Working Paper Series /
Cahiers de recherche

December 2017 décembre

The Impact of Emerging Market Competition on Innovation and Business Strategy: Evidence from Canada

Lorenz Kueng (Kellogg School of Management)
Nicholas Li (University of Toronto)
Mu-Jeung Yang (University of Washington, Seattle)

Productivity Partnership
Partenariat productivité
productivitypartnership.ca
partenariatproductivité.ca

The Impact of Emerging Market Competition on Innovation and Business Strategy: Evidence from Canada

Lorenz Kueng (Kellogg School of Management & NBER)
Nicholas Li (University of Toronto)
Mu-Jeung Yang (University of Washington, Seattle)

This Version[1]: December 2017

Abstract

How do firms in high-income countries adjust to emerging market competition? We estimate how a representative panel of Canadian firms adjusts innovation activities, business strategies, and exit in response to large increases in Chinese imports. Whether firms invest in process or product innovation matters: on average, the number of process innovations declines more strongly than the number of product innovations. In addition, firms that initially pursue process innovation strategies and survive have higher profits ex-post, but are ex-ante more likely to exit. In contrast, firms that initially pursue product innovation strategies have higher profits if they survive, without significant impact on exit. Both empirical patterns are consistent with our theory, which suggests that innovation strategies do not ensure insulation against competitive shocks, but instead increase risk.

[1] We would like to thank Nick Bloom, John Van Reenen, Pian Shu, and the seminar participants at the NBER PIE Spring Meetings, the University of Toronto, the WEAI Summer meetings, and the Sumantra Ghoshal Conference for helpful comments. We would also like to thank Loren Brandt and Peter Morrow for sharing data on processing trade with us. All remaining errors are our own.

1. Introduction

What is the impact of trade integration with low-income countries on firm dynamics in high-income countries, including innovation activities and business strategy? A large empirical literature has documented that low-cost competition in the wake of China's entry into the WTO has led firms in the US and Europe to cut jobs, lose market share, or shut down altogether; see Bernard, Jensen, and Schott (2006) and Autor, Dorn, and Hanson (2013).

However, recent work has emphasized the importance of innovation responses by firms in response to Chinese import competition. The reason is that innovation might add either significant dynamic costs as in traditional R&D-based models of endogenous innovation[2] or significant dynamic gains as in models of quality differentiation, such as Sutton (2012) and Amiti and Khandelwal (2013), or trapped factor models, such as Bloom, Romer, Terry, and Van Reenen (2014). Correspondingly, empirical studies have found mixed results, with Bloom, Draca, and Van Reenen (2015) documenting positive innovation responses to Chinese competition in Europe, while Autor, Dorn, Hanson, Pisano, and Shu (2016) find that US public firms systematically reduced innovation. Much of this current theoretical and empirical literature has focused on innovation investments and outcomes, without considering the business strategy choices of firms. We define business strategy as a long-term plan to pursue specific performance advantages based on novel products, better quality, or lower costs, and we focus in particular on innovation strategies. Such strategies are often costly to reverse, and manufacturing firms such as Intel, General Electric, Nucor, and Ford rarely decide to change innovation investments on a year-to-year basis but rather view such investments as part of a long-term commitment to a strategy of innovation. But such long-term strategic commitments in turn imply the possibility of considerable risk, as firms that are stuck with an irreversible innovation strategy might suffer losses when the business environment changes rapidly, particularly if their innovation attempts fail. In other words, the choice of an innovation strategy and its interaction with rising Chinese competition involves important risk-return tradeoffs, which have been ignored in the current literature.

This paper makes two main contributions to this literature. First, we develop a baseline theory to clarify the implications of different innovation strategies for the effect of emerging-market competition on firm outcomes and to derive theoretical predictions that help us interpret the data. Second, we use exogenous changes in import competition caused by China's entry into the WTO to identify the causal effect on firms' innovation activities and business strategies. The heterogeneous effects by initial innovation strategies can potentially shed light on conflicting results in the recent empirical literature.

The theoretical contribution shows that if one has access to data on initial strategies, then the

[2] Leading examples include Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), Klette and Kortum (2004), and Atkeson and Burstein (2010).

difference between the average performance of innovators – including successful and failed ones – and non-innovators identifies the risk of an innovation strategy. This performance difference is therefore the key data moment that our empirical analysis seeks to identify. In addition to irreversible strategy choices and risky innovation investments, our model features endogenous exit as well as a clear theoretical distinction between product and process innovations. Both of these features turn out to be important to rationalize our empirical results. In the model, successful product innovations allow firms to shield themselves against the impact of low-cost competition ("product differentiation"), while process innovations increase firm efficiency but do not shield firms against competitors. This difference in innovation type allows us to account for the fact that measured process and product innovations behave differently in the data. Furthermore, a model of risky innovation investments without endogenous selection would imply that the responses of firm exit and average profits of surviving firms always move in opposite directions. We therefore need endogenous exit to understand why this strong "opposite directions" prediction might not hold in the data.

Our second contribution is to identify differential impacts of competition shocks by innovator firm type. We estimate the impact of Chinese import competition on innovation activities and business strategies using a novel, representative sample of Canadian firms. Our analysis uses unique self-reported measures of intended innovation strategies, which allow us to measure whether firms initially pursue innovation or low-cost strategies.[3] The lack of such data has prevented previous studies from considering how international competition could have differential effects on firm performance due to different strategic choices by firms. Our measures of intended strategies have the additional advantage that they are not outcome variables like patenting or TFP, hence they do not confound the effect of intended strategic choices with the effects of luck and ex-post selection. This allows us to analyze the risks associated with innovation activities. The data also provide many measures of innovation activity, including investments in novel business processes protected by trade secrets or incremental product innovations. We then use administrative tax records to validate these self-reported innovation measures, showing that they strongly correlate with reported revenues and operating costs that are consistent with firms' tax records. These new measures of innovation activities allow us to extend the analysis to young and small firms, which typically do not yet own patents and do not have large R&D expenditures and hence are often excluded from previous studies.[4]

