Second, we include the log of wage per worker averaged over our sample period.[33] Similar to Bernard *et al.* (2006) and Bloom *et al.* (2016), we use these variables as proxies for the initial technology level. Third, we include dummies for foreign-controlled firms and for the enhanced SR&ED tax credit recipients.[34] The coefficient for

[30] We also allow the time trends to differ by 3-digit NAICS industry.
[31] Card (2001) uses past shares of immigrants in the total population in a given region to instrument for the shares of immigrants in subsequent periods.
[32] In our data, these sectors tend to be in textile, clothing, fabric, electronics and computer-related manufacturing. They exhibit a high degree of the Chinese import competition during the 1990s and large increases in the competition measure over the following years.
[33] Wage is defined as payroll divided by average labour unit. Since the average labour unit is defined as the total payroll divided by average annual wage of a typical worker in the firm's 4-digit NAICS industry, province and firm size class, wage would be defined not at the firm-level but at the 4-digit NAICS industry x province x firm size class level.
[34] We find that the control variables are jointly significant.

ΔIP remains negative and statistically significant with these control variables. We also tried defining all the control variables for the initial technology level at the 4-digit NAICS industry-level and found similar results.

As discussed in section IV, the role of ICT-related industries could potentially be important in driving the total impact (through 2SLS) reported above. Thus, we estimate the R&D equation: 1. on the sample excluding firms in NAICS 3341 or NAICS 3342 (computer or communication equipment manufacturing); 2. by including dummies for NAICS 3341 and NAICS 3342; 3. by interacting ΔIP with the indicator for NAICS 3341 or NAICS 3342. However, we find that the coefficient on ΔIP hardly changes in the first two tests. For the third specification, we find that the coefficients for the two groups (*i.e.* firms not in NAICS 3341 or 3342 and firms in one of the two industries) remain very close to the aggregate estimate reported in column (2) in Table 1. The coefficient for non-ICT-related firms is slightly greater than that for ICT-related firms but we find no statistical evidence that they are different.

In Appendix II, we provide further analysis on R&D by exploring potential firm heterogeneity. We examine the differential response in R&D expenditure between domestically-controlled and foreign-controlled firms; between enhanced R&D tax credit recipients and regular recipients; and between start-ups and established firms. In summary, we find that foreign-controlled firms, regular tax credit recipients, and established firms scaled down R&D investment to a greater extent for a given increase in Chinese import competition. More detailed discussion of the results and our reasons for analyzing firms in these dimensions are provided in Appendix II.

2. Explaining the negative effect

Our results indicate that manufacturing firms in Canada have reduced their R&D investment over the 2000-2012 period in response to increasing competition from China. This is consistent with the finding in Autor *et al.* (2017) who find that R&D expenditure growth fell in response to an increase in Chinese import competition in the United States. However, our results contradict those in Bloom *et al.* (2016) who find a positive effect of increasing Chinese imports on R&D investment growth for firms in European countries. Such contradiction is theoretically possible as discussed in Section I.

It is possible that increasing Chinese imports leads to declining R&D expenditure by creating competitive pressure on firms, reducing their expected rents after R&D relative to rents before R&D. However, with differential degrees of competition initially faced by firms, the impact of increasing competition on R&D investment may not be uniform across all firms. Firms with significant market power (*e.g.* larger firms) may be less responsive in adjusting their R&D effort. Their rents would not be significantly affected by rising competition as it would be difficult for laggards (*i.e.* Chinese manufacturers) to overtake leaders (*i.e.* large Canadian manufacturers) or Chinese manufacturers may operate in different product markets. On the other hand, for firms already facing a high degree of competition with technology gaps (*e.g.* smaller firms), increasing competition may substantially hurt their profit margins, implying less room to finance innovation and/or to capture rents after R&D. As a result, if such firms survived, they might have been more responsive in reducing their expenditure on R&D as competition rises.

To empirically examine this idea, we estimate the R&D equation in which we interact ΔIP with the size indicator to examine whether the coefficient differs by size group (in terms of the initial employment size).[35] Small firms tend to be not only less profitable (or operating in more competitive markets) but also less productive in the initial period (see Table A2 in Appendix IV). In column 1, we find that the coefficient for medium-sized and large firms are smaller in magnitude than that for small firms indicating they made smaller adjustment in R&D investment in response to a given increase in import competition. However, the evidence for their statistical significance is weak and one may conclude that the aggregate estimate of the China effect on R&D investment is mainly driven by small firms.[36] That is, there is statistical evidence that only small firms' R&D was negatively affected by increasing Chinese import competition.

Table 2: R&D and Profit Equation, 2SLS, Manufacturing, 2000-2012

	Δln(R&D investment)	ΔProfitability	
	1	2	3
ΔIP	-	-0.057***	-
		(0.018)	
ΔIP x initially small	-1.299***	-	-0.068***
	(0.468)		(0.022)
ΔIP x initially medium-sized	-1.056	-	-0.014
	(0.950)		(0.031)
ΔIP x initially large	-0.991	-	-0.013
	(0.836)		(0.025)
No. observations (firm x period)	116,683	103,816	103,816
No. firms	17,066	15,956	15,956

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Initial employment size is measured as the average labour unit (ALU) observed in the initial year (*e.g.* ALU in 2000 for the 2000-2005 sub-period). We define the three size groups based on the average labour unit (ALU) observed in the initial period: small (ALU<100); medium (100≤ALU<500); and large (500≤). Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit. *** $p<$ 0.01; ** $p<$0 .05; * $p<$ 0.10.

It is likely that small firms' profit margins were negatively affected (or competitive pressure faced by them is increased) by rising import competition, leading them to reduce R&D expenditure. We estimate the impact of increasing Chinese imports on the profitability of firms performing R&D in manufacturing. Given the data availability in the T2-LEAP-SRED database, we define profitability as profit divided by sales where we use net income or loss before tax as profit. In column 2 in Table 2, our 2SLS estimate indicates that increasing Chinese import competition indeed reduced the profitability of firms. A further analysis by size in column 3

[35] We define the three size groups based on the average labour unit (ALU) observed in the initial period: small (ALU<100); medium (100≤ALU<500); and large (500≤). We use the conventional definition for small, medium and large firms. These cut-offs are based on the number of employees which is not equivalent to the average labour unit. Thus, based on the distribution of ALU in T2-LEAP we translated these numbers to ALU and carried out all the analyses. The qualitative results remained the same.

[36] We also estimated the equation based on two size groups by aggregating medium-sized and large firms. However, we found the same qualitative results.

indicates that only small firms were negatively affected by increasing import competition from China. We find no evidence that the profitability of larger firms is affected by Chinese imports. This implies that rising Chinese import competition translated into increased competitive pressure (*i.e.* decreasing mark-ups) mostly for small firms.[37]

We carry out some robustness checks. A key relationship to show is that a higher initial level of competition faced by firms or a lower initial level of productivity is associated with a larger negative effect of rising Chinese competition on their R&D expenditure.

First, we divide the observations into three groups by their profitability level observed in the initial year: high, mid, and low. We assign firms with zero or negative initial profitability to the low group and firms in the top five per cent of the distribution for the initial profitability to the high group. The rest of the firms are assigned to the mid group.[38] The low group accounts for roughly 25 per cent of the observations. Then, we estimate the R&D equation allowing for a different effect of ΔIP for each group. The regression results are reported in Table A4 in Appendix IV. We find that the coefficient for the low group is negative and statistically significant while those for the mid and high groups are not statistically different from zero.[39] In column 2, we also tried separating the sample into two group using the mean initial profitability as a cut-off (*i.e.* firms below and above the mean within period x 4-digit NAICS industry). We found that the coefficient for the group with profitability below the mean was negative and statistically significant while the other group was statistically insignificant.

As a second test, we carry out a similar exercise by separating the observations by the initial TFP level (measured as relative to the industry average). We separate them into two groups: firms below and above the mean initial TFP level. We find that the firms that were initially less productive scaled back their R&D investment while their better-performing counterparts did not respond – see column 4 in Table A4.[40] This is consistent with Melitz (2003) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005). The former suggests more productive firms are better positioned to benefit from increasing trade and the latter suggests increasing competition reduces the incentives to innovate for firms operating in highly competitive markets with technology gaps. Autor *et al.* (2017) also find that initially less profitable or less productive firms scaled back innovative effort by more than their better-performing counterparts.

[37] These results (both R&D expenditure and profit margins by size) are not driven by very small firm or "micro-firms" in our sample. We tried dropping increasingly larger "micro-firms" (*e.g.* firms with ALU<2, ALU<3, ALU<4 and so on) but the significance level and the sign of the coefficients remained the same. Also, the magnitude of the coefficients did not change significantly. We also tried including industry fixed effects since small firms tend to be in industries with large increases in Chinese import penetration ratio during our sample period (see Table A2 in Appendix IV). With the industry fixed effects, we still found that only small firms experienced declines in their R&D expenditure and profit margins due to rising Chinese import competition.

[38] We tried different cut-off values to assign firms into three groups but the qualitative results did not change.

[39] We carried out the same analysis for the profitability equation and found similar results. As another check, we also regressed Δln(R&D investment) on Δprofitability and found that increasing (decreasing) profitability is indeed associated with increasing (decreasing) R&D investment.