Our identification strategy mirrors the empirical approach by Autor, Dorn, and Hanson (2013) and Bloom, Draca, and Van Reenen (2015), who utilize the massive expansion of Chinese exports in the wake of China's WTO accession as a natural experiment. Guided by our theory, we develop

[3] Yang, Kueng, and Hong (2015) provide a detailed analysis of firms' business strategy choices.
[4] Another advantage of using survey data on innovation rather than patent data is the increasing popularity of patenting as a strategic tool by incumbents vs. entrants (Boldrin and Levine, 2013) as well as a rent extraction tool by patent trolls (Tucker, 2014). From this perspective, a fall in patenting in response to more competition from China might just reflect the fact that domestic firms in high-income countries recognize that they cannot enforce domestic patents against Chinese competitors and therefore they reduce patent applications.

two sets of results. First, we analyze how Canadian firms adjust their innovation activities and business strategies to this "China shock." As these responses are not conditioned on firms' initial strategies, we refer to these as "unconditional moments." We find that Canadian manufacturing firms systematically reduce innovation activities, consistent with the results of Autor, Dorn, Hanson, Pisano, and Shu (2016), Gong and Xu (2017), and Li and Zhou (2017) for large US firms. This reduction in innovative activities is strongly driven by a drop in process innovation rather than product innovation, consistent with similar findings by Bena and Simintzi (2015) for US firms. Furthermore, we find no evidence of systematic changes in innovation strategies by Canadian companies, which motivates us to model business strategies as irreversible, at least in the medium run.

Since innovation strategies are unaffected in the medium run, we can use initial strategies (either process- or product-oriented) to explore heterogeneity in the effect of import competition on firm performance. We refer to these results as "conditional moments." We find that firms that initially pursue process innovation strategies exhibit higher profits if they survive, but they are more likely to exit in response to Chinese competition. In contrast, firms that initially pursue product innovation strategies perform better, conditional on survival, with no notable change in exit probability. Both empirical patterns are consistent with our theory, which suggests that both types of innovation strategies carry considerable risk. These conditional performance results therefore provide important extensions of previous findings of the effects of import competition on innovation and quality or product differentiation, such as Khandelwal (2010), Holmes and Stevens (2014), and Bloom, Draca, and Van Reenen (2015). In particular, pursuing innovation strategies does not necessarily shield firms from low-cost competition, but instead can expose them to higher risk.

The remainder of the paper is organized as follows. In section 2, we describe our baseline theory and derive predictions for the moments of interest. Section 3 describes the data and empirical methodology and conducts several validation exercises. Section 4 summarizes our main unconditional results, while section 5 documents our performance results, conditional on initial strategy. Section 6 extends our analysis to the presence of outsourcing and processing trade and investigates the importance of inverted-U-type competition effects. Section 7 concludes.

2. Theory

2.1 Model setup

This section outlines our baseline theory, which serves two purposes. First, we formalize the idea of an irreversible strategy choice that allows us to clarify what type of information the new data on strategic choices helps capture. Second, the model allows us to introduce the distinction between process and product innovations, which in turn will guide our empirical analysis.

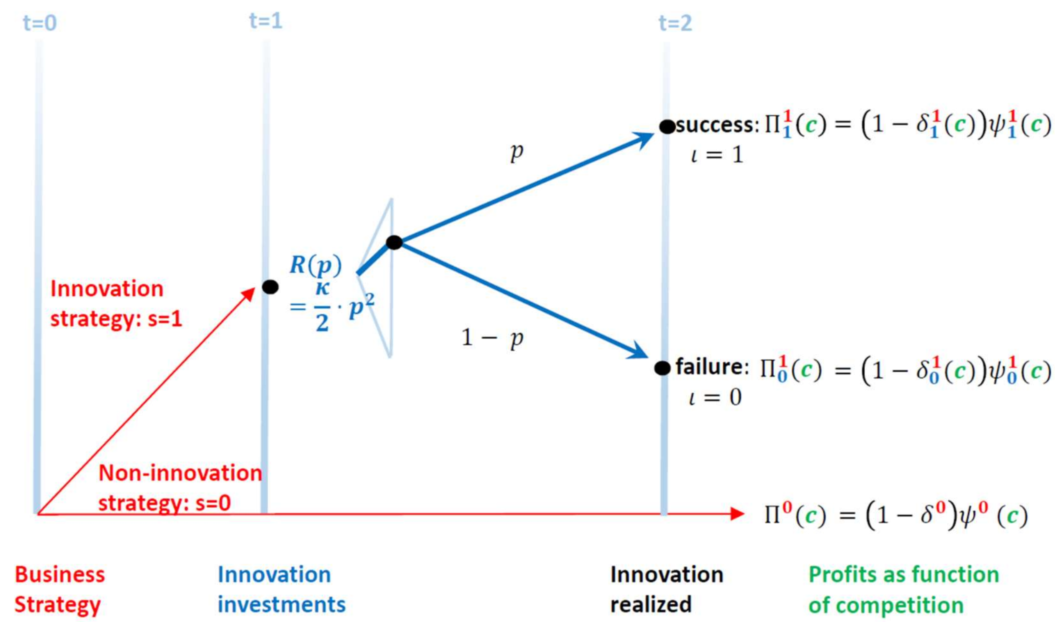

Figure 1: Timing and details of the model of strategy choice and risky innovation with endogenous exit.

We focus on the optimal decisions for a single firm, although it is straightforward to generalize the model to a monopolistic competition industry equilibrium. Demand, production technology, and choices give rise to expected profits $\Pi_\iota^s(c)$, which will be a function of the strategic choice s and indicator ι capturing successful innovations and the level of competition, given by c.[5]

The sequence of events in the model is captured by Figure 1. In stage 0, we assume that firms initially make an irreversible strategy choice of whether to pursue innovation or not; this is captured by the indicator $s \in \{0,1\}$, which is 1 if they pursue innovation.

If firms do not pursue innovation ($s = 0$), the expected profit will not depend on innovation outcomes and will simply be given by $\Pi^0(c)$ in stage 2. We will call such firms "non-innovators." On the other hand, if firms do pursue an innovation strategy ($s = 1$), then their profits will ultimately depend on whether innovations are successful. We use $\iota \in \{0,1\}$ as the indicator for a successful innovation and $p = Prob\{\iota = 1\}$ as the probability of successful innovation. In stage 1, firms that pursue an innovation strategy can increase their chances of successful innovations by investing in R&D, with a cost function given by $R(p) = \frac{1}{2}\kappa \cdot p^2$. After these investments, the probabilistic innovation outcome is realized in stage 2, at which point there will be successful

[5] Higher values of c denote more competition. For example, in a standard trade model with CES preferences, elasticity of substitution η, and P as the CES price index, competition would be captured by $c = P^{-(\eta-1)}$.

innovators ($\iota = 1$) as well as failed innovators ($\iota = 0$). Regarding profits, we define $\pi_\iota(z) = \frac{z_\iota}{c}$ as the post-innovation profits, which depend on the level of competition c as well as the post-innovation firm level productivity index z_ι. After innovations are realized, firms will be heterogeneous, depending on the productivity z_ι, and will only continue operating if they can cover overhead fixed costs

$$\pi_\iota(z) \geq f \tag{1}$$

We use a specific example of the model to facilitate the analysis:

- If innovations are successful, firms are assumed to generate a productivity z_1 that is sufficiently high for them not to exit (i.e. $\delta_1 = 0$).
- Similarly, we assume that exit probabilities for non-innovators (s=0) are constant and their productivity is given by $\bar{z}$.
- Failed innovators realize a productivity $z_0 \in [\underline{z}, \bar{z}]$ with $\underline{z} < \bar{z}$. We assume these productivity draws are continuously distributed with cdf $G(.)$. Together with the previous assumption, we therefore assume that failed innovators' productivity is typically lower than non-innovators. This assumption captures the idea that failed innovation leads to significant costs, such as delayed implementation on other projects and shutdown costs of innovation projects. On a technical level, this assumption is needed to introduce endogenous selection in the simplest, yet most appealing way.

Exit for failed innovators is determined by whether productivity is above a cutoff that is influenced by competition. If $z_0 < z^c(c)$, then failed innovators exit.

In general, for innovation strategy firms, the expected profit, conditional on innovation, is given by:

$$\Pi_\iota^1(c) = (1 - \delta_\iota(c)) \cdot \psi_\iota(c) \tag{2}$$

with $(1 - \delta_\iota(c)) = P(\pi_\iota(z) \geq f)$ as the survival probability and $\psi_\iota(c) = E[\pi_\iota(z) - f | \pi_\iota(z) \geq f]$ as the profits, conditional on survival.

As a result, the optimal investment problem for innovation strategy firms at stage 1 is:

$$p(c) = \arg\max_{\mathrm{p}} \Pi^1(p, c) = p \cdot \Pi_1^1(c) + (1 - p) \cdot \Pi_0^1(c) - \frac{1}{2}\kappa \cdot p^2 \tag{3}$$

Anticipating the degree of competition and optimal investment choices, the initial optimal strategy choice is given by

$$s(c) = \arg\max_{s\in\{0,1\}} \{ \ \Pi^{1-s}(c)\ , \tag{4}$$
$$\Pi^{s}(p(c),c) = \ p(c)\cdot \Pi_1^1(c) + \big(1-p(c)\big)\cdot \Pi_0^1(c) - \frac{1}{2}\kappa \cdot p(c)^2 \ \}$$

This framework now enables us to analyze the impact of competitive shocks, such as increased international competition from China, on optimal choices as well as performance. In addition to the initial strategy choice, the model also allows us to parsimoniously differentiate between product and process innovations, which is important to understand the data.

2.2 Unconditional moments: Optimal responses to competition

The key feature of the model that allows us to differentiate between process and product innovations can be formalized when looking at the optimal innovation investment decision $p(c)$ and its response to changes in competition:

$$p'(c) = \frac{1}{\kappa}\left(\frac{d\Pi_1^1(c)}{dc} - \frac{d\Pi_0^1(c)}{dc}\right) = \frac{\xi(c)}{\kappa} \tag{5}$$

where we defined $\xi(c) = \left(\frac{d\Pi_1^1(c)}{dc} - \frac{d\Pi_0^1(c)}{dc}\right)$ as the differential marginal impact of competition on profit for successful versus failed innovators. Based on $\xi(c)$, one can differentiate two cases.

Case 1: Process innovation: $\xi(c) = \left(\frac{d\Pi_1^1(c)}{dc} - \frac{d\Pi_0^1(c)}{dc}\right) < 0$.
In this case, an increase in competition will lead to a fall in innovation investments, driven by the fact that more competition reduces anticipated profits. In our model, we think of process innovations as increasing firm productivity so that $z_1 > z_0$. Since $\Pi_\iota^1(c) = \frac{z_\iota}{c}$, this case follows immediately from the model.

Case 2: Product innovation: $\xi(c) = \left(\frac{d\Pi_1^1(c)}{dc} - \frac{d\Pi_0^1(c)}{dc}\right) > 0$.
In this case, an increase in competition will have the opposite effect from before and will increase innovation incentives. This will be the case in any model in which successful innovators' profits are less impacted by competition than failed innovators' profits. Previous models such as Aghion, Bloom, Blundell, Griffith, and Van Reenen (2005) exhibited this feature only for "frontier innovations." To simplify our analysis, we will assume that successful product innovations will completely shield successful innovators' profits from the effects of increased competition.