[40] We also tried separating the firms using different criteria (*e.g.* high - top 5%; low - bottom 25%; mid - the rest, which are reported in column 3 in Table A4 in Appendix IV) but the qualitative results that initially less productive firms scaled back their R&D investment in response to rising Chinese import competition did not change.

Moreover, based only on small firms, we estimated the R&D equation including the interaction term between ΔIP and the initial level of profitability and the initial level of TFP (measured as relative to the industry average), respectively. We found a negative coefficient for ΔIP and a positive coefficient for the interaction term. In other words, for a given increase in the Chinese competition, firms make a larger downward adjustment in their level of R&D expenditure over time if they initially faced a higher level of product market competition or if they were initially less productive.

In summary, smaller firms or firms initially operating in more competitive markets with technology gaps appear to be the ones most directly affected by increasing Chinese import competition. Declining profit margins indicates less room to finance R&D[41] and/or lower post-innovation rents implying it is optimal for them to scale down their expenditure on R&D if they survive. This mechanism is consistent with the theoretical model introduced in Aghion, Bloom, Blundell, Griffith, and Howitt (2005). The authors show that if competition is initially high, an increase in competition would most likely to reduce the incentives for the incumbents to innovate.[42] We conclude that the negative effect found at the aggregate level is mainly driven by the negative effect on small firms' ability and incentives to invest in R&D.

In contrast, profit margins of larger firms or firms initially operating in less competitive markets with relatively high levels of technology were not affected much by increasing Chinese competition, and hence, they made less or no adjustment in their R&D investment. These larger firms may have been mostly neck-and-neck competing incumbents (*i.e.* firms competing with each other with similar levels of technology) within their product markets but faced not much competition having less or no incentives to innovate.[43] Or if there were laggards they would quickly catch up the leaders but once they have caught up they would have been slow to innovate further given low competition. At equilibrium, there would be a larger fraction of neck-and-neck competing incumbents with not much innovation. Such initial state (or the competitiveness of the market for these firms) were not affected much when Chinese manufacturers entered the Canadian market so that the incumbent firms maintained the status quo which we have observed

[41] For example, Hall (1992) finds a positive elasticity of R&D investment with respect to cash flow controlling for other factors and that debt is not a preferred form of financing R&D. Her findings imply that R&D is financed out of free cash flow. Using cash flow is likely to be the main avenue to finance R&D since external financing may be costly due to asymmetric information between lenders and borrowers, which induces borrowers to finance risky innovation using debt (*e.g.* Myers and Majluf, 1984) or the existence of moral hazard, which leads lenders not to finance innovation through debt or some agency issues that arise when the interests of shareholders and managers are not aligned leading the managers to pay a premium for external financing (*e.g.* Jensen and Meckling, 1976).

[42] A larger decrease in pre-innovation rents relative to the decrease in post-innovation rents, the so-called "escaping-competition" effect (*i.e.* having incentives innovate to "escape" competition to gain market power) may not be at work for firms with initially low profitability with technology gaps and in direct competition with Chinese manufactures. Compared to them, emerging Chinese manufacturers were much more cost-effective so that the expected net reward for innovation would have been quite low (potentially lower than pre-innovation rents). It would have required these domestic firms to achieve a significant leap in the technology level to gain some market power over these Chinese manufacturers but such leap may have implied large investment which these small firms would have found unprofitable or could not afford with the declining profitability. In other words, increasing competition would have affected more the post-innovation rents for these firms (*i.e.* the basic Schumpeterian effect dominates).

[43] This would be true if the incumbents can collude but not so true if they are in Bertrand competition earning zero profit. The former is more likely to be the case for larger firms (*e.g.* oligopoly). Theoretically, the incentives to collude is negatively related to the degree of competition in the market.

in our data: no effect on their profitability (proxy for mark-up or competitiveness) and hence, not much adjustment in their innovative effort (*e.g.* R&D) in response to rising Chinese competition.[44]

Some large firms may have undergone industry-switching or reorganization such that they shift away from the physical production of goods towards "neuro-manufacturing" where they focus more on the design, engineering, and marketing of their goods or towards producing related professional services.[45] This may have spurred additional R&D investment within these large firms but this would be observed in our data only if their primary industry code did not change to non-manufacturing due to the shift of their economic activity.

Our results imply that firms accounting for a large share of the total R&D expenditure are not likely to reduce R&D in response to increasing Chinese import competition. A small number of medium-sized and large firms account for a disproportionately large share in the total R&D expenditure in Canadian manufacturing. These larger firms account for 14 per cent of the total observations but about 77 per cent of the total R&D expenditure in manufacturing.[46] Hence, the cumulative partial impact of the China shock on the aggregate R&D expenditure in manufacturing may be limited.

VI. Regression results: TFP, Employment, and Survival Equation

In order to assess the impact of China on the technical change in Canadian manufacturing in a broader perspective, we estimate its impact on TFP within Canadian manufacturing firms and on the employment and the survival of firms to assess potential reallocation effects. Using the estimates from these analyses, we carry out a TFP decomposition in section VII to estimate the share of the aggregate TFP change induced by increasing Chinese import competition.

1. Within-effect: TFP Equation

For estimation of firm-level TFP, we experimented with OLS and GMM for a dynamic panel data model introduced in Blundell and Bond (1998) (*i.e.* system-GMM). The choice of the estimation strategy depends on the availability of data and how the data satisfy the underlying assumptions for the chosen estimation strategy. We estimate a firm-level Cobb-Douglas production function by three-digit NAICS industry in manufacturing and use the estimated

[44] This is more likely to be the case for large firms or firms operating in a concentrated market. Medium-sized firms or firms facing the intermediate level of product market competition may have been affected by rising Chinese competition having more incentives to innovate. In the following section, these firms appear to have resorted to other types of productivity-enhancing activities while not scaling back their R&D in response to rising import competition.

[45] Some U.S. examples are Apple and IBM. Apple outsource its production to China and focus more on product development and producing related services in the United States. IBM sold their ThinkPad business line to Lenovo which produces ThinkPad laptops within China. IBM now produces professional services related to data management and system design.

[46] Medium firms (large firms) account for 11 (3) per cent of the total observations but 23 (62) per cent of the total R&D expenditure in manufacturing on average over the 2000-2012 period.

coefficients for inputs to retrieve estimates of firm-level TFP.[47] In this section, we report the results based on OLS as we could not find a completely satisfactory specification for GMM. We carried out all our analyses using firm-level TFP estimated with system-GMM and found that the results were very similar.[48] In Appendix III, we discuss in more detail different estimation strategies including semi-parametric approaches and our reasons for adopting OLS to estimate TFP in our study.

Table 3 reports the results from estimating the TFP equation as described in section IV. Note that, since our estimates are based on a TFP equation defined at the firm-level, we can only capture the within-effect of China on TFP. That is, the coefficient reflects only the TFP change within firms rather than the aggregate TFP change between firms or through inducing firms with different TFP levels to exit or enter markets. As with R&D, we find that increasing Chinese import competition reduces the TFP growth within manufacturing firms as indicated by the negative coefficient in column 1. The negative effect is robust to including industry fixed effects or including the firm-level controls introduced in column 5 in Table 1 or using the alternative instrument.

Table 3: TFP and Profit Equation, TFP Sample, 2SLS, Manufacturing, 2000-2012

	ΔIn(TFP)		ΔProfitability	
	1	2	3	4
ΔIP	-0.137***	-	-0.012***	-
	(0.023)		(0.004)	
ΔIP x initially small	-	-0.164***	-	-0.015***
		(0.024)		(0.004)
ΔIP x initially medium	-	0.140*	-	0.018
		(0.081)		(0.018)
ΔIP x initially large	-	0.063	-	0.003
		(0.111)		(0.012)
No. observations (firm x period)	241,054	241,054	223,886	223,886
No. firms	43,331	43,331	41,984	41,984

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Initial employment size is measured as the average labour unit (ALU) observed in the initial year (*e.g.* ALU in 2000 for the 2000-2005 sub-period). We define the three size groups based on the average labour unit (ALU) observed in the initial period: small (ALU<100); medium (100≤ALU<500); and large (500≤). Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit. *** $p<$ 0.01; ** $p<0$ .05; * $p<$ 0.10.

In most empirical studies, increasing competition is found to induce productivity gains within surviving firms. In response to increasing competition, firms would engage in innovation or other productivity-enhancing activities to remain in the market. Otherwise, they would choose to exit. However, the exact mechanism through which increased competition induces productivity gain within firms is not well understood. Some empirical studies examine what

[47] We also estimated a production function by two- and four-digit NAICS industry and carried out all the analyses. We found that the qualitative results remained the same.
[48] Again, we tried estimating production function using system-GMM by two- and four-digit NAICS industry and found the results did not change significantly.

changes within surviving firms to enhance their productivity.[49] However, as the theories discussed in section I imply, the empirical evidence on the effect of increasing competition on innovation is mixed. Some find positive effects (*e.g.* Bloom *et al.*, 2016; Gorodnichenko *et al.*, 2010; Iacovone, 2012a; Coelli *et al.*, 2016) while others find either no or negative effects (*e.g.* Hashmi, 2013; Autor *et al.*, 2016; Hombert and Matray, 2015; Gong and Xu, 2015; Brandt *et al.*, 2012; Gilbert, 2006; Arora *et al.*, 2015; Keung, Li, and Yang, 2016). The latter implies a potential negative effect on TFP growth within firms. Nevertheless, the studies that find negative effects on innovation (*e.g.* patents and R&D) do not study the effect on the aggregate productivity growth.

The negative within-effect reported in column 1 can be related to our finding based on the R&D sample: in response to rising import competition, initially smaller and poorly-performing firms experienced declining profit margins and scaled back their R&D effort over time. If similar firms that survived in manufacturing scaled back their overall innovative effort and/or did not resort to additional productivity-enhancing activities (*e.g.* better management), then their TFP growth would decline.

As is the case for the R&D sample, we find a negative effect of increasing Chinese import competition on profitability for the TFP sample (column 3 and 4). Importantly, we find that only small firms experienced a negative effect on their profitability while larger firms did not. We estimate the TFP equation by interacting ΔIP with the size indicator (defined based on ALU observed in the initial period) in column 2 in Table 3. Again, only small firms experienced a negative effect on TFP growth.[50] Medium-sized firms actually experienced productivity gain due to increasing Chinese import competition while we find no evidence that large firms' TFP growth was affected.

Medium-sized firms may have focused on other productivity-enhancing activities (*e.g.* better management practices or inventory controls) while not scaling back their R&D investment (if they have invested in R&D) to remain competitive in the market.[51] In contrast, large firms' effort to enhance productivity, if any, did not seem to have much effect on its TFP growth. Large firms are more likely to have monopolistic power having fewer incentives to engage in additional innovative activities in response to increasing market competition. We also estimate the TFP equation while splitting profitability and productivity level into two categories, below and above the mean, and find that the negative effect on TFP growth was mainly on less profitable and less productive firms – the results are reported in Table A5 in Appendix IV.

[49] See Holmes and Schmitz (2010) for a review of this literature.

[50] As is the case in our R&D analysis by size, these results are not driven by very small firm or "micro-firms". We carried out the same sensitivity test as described in footnote 37. Also, small firms tend to be in industries with large increases in the Chinese import penetration ratio (see Table A3 in Appendix IV). We tried including industry fixed effects and still found that only small firms' TFP growth and profit margins were negatively affected.

[51] As suggested in Holmes, Levine, and Schmitz (2008), falling opportunity cost of investment in a productivity-enhancing factor (*e.g.* better management) may have driven the firms' behaviour. When firms innovate, they are likely to forego or delay some output for some period of time (often called switchover disruptions). When competition rises, the market price is likely to decline implying smaller profit lost when investment is made and hence, lower opportunity cost of investment. A similar argument is the "trapped-factors model of innovation" suggested in Bloom, Romer, and Terry, and Van Reenen (2015), which is discussed in section I.

Similar patterns are observed in the R&D sample. In column 1 and 2 in Table 3-1, we report the results from estimating the TFP equation based on the firms that performed or purchased R&D at least once during the 2000-2012 period. We still find a negative effect of increasing Chinese competition on TFP growth within small firms only.[52] A key channel through which increasing Chinese import competition reduces TFP growth within these firms is likely to be its impact on R&D expenditure within firms.

R&D is a key input to innovation and hence, productivity gain. There is a large literature on estimating a firm-level production function or a TFP equation where R&D (owned internally) is a key explanatory variable.[53] The consensus in the literature is that R&D and productivity are positively related. Also, Doraszelski and Jaumandreu (2013) develop a model of endogenous productivity change and assess the effect of R&D investment on the productivity at the firm level. They find that R&D investment is a key factor in explaining the differences in productivity across firms and the evolution of firm-level productivity over time.

Table 3-1: TFP Equation, R&D Sample, 2SLS, Manufacturing, 2000-2012

	Baseline		Controlling for Δln(R&D expenditure)	
	1	2	3	4
ΔIP	-0.127*** (0.034)	-	-0.087 (0.146)	-
ΔIP x initially small	-	-0.177*** (0.040)	-	0.020 (0.155)
ΔIP x initially medium	-	0.057 (0.082)	-	0.005 (0.406)
ΔIP x initially large	-	0.115 (0.143)	-	-0.634 (0.124)
No. observations (firm x period)	85,342	85,342	25,064	25,064
No. firms	14,111	14,111	9,430	9,430

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Initial employment size is measured as the average labour unit (ALU) observed in the initial year (*e.g.* ALU in 2000 for the 2000-2005 sub-period). We define the three size groups based on the average labour unit (ALU) observed in the initial period: small (ALU<100); medium (100≤ALU<500); and large (500≤). Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit. In column 3 and 4, Δln(R&D expenditure) and its lags (τ-1 to τ-5) are included. Given our sample period, it is feasible to control for lags up to τ-7 but including further lags does not change the qualitative results. Δln(R&D expenditure) and its lags (τ-1 to τ-5) are jointly significant. *** p< 0.01; ** p<0 .05; * p< 0.10.

The above idea is further supported by the results from estimating the TFP equation (on the R&D sample) in which we control for R&D expenditure growth. The results are reported in column 3 and 4 in Table 3-1. When we control for R&D expenditure growth and its lags, increasing Chinese import competition has no statistically significant effect on TFP growth within firms (column 3). These findings suggest that the negative within-effect found in column

[52] Again, this is not driven by very small firms in our sample. See footnote 50.
[53] For example, see Hall, Mairesse, and Mohnen (2010), Lychagin *et al.* (2016), Bloom *et al.* (2013), and Kim and Lester (2019). Kim and Lester (2019) use the same database as this study (*i.e.* T2-LEAP-SRED).

1 is mainly driven by declining R&D expenditure induced by rising competition.[54] Further analysis by size in column 4 reveals that the China effect on small firms' TFP growth becomes insignificant when we control for R&D investment, indicating that small firms are not likely to have changed their effort in other productivity-enhancing activities in response to increasing Chinese competition.

2. Between-effect: Employment and Survival Equation

The effect of increasing Chinese imports on the overall TFP in Canadian manufacturing cannot be fully assessed with the within-effect. The aggregate TFP change also includes the change driven by the reallocation of resources. That is, increasing Chinese import competition may have reallocated employment or market share towards more productive firms or induced less productive firms to exit while inducing more productive firms to enter the market. These reallocation effects could be significant in driving the aggregate change in the TFP level in manufacturing.

In this section, we report the results from estimating the effect of increasing Chinese import competition on the employment growth and the survival of firms in manufacturing, particularly focusing on differential effects stemming from different initial technology levels of firms. We would like to study whether more technologically advanced firms are less likely to reduce employment and more likely to survive in response to increasing Chinese competition in the domestic market.

In Panel A of Table 4, we estimate the effect of China on the log change in employment but allow the effect to differ by the initial technology level by interacting ΔIP with the initial technology level. We use two proxies for the technology level: R&D capital stock and the TFP level.

First, we find that increasing Chinese import competition is associated with a lower employment growth. We also find that firms that were already technologically advanced are more likely to grow (in terms of employment) as indicated by the positive and statistically significant coefficient on the initial technology level. More importantly, the negative effect of increasing Chinese import competition on the employment growth is smaller the higher the initial technology level. This is shown as the positive and statistically significant coefficients on the interaction terms (column 2 and 4). These results indicate that high tech firms may have been "shielded" from the negative effect of increasing Chinese imports on employment. As the share of low tech firms in the total employment declines, it is possible that increasing Chinese competition had some positive effect on the aggregate technology level in manufacturing.

[54] We indeed find that R&D expenditure growth is positively related to TFP growth within firms. The coefficients on R&D expenditure growth and its lags are positive and statistically significant.

Table 4: Employment and Survival equation, 2SLS, Manufacturing

TECH variable:	R&D stock		TFP	
	Panel A: Employment equation			
Dependent: Δln(employment)	1	2	3	4
ΔIP	-0.136*	-1.253***	-0.289***	-0.294***
	(0.068)	(0.567)	(0.045)	(0.046)
ΔIP x Initial TECH	-	0.105***	-	0.381***
		(0.053)		(0.094)
Initial TECH	0.026***	0.022***	0.327***	0.310***
	(0.004)	(0.004)	(0.008)	(0.008)
No. observations (firm x period)	38,153	38,153	165,825	165,825
No. firms	9,628	9,628	37,042	37,042
	Panel B: Survival equation			
Dependent: *S*	1	2	3	4
ΔIP	-0.027***	-0.165	-0.033***	-0.032***
	(0.012)	(0.125)	(0.011)	(0.011)
ΔIP x Initial TECH	-	0.013	-	0.068***
		(0.011)		(0.021)
Initial TECH	-0.003*	-0.004*	0.048***	0.043***
	(0.002)	(0.006)	(0.005)	(0.004)
No. firms	6,937	6,937	32,861	32,861

Note: Period fixed effects are included in all columns. Standard errors are in parentheses. Δ denotes a 5-year difference. The dependent variable in Panel A is the log change in employment. The dependent variable in Panel B is *S* which equals one if a given firm survived the entire 2002-2007 period and zero otherwise. We use the average R&D stock and TFP level (measured as relative to the 3-digit NAICS industry average) observed in the initial and the two years prior to the initial year to mitigate potential measurement errors (*e.g.* average over the 2000-2002 period for the 2002-2007 period). Hence, the sample period is 2002-2012 for Panel A and 2002-2007 for Panel B. R&D stock is divided by employment. Similar results are found when we use R&D stock divided by sales. Both technology variables enter the equation in logs. *** $p< 0.01$; ** $p<0.05$; * $p< 0.10$.