Given the distinction between product and process innovations, we can now discuss the implications of competitive shocks on initial strategy choice. Note that firms will choose to pursue an innovation strategy according to (4) if $\Pi^1(p(c),c) - \Pi^0(c) \geq 0$. In other words, the greater the difference between profits of an innovation strategy and the profits of being a non-innovator, the more likely firms will choose an innovation strategy. The impact of a competitive shock on initial strategy choice can therefore be summarized by

$$\frac{d\Pi^1(p(c),c)}{dc} - \frac{d\Pi^0(c)}{dc} = \left(\frac{d\Pi_0^1(c)}{dc} - \frac{d\Pi^0(c)}{dc}\right) + \left(\frac{1}{\kappa}\right)\left(\Pi_1^1(c) - \Pi_0^1(c)\right)\cdot \xi(c) \tag{6}$$

where a positive value will imply that innovation strategies are more likely to be chosen, while negative values will imply that firms will be more likely to choose non-innovation as a strategy in response to competition. A key insight from explicitly modeling the innovation strategy choice is that information from optimal innovation investment by itself is not sufficient to understand how competition shapes initial strategy choices. This can be seen in (6) by recognizing that the strategy choice does not just depend on the sign of the term $\xi(c)$, which was sufficient to understand innovation investments. Intuitively, we need to know more than how competition differentially impacts the profits of successful and failed innovators. We also need to understand how competition affects the profit difference between non-innovators and failed innovators, as captured in the first term of the right-hand side of (6). This term is typically positive in our model, as we assume that failed innovators have a lower productivity than non-innovators: $z_0(\omega) < \bar{z}$.

	Process innovations	Product innovations
Innovation investments $R'(c) \propto p'(c) \propto \frac{d\Pi_1^1(c)}{dc} - \frac{d\Pi_0^1(c)}{dc}$	↓	↑
(Business) strategy choice $\frac{d[E[\Pi^1] - R(p) - \Pi^0]}{dc}$	?	↑
Exit $\frac{d[\delta^1(c) - \delta^0]}{dc}$	↑	?
Performance, conditional on survival $\frac{d[E[\ln \psi^1] - \ln \psi^0]}{dc}$	?	↑

Table 1: Theoretical predictions of risky innovation model with endogenous exit. The superscript $s = 1$ denotes firms with an initial innovation strategy, while firms with an $s = 0$ superscript denote non-innovators. The first two rows capture unconditional moment predictions, while the last two columns capture performance predictions conditional on strategy choice.

The overall impact of the strategy choice will then depend on the sum of the positive first term in equation (6) and the second term, which differs for product versus process innovation. While the impact of competition makes innovation strategies unambiguously more likely in the case of product innovations, the same is not true in the case of process innovations. Competition drives profits from choosing a process innovation strategy in two directions. On the one hand, there is an incentive towards adopting a process innovation strategy, driven by the fact that non-innovators may suffer higher profit losses from competition than failed innovators (first term). On the other hand, successful innovation becomes less likely as firms optimally reduce innovation efforts (second term).

2.3 Conditional moments: Performance impact of competition, conditional on strategy

The previous section discussed optimal innovation investment and strategy choices. In this section, we focus on performance, conditional on an initial strategy choice, since the firm strategy data is an important and novel feature of our empirical analysis. Our theoretical considerations highlight that the strategy data allow us to contrast the differential performance responses of average innovators – including successful and failed innovators – with the performance responses of non-innovators. The theory also shows that we should expect different performance impacts of competition, depending on whether the innovation strategy under consideration is related to process versus product innovations. Finally, we note that these conditional performance predictions can be considered robust with respect to our maintained assumption that initial strategy choices are optimal.

We start out with firm exit. We show in the appendix that the difference in exit rates between innovators and non-innovators is given by

$$\frac{d\left(\delta^1(c) - \delta^0(c)\right)}{dc} = \left(1 - p(c)\right) \cdot \left(\delta_0^{1'}(c)\right) + \frac{\xi(c)}{\kappa} \cdot \left(\delta_1^1 - \delta_0^1(c)\right) \tag{7}$$

where δ^s is the exit rate, conditional on strategy $s \in \{0,1\}$, and $\delta_1^1 > 0$ is the exogenous exit rate for successful innovators, while $\delta_0^1(c)$ is the endogenous exit rate for failed innovators based on selection equation (1). The first term of (7) will typically be positive, as the chance of failed innovation is positive and increased competition will increase exit rates of failed innovators. As before, the impact of competition on exit rates for firms with different strategies depends in part on the difference between product and process innovations, as captured by the sign of $\xi(c)$, as we assume that exit rates for failed innovators are higher than for successful innovators: $\delta_1^1 - \delta_0^1(c) < 0$.

For the case of process innovations, $\xi(c) < 0$, (7) will be positive, so that more competition will unambiguously raise exit rates of firms with innovation strategies relative to non-innovators. In the opposite case of product innovations, $\xi(c) > 0$, the impact of innovation on exit rates of innovation strategy firms relative to non-innovators is ambiguous, as an increase in innovation investments in response to competition will lead to more successful innovators, an effect that is countered by increased endogenous exit, which is the first term in (7). The surprising implication is that even if empirically exit rates do not significantly change in response to increased competition, product innovation strategies should still be considered risky, as the likelihood of bankruptcy increases. But this increase in firm exit is hidden in the case of product innovation strategies, as innovation investments increase.

While the predicted response of exit to competition is unambiguous for process innovation strategies and ambiguous for product innovation strategies, the reverse is true for the predictions of profits conditional on survival. As shown in the appendix, for the case of process innovation strategy, the difference in profit responses to competition between firms that pursue innovation strategy and those that do not is given by

$$d \ln \Pi^1(c) - d \ln \Pi^0(c) = \frac{\xi(c)}{\kappa} \cdot \left(\ln \psi_1^1 - \ln \psi_0^1(c)\right) + \left(1 - p(c)\right) \cdot d \ln \psi_0^1(c) \tag{8a}$$

This term has an ambiguous sign for the process innovation strategy case of $\xi(c) < 0$. The first term is negative and captures the fact that firms with a process innovation strategy reduce their innovation investments, which leads to more failed innovators with low productivity. This is partially countered by the second effect, which captures the selection effect of more competition forcing out the lowest-productivity firms so that productivity conditional on survival is higher.