Next, we estimate the survival equation. For the survival analysis, we focus on a cohort of firms that was alive in a given initial year. We model the probability of their survival following these firms for five years. Our sample period in this analysis is 2002-2007 since we use as a measure of initial technology level the average R&D stock or the average TFP level (measured as relative to the 3-digit NAICS industry average) measured based on the initial and the two years prior to the initial year to mitigate potential measurement errors. We continue to base our analysis on a 5-year sub-period to be consistent with the other analyses in the paper.

The results reported in Panel B of Table 4 indicate that firms in industries with larger increases in the Chinese import penetration ratios are less likely to survive (or more likely to exit). A one-percentage-point increase in the penetration ratio is associated with a decrease in the survival probability of 0.027 to 0.033 percentage points according to column 1, 3, and 4 in Panel B.[55] Again, we find that more technologically advanced firms (as proxied by the average TFP level) are "shielded" from the negative effect of increasing Chinese imports as indicated by the

[55] Note that the mean exit rate of this cohort is 6.1 per cent for the 2002-2007 period. Using the mean ΔIP and initial technology level, our estimates in column 4, for example, represent roughly 18.5 per cent increase (or 1.23 percentage-point-increase) in the mean exit rate.

positive and statistically significant coefficient on the interaction terms in column 4.[56] Our regression results imply that increasing Chinese import competition in Canada may have positively contributed to the aggregate TFP in manufacturing by inducing less productive firms to exit.[57]

These findings are consistent with Bernard *et al.* (2006) and Bloom *et al.* (2016) where the authors show similar results for the U.S. and the European manufacturing firms and establishments. Also, Hombert and Matray (2017) find that more R&D-intensive firms experienced much less negative effects on their employment when Chinese import competition rose in the United States. Our findings in this section are broadly consistent with theirs.

VII. Quantifying the Role of China

Using the results from our regressions, we contextualize the findings to provide a broad picture of the role of China in driving the technical change in Canada. We would like to ask: *for a given period, how much of the total change in real R&D investment and the TFP level in Canadian manufacturing can be explained by increasing Chinese import competition?*

1. R&D Expenditure

We calculate the predicted change in the aggregate R&D expenditure driven by increasing imports from China as follows:

$$(7)\quad \widehat{\Delta R\&D}_{\tau}^{China} = \sum_i \beta^{R\&D} * \widetilde{\Delta IP_{j,\tau}} * R\&D_{i,j,0}$$

where $\beta^{R\&D}$ is the marginal response of R&D expenditure growth with respect to an increase in Chinese import penetration ratio and $\widetilde{\Delta IP_{j,\tau}}$ is the exogenously-driven change in the Chinese import penetration ratio for manufacturing sector j over period τ. We estimate $\widetilde{\Delta IP_{j,\tau}}$ by discounting the actual $\Delta IP_{j,\tau}$ by the R-squared from the first stage regression. $R\&D_{i,j,0}$ is the actual level of R&D expenditure for firm i in sector j at the start of period τ.

According to our sample from the T2-LEAP-SRED database covering incorporated firms in manufacturing, real expenditure on domestically performed R&D increased by 21.5 per cent between 2000 and 2005 but declined by 19.3 per cent between 2005 and 2010. Real R&D expenditure in manufacturing increased annually between 2000 and 2005 except for the 2001-2002 period (declined by 1.72 per cent) while it declined continuously year over year for the 2005-2010 period.

[56] When R&D stock is used to proxy the initial technology level (column 2), we find the coefficient on the interaction term is insignificant but positive.

[57] Our sample and the estimates imply that increasing Chinese imports decreased the exit rate of high tech firms and increased the exit rate of low tech firms. For example, based on the estimates from column 4 and the mean ΔIP and initial TFP level observed for the 2002-2007 period, the firms in the top 30 per cent of the initial TFP level distribution have a predicted mean exit rate of 2.4 per cent which is lower than their actual mean of 3.9 per cent while the firms in the bottom 30 per cent have a predicted mean exit rate much higher than their actual mean rate (13.2 per cent vs.9.4 per cent).

Table 5 reports the change in real R&D expenditure induced by increasing Chinese import competition for the 2000-2005 and 2005-2010 period, respectively. The estimates are based on the size-specific coefficients from column 1 in Table 2.[58] First, we estimate that increasing Chinese import competition led to a decline of $98 million CAD in R&D expenditure between 2000 and 2005. For this period, R&D expenditure in manufacturing increased by $1,220 million CAD. Had there been no increase in Chinese import competition, R&D expenditure would have increased by about 8 per cent more (*i.e.* $1,318 million instead of $1,220 million). This counterfactual translates into a growth rate of 23.2 per cent between 2000 and 2005, a 1.9 percentage-point-increase from the actual growth rate of 21.5 per cent.

Between 2005 and 2010, R&D expenditure in manufacturing fell by $1,360 million CAD. Our estimates imply that China can explain about 6.5 per cent of the total decline for this period. Or the decline in R&D expenditure in manufacturing would have been 6.5 per cent lower had there been no change in Chinese import competition in Canada. We estimate that $89 million CAD of the total decline of $1,360 million CAD was driven by increasing Chinese import competition. This implies that if the Chinese import penetration ratio did not change between 2005 and 2010, R&D expenditure in manufacturing would have fallen by 18.0 per cent instead of 19.3 per cent.

Table 5: Change in R&D Expenditure due to China, Manufacturing, Millions of 2007 CAD, 2000-2010

	2000-2005
(1) R&D expenditure in 2000	5,670
(2) Actual change	1,220
(3) Actual % change	21.5%
(4) Induced change in R&D due to China	-98
(5) Counterfactual change in R&D (2 - 4)	1,318
(6) Counterfactual % change (5/1)	23.2%
	2005-2010
(1) R&D expenditure in 2005	7,060
(2) Actual change	-1,360
(3) Actual % change	-19.3%
(4) Induced change in R&D due to China	-89
(5) Counterfactual change in R&D (2 - 4)	-1,271
(6) Counterfactual % change (5/1)	-18.0%

Note: Estimates are computed based on the coefficients reported in column 1 in Table 2. R&D expenditure includes only domestically performed R&D in manufacturing.

[58] We carried out the same calculations assuming only small firms adjusted their R&D in response to rising Chinese import competition. We found that the role of China in explaining the total change in R&D falls roughly by a half. We also tried using the aggregate coefficient from column 2 in Table 1. With this, in an increase in the role of China by roughly 80 per cent. The former is potentially a lower bound since we assume all medium-sized and large firms did not adjust their R&D. The latter is potentially an upper bound since we impose the larger aggregate coefficient (driven mainly by small firms) on all firms in our sample.

2. TFP

To assess the role of increasing Chinese imports in driving the aggregate TFP in Canadian manufacturing, we carry out a standard productivity decomposition using the estimates from Equation (1), (2), (4), and (5) following a similar decomposition methodology introduced in Baily, Hulten, and Campbell (1992), Foster, Haltiwanger, and Krizan (2000), and Bloom *et al.* (2016):

(8) $\Delta \mathrm{P}_t = \sum_{i=1}^{N} s_{i,0}\left(p_{ijt} - p_{ij0}\right) + \sum_{i=1}^{N} p_{ij0}(s_{it} - s_{i0}) + \sum_{i=1}^{N}(s_{it} - s_{i0})\left(p_{ijt} - p_{ij0}\right) -$
i∈exitsi0exitpij0exit−pj0+i∈entrantsitentrantpijtentrant−pjt

where P_t denotes the aggregate TFP level at a given point in time t. $\Delta\mathrm{P}_t$ represents the aggregate change in TFP between time 0 and t. $s_{i,t}$ denotes the employment share of firm i at time t (*i.e.* firm employment divided by total employment in manufacturing).[59] $\bar{p}_{jt}$ is the average TFP of all firms in sector j at time t. N is the total number of firms in manufacturing.

The first term in Equation (8) is the within-firm effect which is the change in TFP level holding employment shares constant. The second term is the between effect, the change in TFP level due to shifting employment from less productive firms to more productive firms holding the initial productivity level constant. The third term is the cross effect which is simply the correlation between the change in TFP level and the change in employment share within firms. The second last term is the exit effect which represents the change in TFP level due to firm exits. The last term represents the entry effect. The contribution of entrants and exitors depends on entering or exiting firms' p_i relative to the average p_i of the incumbents.

We explicitly model each term in Equation 8 (except for the entry effect). Following Bloom *et al.* (2016), we can re-write Equation 8 in terms of our estimates from Equation 2, 4, and 5. Using our estimates from TFP, employment, and survival equations, we have:

(9) $\Delta P_t^{China} = \sum_{i=1}^{N} s_{i,0}\left(\beta^{TFP}\Delta IP_j\right) + \sum_{i=1}^{N} p_{ij0}({s_{it}}^{between} - s_{i0}) + \sum_{i=1}^{N}({s_{it}}^{between} -$
si0βTFPΔIPj−i∈exitsi0exitpij0exit−pj0

where β^{TFP} is the coefficient from Equation 2. ${s_{it}}^{between}$ is the predicted share of employment for incumbent firms and s_{i0}^{exit} is the predicted share of employment in exiting firms as defined in the following.

$$ {s_{it}}^{between} = \frac{N_{i0}(1 + \beta^N \Delta IP_j + \lambda^N \Delta IP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1 + \beta^N \Delta IP_j + \lambda^N \Delta IP_j p_{ij0})} $$

where β^N and λ^N are the coefficients from Equation 4. N_{i0} is the employment level in firm i at time 0.

[59] Output shares could be used as weights in TFP decomposition. We adopt labour shares as weights in our decomposition given our econometrics framework based on Bloom *et al.* (2016).

$$s_{i0}{}^{exit} = \frac{N_{i0}(1 - \beta^S \Delta IP_j - \lambda^S \Delta IP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1 - \beta^S \Delta IP_j - \lambda^S \Delta IP_j p_{ij0})}$$

where β^S and λ^S are the coefficients from Equation 5.

Finally, we can compute the magnitude of each component in Equation 9 by computing the ratio $\frac{\Delta P_t^{China}}{\Delta P_t}$ where ΔP_t is the actual change in the aggregate TFP level in manufacturing over the period 0 - t.

We cannot directly quantify the entry effect at the firm-level as it is not possible to observe their lagged technology levels (*i.e.* technology level of a given firm before entry).[60] Therefore, we implicitly assess the magnitude of the entry effect by estimating an industry-level version of Equation 2 and compare its coefficient (*i.e.* β^{TFP}) with the corresponding firm-level coefficients.[61]

According to the CPA data covering the 1990s, TFP in Canadian manufacturing grew rapidly during the 1990s before it stabilized from the early 2000s. The aggregate TFP level did not change much between 2000 and 2005. However, the TFP level started to decline substantially after 2005 until it recovered shortly after the recession following the financial crisis in 2007. Between 2005 and 2010, the TFP level in Canadian manufacturing fell by 5.90 per cent according to the CPA data or 5.43 per cent according to our estimates from the T2-LEAP-SRED database.

Table 6 reports the results from our productivity decomposition focusing on the period 2005-2010.[62] Note that the magnitudes are presented as a share of the actual *decline* in the aggregate TFP level in manufacturing between 2005 and 2010. Hence, a negative (positive) sign implies that increasing Chinese import competition has positively (negatively) affected the total change in the TFP level.

[60] This is a well-known empirical issue in decomposing productivity using firm-level data. Note that it is not appropriate to use the technology level at the time they enter as it is likely to be endogenous. This is similar in nature to a problem often found in empirical labour economics where researchers cannot observe the reservation wage and wage offers of a given worker prior to employment. What we observe in data is the final wage offer accepted by a worker since the offer was greater than his or her personal reservation wage. The wage would probably be correlated with unobserved characteristics of that worker which may have affected his or her decision for entry.

[61] The rationale is that, if Chinese import competition had discouraged entry of innovative firms, then our firm-level results would overestimate the effect of China on productivity performance in manufacturing. Note that industry-level coefficients reflect the combination of within, between, and entry effects.

[62] We also analyzed the 2000-2005 period and the qualitative results were the same -- as is the case for the 2005-2010 period, the sum of the between- and exit-effect was positive and more than offset the negative within-effect. However, the impact of China was not economically significant. The magnitude of the role of Chinese imports for this period was much lower than that estimated based on the 2005-2010 period. Also, the actual TFP growth between 2000 and 2005 was very small (*e.g.* 0.42 per cent based on the CPA data or 0.02 per cent based on the T2-LEAP-SRED database). Our estimates from the decomposition exercise imply that increasing Chinese import competition explains less than 2 per cent of the total increase in the TFP level in manufacturing for this period.

We find that the TFP level declined within manufacturing firms between 2005 and 2010, negatively affecting the aggregate TFP level in manufacturing.[63] We estimate that the within-effect driven by increasing Chinese import competition can explain roughly 5 per cent of the total decline in the TFP level in Canadian manufacturing. However, as hinted by our estimates from the employment equation, there were substantial gains in the aggregate TFP level through the reallocation of resources. In response to increasing Chinese import competition, employment shifted from less productive firms to more productive firms, positively contributing to the aggregate TFP change in manufacturing. Also, less productive firms exited the market although the overall impact on TFP is relatively small. The extent of decline in the TFP level would have been greater by roughly 21 per cent (17.1 plus 3.9) had there been no reallocation effect driven by increasing Chinese import competition. Such effects were large enough to more than offset the negative within-effect, resulting in a net positive effect of China on the aggregate TFP change between 2005 and 2010. That is, had there been no increase in Chinese import competition in Canada, the per cent change in the aggregate TFP level would have been -6.31 per cent instead of -5.43 per cent between 2005 and 2010 (or -1.26 per cent per year instead of -1.09 per cent per year).[64] As is often the case in other empirical studies, the cross-effect is negligible.

Table 6: Change in TFP due to China, Manufacturing, 2005-2010

	As a % of the *decline* in the TFP level between 2005 and 2010
Within (-)	5.4%
Between (+)	-17.1%
Exit (+)	-3.9%
Cross (+)	0.0%
Total (+)	**-15.6%**

As discussed, our firm-level estimates do not include the entry effect. To assess the entry effect indirectly, we estimate the TFP equation at the 4-digit NAICS industry level. Since the industry-level measure reflects the behaviour of both entrants and incumbents, its regression estimate would include not only the within- and between-effect but also the entry effect. Since the between effect is estimated to be in the opposite direction and larger in the absolute terms than the within-effect, we expect the estimate to be either less negative than the firm-level coefficient or positive. If the former is the case, then the entry effect is negative and substantial enough to offset the positive between-effect. If the latter, the entry effect is either negative but not offsetting the net effect of between- and within-effect or is positive.

Our industry-level regression has a coefficient of roughly 0.359 which indicates that increasing Chinese import competition has a net positive effect on TFP in manufacturing. Using the shares reported in Table 6, one can compare the industry-level estimate with the firm-level estimate (-0.137) and presume that the entry effect is positive (*i.e.* increasing Chinese

[63] For the within-effect, we use the coefficient reported in column 1 in Table 3. If we use the size-specific coefficients reported in column 2, the within effect becomes positive (a positive contribution to the overall TFP change) but the absolute per cent level is nearly zero, increasing the total impact by about 6 percentage points. Hence, one may conclude that the within effect is either negative but relatively small or zero.

[64] Or -6.82 per cent instead of -5.90 per cent (or -1.36 per cent per year instead of -1.18 per cent per year) based on the CPA data.

competition induced technologically-advanced firms to enter the market) but its magnitude is potentially small.[65] A back-of-the-envelope calculation shows that the entry effect adds about 2.5 percentage points to the total magnitude of the effect of increasing Chinese import competition (*i.e.* 18.1 per cent instead of 15.6 per cent). A key implication is that the total effect reported in Table 6 could be an underestimate.

Our estimates imply that the reallocation of resources appears to be the main channel through which rising import competition raised the overall productivity performance in Canadian manufacturing. The within effect is negative but potentially small since the effect was pronounced in small firms which tend to be less productive in the initial period.

Our results are consistent with other empirical studies on assessing the impact of trade or trade liberalization on the aggregate productivity performance in the domestic economy in that the productivity gain from the reallocation effect (*i.e.* between effect) is larger than the within effect. For example, Pavcnik (2002) estimates the effect of trade liberalization on productivity at the plant-level in Chile and finds that the between-effect accounts for 12.7 per cent of the total increase in the aggregate productivity while the within-effect accounts for 6.6 per cent. However, our finding that the within-effect is negative (or potentially zero – see footnote 63) is not consistent with Pavcnik (2002) and some other empirical studies. For example, Bloom *et al.* (2016) finds a positive within-effect induced by increasing Chinese import competition in European countries and its magnitude is as large as their estimated (positive) between-effect. However, de Loecker (2011) finds that the productivity gains within firms from trade liberalization (as measured by the abolishment of quota protection for the Belgian textile manufacturers) is positive but the effect is relatively small or sometimes negligible. He finds that trade liberalization led to productivity gains mostly through inducing less productive firms to exit the market.

VIII. Conclusion

Utilizing as a natural experiment the rapid increase Chinese import share in the total domestic absorption in Canadian manufacturing, we find that rising Chinese import competition led to declines in R&D expenditure and TFP within firms. Especially, the declines in R&D and TFP were pronounced in smaller, less profitable, and less productive firms. We find evidence that the profit margins of these smaller and poorly-performing firms declined due to rising import competition. Since firms tend to finance innovation using internal cash flows rather than costly external financing, a larger reduction in R&D and TFP for these firms can be explained by the shrinking room to finance R&D and other innovations. Or in a different perspective, these firms already operated in highly competitive product markets and an increase in competition may have reduced more the post-innovation rents than the pre-innovation rents (*i.e.* the basic

[65] To do so, first notice that, according to Table 6, the ratio of the total within and between-effect to the between-effect is 0.565 and our estimated firm-level coefficient is -0.137, which presumably represents only the within-effect. Hence, the implied coefficient representing the sum of the within- and between-effect is about 0.297 which can be compared against our estimated coefficient at the industry level (0.359) representing the within-, between-, and entry-effect. One can carry out a similar back-of-the-envelope calculation to infer the implied share of the entry effect discussed in the following sentence in the main text. These calculations are rough but show a key implication of our industry-level estimate on the entry effect.