While the profit predictions for firms pursuing a process innovation strategy are ambiguous, they are unambiguous for the case of product innovation strategy. In that case, the differential profit effect between innovators and non-innovators is given by

$$\begin{aligned} &d \ln \Pi^1(c) - d \ln \Pi^0(c) &(8b)\\ &\qquad = \frac{\xi(c)}{\kappa} \cdot (\ln \psi_1^1 - \ln \psi_0^1(c) + \ln c) + \left(1 - p(c)\right) \cdot d \ln \psi_0^1(c) + p(c) \cdot \frac{1}{c} \end{aligned}$$

In this case, $\xi(c) > 0$, and both the innovation investment effect and the selection effect tend to increase profits, conditional on survival.

3. Data and Methodology

3.1 Data overview

Our confidential firm-level data come from Canada's Workplace and Employment Survey (WES), a random stratified sample conducted by Statistics Canada with the universe of Canadian firms as the sampling frame.[6] The survey is stratified by (NAICS 4-digit) industry, firm size, and region, and we use the population weights provided for all summary statistics and regressions. We use data from the 1999, 2001, 2003, and 2005 waves of the survey.[7] The data are a panel with re-sampling to replenish the sample after firm exit or attrition. We restrict our attention to manufacturing firms (NAICS industry codes with 3 as the first digit) since Chinese exports are heavily concentrated in manufacturing, with an export share of more than 80% over our sample period; see Autor, Dorn, and Hanson (2016). This gives us a starting sample of 1,370 firms, of which about 900 survive until the end of the period depending on which outcomes we examine. We apply sampling weights to these firms to make them representative for all employer firms – firms with at least one employee – in the Canadian manufacturing sector.

A unique aspect of the WES data set is that it contains detailed measures of firms' [ex-ante] intended strategies to deal with competition as well as firms' [ex-post] outcomes, such as realized innovations and current performance. Table 2 presents summary statistics for our main variables, which we now describe in detail. Note that the sample contains a good mix of small, medium, and large firms, although the latter two classes are significantly over-sampled on purpose and make up a much smaller share of the total firm population.

Firms' business strategies are measured in Section G of the WES. Firms are asked to rate the importance of 15 different strategies on a five-point scale from "Not important"' to "Crucial,"' with strategies ranging from expansion to new markets, new products, quality management, and cost reductions. We focus on three sets of strategies. We are mainly interested in two types of innovation strategies, but we also consider low-cost strategies.

Innovation strategies differ by whether they pursue product or process innovations. These strategies are measured as follows. First, the product innovation strategy corresponds to the two factors of "Undertaking research and development" and "Developing new products/services,"' while the process innovation strategy corresponds to Undertaking research and development" and "Developing new production/operating techniques." *Low-cost strategy* corresponds to two different questions: "Reducing labor costs" and "Reducing other operating costs."

[6] See http://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=2615 for the WES questionnaire. The online appendix reprints sections G and H of the survey for convenience.
[7] The survey was conducted every year from 1999 to 2006. Information about business strategies was asked every other year.

Table 2: Summary Statistics

Panel A: Initial levels in 1999	N	Population-weighted Mean	S.D.
Process innovation strategy top priority	1370	0.117	0.321
Product innovation strategy top priotity	1370	0.152	0.359
Low-cost strategy top priority	1370	0.181	0.385
Exit by 2005	1370	0.169	0.375
Chinese share of Canadian imports	1359	0.029	0.047

Panel B: Changes from 1999-2005	N	Population-weighted Mean	S.D.
Perceived non-US foreign competition	868	0.016	1.573
Perceived US competition	868	0.005	1.363
Cumulative product innovations	913	4.436	3.263
Cumulative process innovations	913	3.917	3.287
Cumulative technology expenditures / 1999 revenue	911	0.084	0.214
% change in revenue	864	0.256	0.704
% change in employment	868	0.036	0.578
% change in gross payroll	868	0.275	0.654
Change in gross profits/1999 revenue	864	0.142	1.039
Chinese share of Canadian imports	1222	0.050	0.063

An important measurement issue we face is that respondents are asked to assign a numerical value from 1 to 5 to the importance of factors like "improving quality" or "lowering cost," with higher values reflecting higher strategic importance. These numerical values by themselves seem problematic, especially when comparing responses across respondents. Specifically, it seems that some respondents systematically rate all strategic factors higher on average, considering more or less everything as important, while others rate all factors particularly low. These different reference points make a direct comparison of numerical Likert-scores across respondents – and therefore across firms – potentially problematic. To deal with this issue, we construct two different strategy measures, which capture the essence of the specific research questions we aim to answer.

First, for cross-firm comparisons, such as differences in the competitive response as functions of initial strategy, we construct top strategic priorities. These are defined as indicator variables equal to one if the firm considers the factors to be more important than, or at least as important as, any other strategic factors listed. We also require a strategic factor be considered at least "important" (a score of 3) to be considered a strategic priority. This strategic priority variable has the advantage that it extracts mostly ordinal information on the strategic priorities of the firm and therefore avoids the comparison of mean responses across respondents. We use it especially for comparing differential responses to Chinese competition across firms, as a function of these priorities.