Schumpeterian effect dominates for these firms). It also appears that these firms may not have resorted to additional productivity-enhancing activities other than R&D (*e.g.* better management practices or inventory controls) to remain competitive in the market, resulting in lower TFP growth. We find evidence that, in response to rising import competition, some larger firms did engage in productivity-enhancing activities other than R&D to remain competitive in the market and hence, their TFP improved.

We estimate that rising Chinese import competition accounts for about 7 per cent of the total decline in the real R&D expenditure in Canadian manufacturing between 2005 and 2010. Rising import competition reallocated employment towards more productive firms and drove less productive firms out of the domestic market. We find that the reallocation of resources plays an important role. We estimate that, had there been no increase in Chinese import competition between 2005 and 2010, the actual decline in the TFP level in Canadian manufacturing would have been 16 per cent greater for this period. In other words, the aggregate TFP level in manufacturing would have declined by 1.26 per cent per year instead of 1.09 per cent per year. This implies that the positive between- and exit-effects more than offset the negative within-effects on TFP. The negative within-effect is potentially small as the effect was pronounced mostly in smaller firms which tend to be less productive in the initial period.

Our findings imply rising Chinese import competition had evident distributional effects on firms' innovation and their outcomes (*i.e.* TFP, employment, survival). Given these effects, a further discussion on appropriate policy responses to trade liberalization would be desirable.

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Appendix I: Constructing Firm-Level R&D Capital Stock

In our analysis, we need estimates for R&D capital stock at the firm-level (see equation 4 and 5 in section IV). To construct a time series for R&D capital stock for each firm, we first need to estimate their initial R&D capital stock (*i.e.* R&D capital stock in 2000). This is a difficult task since the perpetual inventory method which is the usual approach in the literature is not best suited to firm-level data. Therefore, researchers need to make a series of adjustments in the methodology to avoid undesirable properties. For example, it may result in negative capital stock if firm-level equilibrium growth rates are estimated to be negative and larger in the absolute value than the assumed depreciation rate. If their absolute values are smaller but very close to the depreciation rate, then the R&D stock would be extremely large.

To estimate the initial R&D stock, we start with equation (1A)[66]:

$$(1A) \quad K_{i2000} \approx \frac{\bar{I}_i}{g_i^* + \partial_i}$$

where $\bar{I}_i$ and g_i^* are the equilibrium level and growth rate of R&D investment for firm i. ∂_i is the depreciation rate for R&D stock – we assume 15 per cent for all firms.

To better estimate firm-level R&D stock, we follow the algorithm developed by Kim and Lester (2019). They make a series of adjustments to the usual perpetual inventory method to prevent negative and implausibly large values for R&D capital stock.[67]

First, we use a modified version of equation (1A) for firms born between 1985 and 1999 since they would have a shorter period of R&D investment than firms born before 1984 – T2-LEAP covers incorporated firms born in 1984 or after.[68] Equation (1A) is appropriate for firms that perform R&D consistently and have existed for long enough so that their earlier investment is fully depreciated by 2000.[69] We also make adjustments for intermittent R&D performers and firms that stop performing R&D before 2012. The average annual growth rates for these firms are more likely to take a negative or a positive but extreme value, compared to continuous performers, which would lead their initial R&D stock to take a negative or a very large positive value (see equation 1A).[70]

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[66]Equation 1A is derived based on the assumption that the growth rate of the R&D capital stock can be approximated by the growth rate of R&D investment.

[67]If we apply the standard perpetual inventory method to our data without any adjustment, we are left with a non-negligible number of observations with negative or implausibly large values for R&D capital stock.

[68] We use a standard formula for the future values of a time series growing at a constant rate (g_i^*) for n periods. That is, $K_{i2000} = \bar{I}_i/(1+g_i^*)^n \left[\frac{(1-\partial)^n-(1+g_i^*)^n}{-\partial-g_i^*}\right]$.

[69] For example, the value of R&D performed in 1984 would have been depreciated by roughly 93 per cent by 2000 with our assumed depreciation rate.

[70]For non-continuous R&D performers, we calculate the average annual growth rate excluding increases in R&D from zero and/or decreases to zero. For all firms, we set a floor for the average annual growth rate of -8.3%, which is the 2000-12 average annual growth rate based on the change in R&D investment from 2000 to 2012 (*i.e.* -100%/12) for a firm that performs R&D in 2000 but not in 2012.
the 2000-12 average annual growth rate based on the change in R&D investment from 2000 to 2012 (*i.e.* -100%/12).

For $\bar{I}_i$, we use firm-level sample averages in R&D investment. g_i^* is estimated based on the James-Stein estimator (JSE) which, in theory, results in lower mean squared errors compared to MLE (*i.e.* using sample averages). The estimator relies on "shrinking" the mean values of growth to a point chosen based on prior notions of the true equilibrium growth rate.[71]

For g_i^*, we implement JSE based on the following equation:

$$\text{(2A)}\ g_i^* = \bar{g} + c_i(g_i - \bar{g})$$

where g_i^* represents our estimate of the equilibrium growth rate in R&D investment for firm i; $\bar{g}$ is the shrinkage point; g_i is the average annual growth rate from 2000 to 2012 for firm i; and c_i is the shrinkage factor[72]:

$$\text{(3A)}\ c_i = \left(1 - \frac{(n-3)\sigma_i}{\sum_{i=1}^{n}(g_i - \bar{g})^2}\right)^+.$$

where *n* is the number of firms and σ_i is the standard deviation in annual growth rates for firm i:

$$\text{(4A)}\ \sigma_i = \frac{1}{T_i}\sum_{t=1}^{T_i}(g_{it} - g_i)^2$$

where T_i is the number of years firm i has a non-missing annual growth rate in R&D investment.

Equation 3A and 4A imply that c_i would differ across firms, varying inversely with the standard deviation of annual firm-level growth rates. A large standard deviation indicates a high degree of uncertainty in our measurement. Therefore, we attribute any large measurement more to random deviations than to a genuinely large equilibrium rate.[73]

We tried various shrinkage points and evaluated their performance by comparing the resulting estimate of the aggregate R&D stock in 2000 with that based on official surveys of R&D spending at Statistics Canada (*i.e.* RDCI). This experiment led us to use as the shrinkage point the average growth rate in 4-digit NAICS industry-level R&D investment.[74] The estimate of the aggregate 2000 R&D stock was very close to our benchmark 2000 estimate based on the

[71] See Stein (1956), James and Stein (1961), and Efron and Morrison (1973, 1977).
[72] Note that the shrinkage factor can take a negative value for some firms. Hence, we use the positive-part James-Stein estimator which is a JSE-dominating estimator (*i.e.* it performs better than the standard JSE based on some decision rule such as mean squared errors) – see Baranchik (1964). This modification involves simply limiting the shrinkage factor to be non-negative.
[73] See Efron and Morris (1977) for a similar treatment applied to their analysis on the distribution of the disease toxoplasmosis in El Salvador at the city-level.
[74] It may not be correct to specify a single shrinkage point for *all* firms. It is possible that equilibrium rates are heterogeneous across industries. Therefore, we establish our prior notion that the equilibrium growth rate in R&D investment can be related to the industry in which a given firm operates. Specifically, we define the shrinkage point and the shrinkage factor for each firm using statistics defined based on the firm's 4-digit NAICS industry (*i.e.* n_k and $\bar{g}_k$ where k denotes 4-digit NAICS industry). We tried different NAICS levels but the qualitative results were the same.

aggregate RDCI data.[75] Using other shrinkage points such as the average of all firm-level average growth rates following Efron and Morris (1977) resulted in the aggregate R&D stock in 2000 far below the estimate based on the RDCI data. We also experimented with various maximum likelihood methods (*i.e.* using sample means) but their performance was unsatisfactory.

We refer the readers to Kim and Lester (2019) for more detailed description and analysis of the methodology.

[75] Our benchmark 2000 R&D stock is adjusted for the fact that our estimate based on the T2-LEAP-SRED database does not include R&D performed by firms that drop out prior to 2012.

Appendix II: Firm heterogeneity in the China shock effect on R&D expenditure

In this section, we explore whether firms with certain characteristics face differential effects of increasing Chinese import competition. First, we examine whether the effect differs by the country of control. Specifically, we analyze whether domestically-controlled firms respond differently than foreign-controlled firms. Second, in Canada, small (in terms of profit and tangible capital stock) and domestically-controlled firms receive enhanced SR&ED tax credits (*i.e.* higher subsidy rates). We examine whether different subsidy rates lead to different firm-level responses to increasing Chinese import competition. Third, we study whether there is any difference between start-ups (defined as firms that are less five years old) and established firms.

Table A1: R&D Equation, 2SLS, Manufacturing, 2000-2012

	1	2	3
ΔIP x domestically controlled	-1.084**	-	-
	(0.459)		
ΔIP x foreign controlled	-1.808***	-	-
	(0.620)		
ΔIP x enhanced recipients	-	-0.987**	-
		(0.478)	
ΔIP x regular recipient	-	-1.982***	-
		(0.616)	
ΔIP x start-up	-	-	3.353**
			(1.433)
ΔIP x established firm	-	-	-1.528***
			(0.419)
No. observations (firm x period)	112,821	112,821	112,821
No. firms	16,664	16,664	16,664

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. We include fixed effects for size groups, foreign controlled, enhanced tax credit recipients, and start-ups.
*** $p< 0.01$; ** $p<0.05$; * $p< 0.10$.

In column 1 in Table A1, we interact ΔIP with the indicator variable for the foreign and domestically-controlled firms. Our results indicate the effect of increasing Chinese import competition on the R&D investment growth is greater for foreign-controlled firms than for domestically-controlled firms although we cannot reject the null hypothesis that they are the same in magnitude. Since most of our observations are domestically controlled (95.4 per cent of the total observations), the aggregate estimate (column 2 in Table 1) is close to that for domestically controlled firms. However, we note that the large marginal impact on foreign-controlled firms is potentially important in explaining the total decline in R&D expenditure in manufacturing. Despite the small number of foreign-controlled observations in our sample (4.6 per cent of the total observations), on average over the 2000-2012 period, they account for 24.3 per cent of the total R&D expenditure in manufacturing.

In response to increasing foreign competition in the domestic market, firms may choose to reduce their R&D performed domestically especially if their R&D interacts with the production process (*e.g.* production design and process innovation).[76] It may cost less for foreign-controlled firms to adjust their domestic R&D activity by relocating their research effort abroad (if they operate production facilities in other countries) or make use of R&D performed abroad if they own any research lab in countries other than Canada.[77] Hence, we observe a larger marginal adjustment in domestic R&D investment for foreign-controlled firms in response to an increase in Chinese import competition.

Second, it would be interesting to examine whether R&D investment within firms eligible for higher subsidy rates is differentially affected by rising Chinese import competition. In Canada, small firms are eligible for enhanced credits for their R&D expenditure.[78] For example, combined federal and provincial tax-based subsidy rate for the enhanced credit recipients was higher than that for regular recipients by roughly 19 percentage points on average over the 2010-2012 period (see Kim and Lester, 2019). A high subsidy rate (hence, a lower required rate of return on R&D) for smaller firms may "shield" them from rising Chinese competition, alleviating the negative effect on innovation. If so, such innovation policy targeting small firms would be complementary to trade liberalization since we find in the main text that only small firms scaled back their R&D in response to rising import competition.

According to column 2, both the enhanced and regular recipients scale back their R&D expenditure in response to an increase in the Chinese import competition in Canada. However, the marginal response of the regular recipients is larger than that for the enhanced credit recipients. Although we cannot reject the null hypothesis that the two coefficient are the same with a p-value of 0.202, this implies that a higher subsidy rate may play a role in alleviating the negative impact of Chinese imports on R&D expenditure.

The response of start-ups is potentially important for technical change in the overall economy as there is some empirical evidence that R&D performed by start-ups tends to generate much greater technology spillovers to the rest of the economy than that by established firms.[79] Hence, the response of start-ups is potentially important in assessing the overall effect of Chinese imports on the aggregate technical change in Canadian manufacturing.

In column 3, we report the results from estimating the R&D equation allowing separate coefficients on ΔIP for start-ups and established firms. We find evidence that start-ups increased their expenditure on R&D in response to an increase in the Chinese import competition. Start-ups are likely to be in the product development stage. So, innovation tends to be the main activity for start-ups especially venture-capital-funded ones. Rising imports from China may mean expanding future opportunities for them in the product market rather than competition. Or

[76] See for example, Pisano and Shih, 2012, Fuchs and Kirchain (2010), and Branstetter, Chen, Glennon, Yang, and Zolas (2017).
[77] Note that our data include only domestically performed R&D.
[78] Eligibility for the enhanced credit depends on the amount of R&D expenditure, profits and assets. The eligibility criteria changed over time. For example, in 2012, the maximum amount of R&D expenditure eligible for the enhanced credit was $3 million CAD, which reduced to zero as taxable income increased from $500,000 to $800,000 and as assets increased from $10 million to $50 million.
[79] See, for example, Kortum and Lerner (2000) and Schnizer and Watzinger (2014).

rising Chinese competition in within 4-digit NAICS industries could be correlated with expanding opportunities in the domestic market for start-ups and new entrants from abroad. Hence, the incentives for start-ups to complete their product development and/or to improve their product development may have increased, leading them to scale up their R&D expenditure. Also, they could have learned from competitive Chinese manufacturers entering the domestic market about new production processes or new materials. This may have spurred additional R&D complementary to their existing R&D.

Appendix III: Estimating TFP at the Firm Level

We first assume output is a function of inputs employed and the firm's productivity. Then, we measure TFP for this firm as the residuals from the functional relationship between output and input. In this paper, we adopt a Cobb-Douglas production function to define such relationship. The exact functional form depends on the estimation methodology we employ. The baseline form is given as follows:

(5A) $Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l}$

where Y_{it} is output measured as real value added for firm i at time t. K_{it} and L_{it} are real tangible capital stock and labour input (measured as average labour unit) employed by firm i at time t. A_{it} is the Hicksian neutral efficiency level of firm i at time t, which is unobservable to the econometrician.

Taking natural logs leads to a linear production function:

(6A) $y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + v_{it} + u_{it}$

where lower-case letters represent natural logarithms and we define $\ln(A_{it}) = \beta_0 + v_{it} + u_{it}$.

We assume that A_{it} can be decomposed into the mean efficiency level across firms (β_0) and firm- and time-specific deviation from the mean observable to firms (v_{it}) and unobservable to firms (u_{it}). We denote the log of firm-level productivity (or TFP) as $w_{it} = \beta_0 + v_{it}$. Following Olley and Pakes (1996), we identify the productivity term by w_{it}assuming that w_{it} is a state variable that affects firms' production decision. u_{it} is an *i.i.d.* component, reflecting unpredictable deviations from the mean due to external factors (*e.g.* unexpected delays in the delivery of intermediates) or measurement error.

Hence, we estimate w_{it} as follows:

(7A) $\widehat{w_{it}} = \widehat{\beta_0} + \widehat{v_{it}} = y_{it} - \widehat{\beta_k} k_{it} - \widehat{\beta}_l l_{it}$

where we retrieve firm-level TFP in levels by exponentiating $\widehat{w_{it}}$.

There are several empirical issues in estimating a firm-level production function. First, v_{it} and input choices are likely to be positively correlated (simultaneity bias), resulting in biased input coefficients which would bias our TFP estimates.[80] Also, in practice, we deflate nominal values for output and input by industry-level price indices in the absence of firm-level price information. However, if input choice is correlated with firm-level price variation in the presence

[80] Endogeneity arises since firms could have prior knowledge of v_{it} when they make decisions on inputs. A positive (negative) shock to productivity would lead firms to increase (decrease) the amount of variable input employed – upward bias in the input coefficient. The direction of bias for fixed or quasi-fixed inputs (*e.g.* tangible capital) is difficult to assess. Levinsohn and Petrin (2003) suggest that the coefficient for tangible capital is likely to be biased downward if there is a positive correlation between labour and tangible capital.

of imperfect competition, then using industry-level price deflators will result in biased input coefficients and hence, biased TFP estimates. Lastly, there is a number of firms that produce more than one type of product (*i.e.* multi-product firms). Then, estimating a production function at the firm-level would lead to biased TFP estimates since we are assuming identical production technology and identical final demand (since we use the common price deflator for output) across products of a given firm.

We cannot resolve all the issues summarized above due to the limitation on empirical strategies and on our data. Various estimation strategies have been developed and explored in the literature (*e.g.* OLS, FE, GMM, semi-parametric approaches as suggested by Olley and Pakes, 1996 and Levinsohn and Petrin, 2003, and more recently developed methods that build on the existing ones such as Wooldridge, 2009 and de Loecker, 2011). However, not all methodologies are ideal in our empirical analysis due mostly to the nature of our firm-level data and some data restrictions.

A semi-parametric approach suggested by Olley and Pakes (1996) requires us to have a sufficiently large sample of firms with positive tangible investment. Moreover, it requires the assumption that firm-level investment decision responds completely to TFP shocks in a timely manner. However, this may not be a valid assumption due to time to build, costly adjustment, or if firms adjust investment only to a more permanent change in TFP. Also, investment may respond to unobservable factors unrelated to productivity shocks making the assumption of monotonicity condition to break down.[81] In our data, nearly half of the total observations have either missing or zero tangible investment. Therefore, we choose not to pursue this approach.

Following Levinsohn and Petrin (2003), one may argue that using intermediate inputs as a proxy could be a good alternative as data for investment are not readily available. However, the assumption that firms can costlessly adjust intermediate inputs immediately to new information on their TFP may still not be defensible. Moreover, it requires intermediate inputs to be highly correlated with TFP. In the T2-LEAP database, there is no separate information on intermediate input, requiring us to compute it by subtracting wages and gross profit from sales (or sales minus value added). However, as is the case in Leung, Meh, and Terajima (2008)[82], we find that the intermediate input variable computed as sales minus value added is highly volatile. It may not be correlated with TFP to the extent required to implement the Levinsohn-Petrin method. Also, due to some data errors, a non-negligible number of observations in our data have a negative (sales<value added) or missing value (missing value for sales) for the intermediate input. Hence, we do not pursue the Levinsohn-Petrin approach.