Second, we construct a more continuous measure to analyze within-firm changes in strategies as a response to the increase in emerging market competition. Our rationale is that when we ask "How much did the importance of this strategy change over time?" we ideally want to rely on within-firm variation. However, even when we only use within-firm variation, there remains an issue if survey respondents change over time within the same firm. To deal with this issue, we adjust these measures of strategic changes by subtracting the average importance of the relevant strategy questions relative to other strategic factors. Specifically, we first subtract the mean importance score of all 15 strategy questions for each firm (thereby normalizing the importance of a particular strategy relative to the others within a firm) and then average across the relevant questions for the innovation strategies or low-cost strategy listed above. Table 2, Panel A, reveals that innovation strategies were relatively rare in Canadian manufacturing in 1999.

Section G of the WES also contains several questions measuring perceptions of competition. Firms are asked "To what extent do these firms offer significant competition to your business?" and respond based on a similar five-point importance scale (with "don't know" as an additional category), with separate items for locally-owned firms, Canadian-owned firms, US-owned firms, and other internationally-owned firms. This allows us to assess whether the increase in Chinese import competition we measure in the data is actually salient to Canadian firms, something that is typically taken for granted. As revealed in Table 2, Panel B, among firms that survived from 1999–2005, the increase in perceived importance of competition from "Other internationally-owned" firms was over three times as large as for US firms (16% vs. 5%).

The WES asks detailed questions about innovation outcomes and technology expenditures. Section H asks whether the firm introduced new or improved products during the previous year and whether it introduced new or improved processes. Based on the response, we construct distinct measures of product versus process innovation for each firm by taking the cumulative number of years the firm innovated either an incremental or radical innovation over the period we examine (1999–2005 for our main analysis, two-year periods for our robustness check). In constructing our innovation measures, we count incremental as well as radical innovations, since doing so makes our innovation measures more strongly correlate with performance, as we show below.

Note that the average firm in our data innovates quite frequently based on this variable. Table 2 reveals that for the average firm that survived the seven-year period from 1999 to 2005, there were 2.2 years involving some product innovation and 1.7 years involving some process innovation. There are several reasons why the number of innovations is so high in our data. First, product and process innovation need not correspond to a patent or world-first innovation. The survey explicitly recognizes that an innovation could be a world-first but could also be a Canada first or a local market first, which may simply involve adoption of existing ideas and technologies. Second, firms often pursue product and process innovations together. Although the mean innovation is high, the standard deviation is also high, consistent with a wide variance of innovation outcomes across firms. Section I asks about the firm's technology use, classified as computers, computer-controlled/computer-assisted technology (e.g. robotics, optical, or laser technology), and other major implementations of technologies or machineries. Our measure of technology adoption is simply the total estimated cost of adopting any of these new technologies cumulated over the relevant period, normalized by initial revenue in 1999. The average surviving firm in our data spent resources equivalent to 8.4% of its 1999 revenue on technology adoption over the 1999-2005 period.

The WES contains several variables that can be used to assess firm performance. Firms are asked to report their revenues, total employment, gross payroll, and operating profits (defined as revenues minus operating expenses) from the previous year. [8] We use and report these variables in log changes except for profits (due to negative values), for which we calculate the change in operating profits normalized by initial revenues, i.e., the operating profit margin. The average Canadian manufacturing firm that survives from 1999 to 2005 sees substantial growth of revenue, payroll, and profits over the period (from 15–25% total over a six-year period) but very low employment growth (under 4% over a six-year period).

It is worth emphasizing that special care was taken to ensure that our firm exit variable captures either bankruptcy or plant shutdown but not events such as non-response or M&A. In particular, the protocol that analysts at Statistics Canada followed in case of non-response was to first re-contact establishments and in case of persistent non-response to check in administrative tax data whether the firm had declared bankruptcy or the plant had shut down. Only in these circumstances is our variable recording an "exit," while neither mere non-response nor restructuring events such as an acquisition or merger will be measured as an exit.

3.2 Validating innovation measures

Since our study relies on self-reported innovation measures, we first provide evidence corroborating the validity of these potentially noisy measures. Because innovation outcomes are self-reported by firms and claims of novelty are not verified by outside observers such as patent officers, we take two steps to confirm validity. First, we offer additional evidence from a related innovation survey, in which respondents have been directly asked about the economic significance of the self-reported innovation outcomes. In particular, the Survey of Innovation and Business Strategy (SIBS), which is a repeated cross-section with data for 2009 and 2012, asked respondents who reported process or product innovation about the quantitative importance of these innovations for costs and sales. Firms reporting successful process innovations in the last 3 years claim that this led to an average unit cost reduction of 7.3%. In contrast, firms reporting successful product innovations in the last 3 years claim that these product innovations account for an average of 5.2% of revenue.

[8] We cross checked the reported revenue and cost data from the WES against balance sheet and cash flow data from the General Index of Financial Indicators (GIFI), which itself is based on corporate tax disclosures. Additionally, we cross checked WES revenue data for all manufacturing firms against reported revenues in the Annual Survey of Manufacturing (ASM).

Table 3: Validating self-reported innovation measures

Dependent variable	Revenue growth	Operating cost growth
	(1)	(2)
Product innovation	0.022**	0.045***
	(0.011)	(0.012)
Process innovation	0.001	-0.031**
	(0.011)	(0.012)
Observations	871	875
R-squared	0.160	0.165

Notes: Standard errors are clustered by 4 digit NAICS

Second, while the WES survey we use does not directly ask respondents about the economic significance of reported innovation outcomes, the panel nature of our data does allow us to validate our innovation measures using other observable outcomes. In particular, the data include information on operating revenue and operating costs, which we cross checked with the corresponding revenue and cost reports of the same firms in administrative tax data. If our self-reported innovation measures are indeed related to real effects at companies, as these companies claimed in the SIBS, then we would expect those measures to significantly impact reported revenues and costs that we have ensured are consistent with administrative tax data.

Table 3 reports our results of regressing revenue and operating cost growth on our measures of product and process innovations, for the sample of continuing firms. Consistent with our expectations, we see a significant impact of product innovations on revenue growth. Product innovations also significantly increase operating cost growth, presumably because they lead to an increase in overall firm inputs. Process innovations have a significantly negative impact on operating cost growth, as expected. Ideally, we would have used unit costs, but these are not reported in the WES, which also lacks information on output quantities.

3.3 Identification and empirical strategy

Our main objective is to estimate the causal effect of increases in Chinese import competition on various outcomes for Canadian firms. We measure the strength of Chinese import competition using the share of Chinese imports over total imports within a 4-digit NAICS industry. Between 1999 and 2005, the average 4-digit NAICS manufacturing sector experienced a rise in Chinese import share from 2.8% to 7.4%, but for some industries the increase was much larger. Figure 2 plots the initial share of Chinese imports in 1999 for each of the 85 4-digit NAICS industries against the subsequent change, revealing a wide dispersion across industries that serves as our main source of identifying variation. For instance, China's contribution to Canadian imports in 1999 was particularly high in "apparel accessories" and "footwear," with shares of about 25%. Accordingly, in the six-year period from 1999 to 2005, in which China's exports increased dramatically, these shares increased by another 13–15%. On the other hand, industries like "dairy" or "printing" had low Chinese import shares in 1999 and also experienced only modest increases over the subsequent six years.

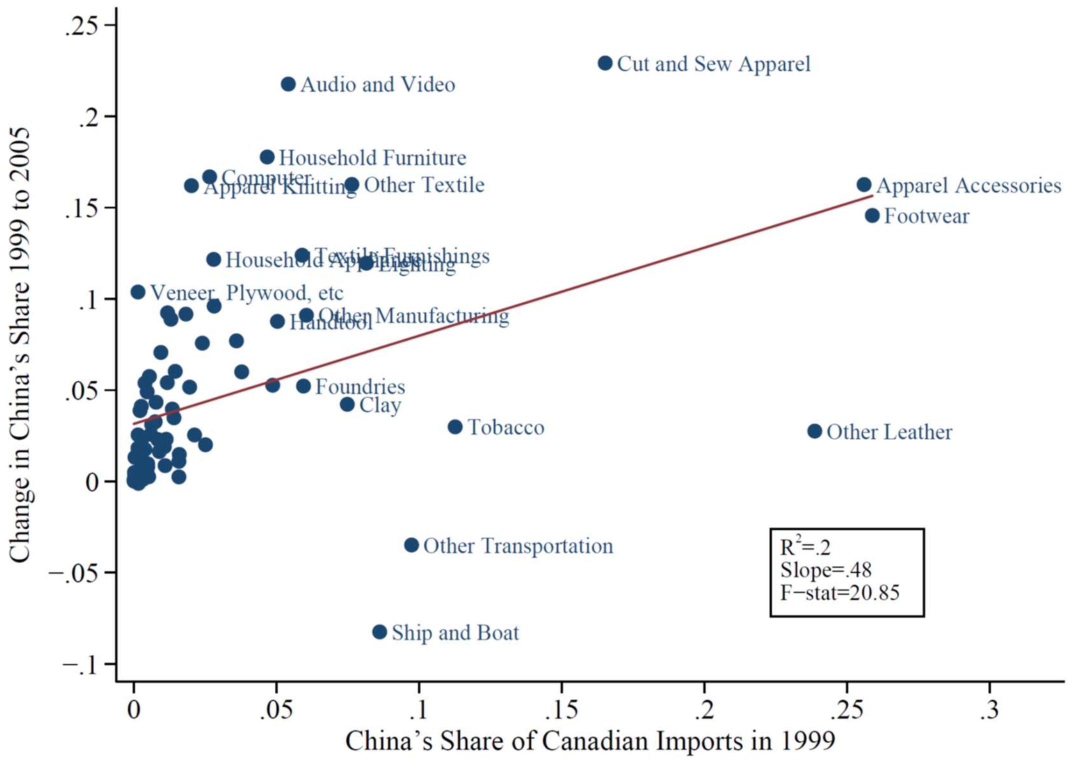

Figure 2: Predictive power of the initial import shares on changes in future shares.

Our estimation strategy is based on using cross-industry differences in the change in Chinese import shares to identify the effects of competition on Canadian firms, where we include firm and time fixed effects. That is, we estimate specifications like equation (9):

$$y_{i,k,t} = \alpha + \beta \cdot c_{k,t} + D_i + \epsilon_{i,k,t} \tag{9}$$

where $y_{i,k,t}$ is the firm-level outcome of interest and $c_{k,t}$ is the Chinese import share in industry k at time t. We would not expect the impact of Chinese competition on strategy, innovation and performance to be significant in the short run, and therefore we focus on long-run outcomes similar to specifications of Bloom, Draca, and Van Reenen (2015) and Autor, Dorn, Hanson, Pisano, and Shu (2016). Our main specification uses a long-differenced version of equation (9) where we take differences from 1999 to 2005 within each firm for the set of firms that survive throughout the period. For regressions where firm exit is the outcome of interest, we simply use a dummy variable equal to one for firms that exited by 2006 and zero otherwise.

One potential concern about estimating equation (9) by OLS is that the changes in Chinese import share that we observe are correlated with industry-level Canadian demand shocks or industry-level Canadian technology/supply-side shocks. For instance, Canadian demand for textiles might have increased in this six-year period, which could have led to an increase in China's import share in this industry. Alternatively, suppose better value-chain management by Canadian firms makes it less costly to off-shore production to China. This better technology makes textiles cheaper and hence increases sales. At the same time, it also makes off-shoring to China more likely and thus increases import shipments of textiles from China to Canada. We return to this issue explicitly in our robustness analysis.

Our main solution for this problem is to use the initial Chinese share of imports in 1999 as an instrument for future Chinese import growth at the industry level, following Bloom, Draca, and Van Reenen (2015). The idea behind the IV strategy is that WTO accession and productivity growth in China during this period led to growing competitiveness of Chinese goods in industries in which China already held a comparative advantage. Figure 1, which plots the growth of Chinese import shares against the initial Chinese import share for each NAICS 4-digit industry, shows that this correlation is fairly high, and we generally find F-statistics above 10 in the first stage of our instrumental variable regressions.