Collinearity between labour and non-parametric terms (investment in the O-P approach or intermediate inputs in the L-P approach) may cause the labour coefficient to be unidentified. In other words, we need variations in labour input, which is independent of investment or intermediate inputs in order to identify the labour coefficient. A similar argument can be made

[81]Also, the assumption in the O-P approach that productivity dynamics is approximated by a first-order Markov process may not be valid since productivity evolves over time responding to many observable and unobservable factors. Moreover, Power (1998) suggests that productivity does not appear to be closely related to investment and that fixed effects (*i.e.* firm heterogeneity) appear to play a larger role in explaining firms' productivity evolution.
[82] The authors estimate firm-level TFP using the T2-LEAP database.

by proposing that if labour is also costly to adjust (so not likely to be a completely variable input), then labour becomes another state variable which depends on capital and productivity. So it would no longer be identified in the semi-parametric estimation (see Bond and Söderbom, 2005). This may be the case in reality due to the presence of costs associated with hiring, firing, and training. Bond and Söderbom (2005) suggest that if all inputs are costly to adjust then, the production function can be estimated consistently based on IV techniques while semi-parametric approaches results in inconsistent estimates.

Our preferred estimator depends on how our data satisfy the assumptions underlying the estimation strategy. Thus, we rely on OLS and GMM to estimate TFP. We have all the necessary information in our data to implement these two methods. To implement GMM, we rely on a dynamic version of equation 5A and use all suitably lagged values to instrument for potentially endogenous variables (*e.g.* Arellano and Bond, 1991).[83] Also, as pointed out in Blundell and Bond (1998), in a first-differenced equation, we have weak instrument problems if the output and input series are persistent over time within firms.[84] Hence, we impose additional moment conditions in levels (*i.e.* system-GMM).

We estimate a firm-level Cobb-Douglas production function by three-digit NACIS industry in manufacturing.[85] We found that the samples in roughly half of the three-digit NAICS industries did not pass some important diagnostic tests (*i.e.* the over-identification test and the Arellano and Bond test on serial correlation on error terms) or exhibit the "too-many-instrument" problem as indicated by a close-to-unity *p*-value in the over-identification test.[86] We also found that the common factor restriction is often rejected in these samples. However, in most of the industry groups, the estimated output elasiticities with respect to labour and tangible capital stock were in line with the findings in the literature and with our prior knowledge. Also, the difference-in-Hansen test indicated that the additional moment conditions in levels were valid. However, without a completely satisfactory specification for all the industry groups, we choose OLS as our main estimator for firm-level TFP despite its weakness.

[83] In the dynamic specification, we impose a common factor restriction and the associated coefficients on the factors of input are computed by a Chamberlain-type minimum distance procedure (Chamberlain, 1984; Wooldridge, 2002). If common factor restrictions are rejected, the long-run solution of the model are computed as nonlinear combinations of the estimated coefficients. Then, we use the Delta method to compute the standard errors of the calculated coefficients.

[84]We find this is indeed the case in the T2-LEAP-SRED data. We estimated an AR (1) on value added, labour, and tangible capital stock using OLS, FE, first-differenced GMM, and system-GMM. We found that all the variables exhibit substantial persistence regardless of the estimation strategy as indicated by a statistically significant coefficient on the lagged dependent variable, which is close to unity. OLS estimates tend to be the largest (closest to unity) due potentially to simultaneity bias. On the other hand, FE estimates tend to be the smallest due to dynamic panel bias (*i.e*. Nickell bias –see Nickell, 1981). We find that system-GMM estimates are in between the two, indicating that our GMM strategy potentially mitigates the bias to some extent.

[85]We estimate an unweighted regression equation (giving the same weight to all observations) since we would like to focus on firm-level differences in TFP. A small number of large firms tend to dominate industry output. Hence, if we weight the observations by, for example, their output shares, the estimates in the production function would be more relevant for large firms in our data. This would be useful if we were interested in TFP at the industry level.

[86] We tried collapsing the instrument as in Roodman (2009) or restricting the lag order of the instruments to a shorter window but the results were not satisfactory.

Appendix IV: Additional Tables

Table A2: Summary Statistics, R&D Sample, by Initial Employment Size, Manufacturing, 2000-2012

	Employment	R&D expenditure	Initial profitability	Initial Productivity	ΔIP	ΔIPE	Δln(TFP)	ΔProfitability
Total								
Mean	85	430	-0.009	-0.051	0.049	0.077	0.073	-4.957
Std. Dev.	494	6,606	x	0.685	0.102	0.143	0.788	X
Small								
Mean	24	129	-0.016	-0.068	0.050	0.080	0.057	-5.225
Std. Dev.	32	474	x	0.675	0.099	0.141	0.772	X
Medium								
Mean	182	600	0.035	0.004	0.045	0.065	0.136	-3.520
Std. Dev.	134	2,025	x	0.693	0.109	0.140	0.805	X
Large								
Mean	1,694	9,668	0.055	0.252	0.030	0.042	0.257	-2.440
Std. Dev.	2,543	39,500	x	0.844	0.160	0.204	1.070	X

Note: The number of observations is 116,683 (small: 100,894; medium-sized: 12,740; large: 3,049). Δ denotes a 5-year difference. All the initial values are the values observed in the initial year of a given sub-period. Employment is measured as the average labour unit. We define the three size groups based on the average labour unit (ALU) observed in the initial period (*e.g.* ALU in 2000 for the 2000-2005 sub-period): small (ALU<100); medium (100≤ALU<500); and large (500≤). R&D expenditure is in thousand 2007 constant CAD. Productivity is measured as log of deviation from the industry average. Profitability is defined as net income or loss before tax divided by sales. x indicates that the statistics is suppressed due to confidentiality requirements.

Table A3: Summary Statistics, TFP Sample, by Initial Employment Size, Manufacturing, 2000-2012

	Employment	Initial profitability	Initial Productivity	ΔIP	ΔIPE	Δln(TFP)	ΔProfitability
Total							
Mean	41	0.048	-0.010	0.051	0.073	0.057	-0.695
Std. Dev.	291	x	0.519	0.093	0.133	0.506	x
Small							
Mean	16	0.048	-0.067	0.051	0.074	0.052	-0.742
Std. Dev.	23	x	0.509	0.091	0.132	0.499	x
Medium							
Mean	183	0.050	0.003	0.045	0.062	0.116	-0.017
Std. Dev.	127	x	0.598	0.102	0.130	0.576	x
Large							
Mean	1,578	0.074	0.249	0.029	0.041	0.155	0.013
Std. Dev.	2,366	x	0.765	0.169	0.207	0.672	x

Note: The number of observations is 241,054 (small: 225,697; medium-sized: 12,886; large: 2,471). Δ denotes a 5-year difference. All the initial value is the value observed in the initial year of a given sub-period. Employment is measured as the average labour unit. We define the three size groups based on the average labour unit (ALU) observed in the initial period (*e.g.* ALU in 2000 for the 2000-2005 sub-period): small (ALU<100); medium (100≤ALU<500); and large (500≤). Initial productivity is measured as log of deviation from the industry average. Profitability is defined as net income or loss before tax divided by sales. x indicates that the statistics is suppressed due to confidentiality requirements.

Table A4: R&D Equation, by Initial Condition, 2SLS, Manufacturing, 2000-2012

	Initial profitability		Initial productivity	
	1	2	3	4
ΔIP x initially low	-3.440***	-	-3.971***	-
	(0.745)		(1.078)	
ΔIP x initially mid	0.094	-	0.559	-
	(0.456)		(0.538)	
ΔIP x initially high	0.520	-	-0.562	-
	(0.886)		(0.696)	
ΔIP x below mean	-	-2.459***	-	-1.323***
		(0.734)		(0.450)
ΔIP x above mean	-	-0.239	-	0.044
		(0.422)		(0.768)
No. observations (firm x period)	102,523	102,523	113,537	113,537
No. firms	15,667	15,667	17,260	17,260

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit. Productivity is measured as relative to the industry average. For column 1, we assign firms with zero or negative initial profitability to the low group and firms in the top five per cent of the distribution for the initial profitability to the high group. The rest of the firms are assigned to the mid group. For column 3, firms in the top 5 per cent and the bottom 25 per cent of the distribution for the initial TFP (relative to the industry average) are assigned to the high and low group, respectively. The rest are in the mid group. We tried different cut-off values but the qualitative results did not change. *** $p< 0.01$; ** $p<0 .05$; * $p< 0.10$.

Table A5: TFP Equation, by Initial Condition, 2SLS, Manufacturing, 2000-2012

	Initial profitability	Initial productivity
ΔIP x below mean	-0.140***	-0.135***
	(0.023)	(0.023)
ΔIP x above mean	0.364	-0.090
	(1.048)	(0.091)
No. observations (firm x period)	238,619	241,054
No. firms	43,024	43,331

Note: Period fixed effects are included in all columns. Standard errors are in parenthesis. Δ denotes a 5-year difference. Profitability is defined as profit/revenue where we use net income or loss before tax as a proxy for profit. Productivity is measured as relative to the industry average. Productivity is measured as relative to the industry average. *** $p< 0.01$; ** $p<0 .05$; * $p< 0.10$.