A potential concern regarding our IV strategy is that it does not by itself address potential issues of unobservable long-run trends, which could be correlated with initial trade exposure. We do lack pre-trend data on strategic choices and innovation to be able to completely address this issue, but we instead use long-run data on strategy and innovation until 2012 to estimate unobservable long-run trends in section 6.4.

Our baseline specification (9) allows us to characterize average responses, such as (4) and (5). To capture moments conditional on strategy, such as (7) and (8a, b), we use the following interaction regression:

$$y_{i,k,t} = \alpha + \beta \cdot c_{k,t} + \gamma \cdot c_{k,t} \times s_{i,t} + D_i + \epsilon_{i,k,t} \tag{10}$$

where $s_{i,t}$ is an indicator for an initial strategy, such as product innovation strategy or process innovation strategy. With the dependent variable being either exit $y = \delta$ or profits $y = \ln \Pi$, the interaction coefficient corresponds to the theoretical moment

$$\gamma = \frac{\Delta\left(y^1_{i,k,t} - y^0_{i,k,t}\right)}{\Delta c_{k,t}} \tag{11}$$

where $y^s_{i,k,t}$ is the outcome for firms with strategy s. It therefore identifies the key performance moments, conditional on strategy, according to our theoretical predictions in Table 1.

At this point, we also note that while the theory is focused on firms deciding to pursue either a product or process innovation strategy or a non-innovation strategy, firms in the data will often pursue a joint product innovation and process innovation strategy. We therefore will include the initial strategy variables together to isolate the partial effect of an initial strategic choice – such as pursuing a process innovation strategy – holding other strategic choices constant. We also include low-cost strategies and initial size as additional controls. Both variables are themselves interacted with the trade shocks, to be able to fully account for these factors.

An important requirement for (11) to be correctly identified through the specification (10) is that initial strategy choices are predetermined at the time of the shock. For example, if initial strategic choices would anticipate future competitive shocks, this could undermine identification. To ensure that this predetermination condition for strategic choices is met, we take two additional steps. First, we focus on initial strategy choices in 1999, at least two full years before China's official entry into the WTO at the end of 2001. During 1999, uncertainty about China's entry into the WTO was high, due to difficulties during negotiations as well as the accidental bombing of the Chinese embassy in Belgrade by the US. Second, we utilize data on perceptions of current and future international competition, to ensure that the initial strategy choices are not systematically correlated with current or future competitive perceptions in section 5.1.

4. Unconditional moments: Average responses to competition

4.1 Salience of Chinese competition

We begin with an analysis of the impact of Chinese competition on perceptions of competition in Canadian firms. This analysis serves at least two purposes. First, it helps us evaluate whether Canadian firms were indeed perceiving Chinese competition as an important competitive threat. One concern could be that Canadian firms might not actually have been affected much by Chinese competition or that the effects were not very sizeable. If this is the case, we would expect that perceived competition does not change much either.

Second, the fact that many countries were simultaneously affected by Chinese competition potentially poses a difficult identification issue. For a small open economy like Canada, it is possible that the main competitive effects of China's WTO entry were not related to direct competitors from China, but were instead the consequence of an indirect effect through US competition. From this perspective, Chinese competition might affect US competition, which in turn changes its competitive stance in Canada.

Table 4: Long differences (1999-2005) Chinese imports and perceptions of foreign competition

	(1)	(2)	(3)	(4)
Dependent variable	Perceived non-US competition		Perceived US competition	
	OLS	IV	OLS	IV
Chinese share of imports	4.500***	6.110***	1.290	1.884
	(1.439)	(2.195)	(1.139)	(1.416)
Observations	863	863	863	863
R-squared	0.0301	0.0261	0.00229	0.00156

Notes: Robust standard errors in parentheses are clustered by 4-digit NAICS industry. ***, **, * mark significance at the 1, 5, and 10 percent level, respectively.

To address both of these concerns, we utilize the unique perception data on competitors, by location. We measure changes in the perception of foreign (non-US) competition by taking the perceived importance of competition from "Other internationally-owned" firms and subtracting the mean importance of competition from all four sources (local, Canadian, US, non-US foreign), which like before normalizes our measure to capture changes in the *relative* importance of competition from this source within a firm. We construct a similar measure of perceived competition from US-owned firms, for two reasons. First, it directly allows us to check whether perceptions of US competition changed as a result of Chinese competition, thereby providing information on possible indirect competitive effects. Second, we can interpret it as a placebo test for whether our Chinese import competition measure is simply picking up general foreign vs. domestic competition trends (e.g. driven by Canadian firms in some sectors but leading to perceptions of higher US competition in the same sectors), or picking up the effect of the Chinese competition shock we are after.

As Table 4 shows, Chinese competition had a strong and significant impact on perceived competition by continuing firms that remained in the sample from 1999 to 2005. Furthermore, no such effect is significant for perceived US competition, confirming that our IV strategy is likely capturing only direct effects from Chinese competitors.

4.2 Innovation and strategy choice

Table 5 presents the average effect of Chinese import competition in a sector on firm performance outcomes based on equation (8) estimated in long differences (1999-2005). Standard errors are clustered by NAICS 4-digit industries throughout.

Table 5: Long differences (1999-2005)

	Exit		Profits		Process Innovation		Product Innovation	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Chinese share of imports	0.529	0.842**	-0.675	-0.725	-9.799***	-12.012***	-6.121*	-1.748
	(0.388)	(0.354)	(0.521)	(0.713)	(3.230)	(3.799)	(3.488)	(4.288)
Observations	1,354	1,354	859	859	908	908	908	908
R-squared	0.00931	0.00579	0.000419	0.000410	0.0329	0.0311	0.0124	0.00551

Notes: Robust standard errors in parentheses are clustered by 4-digit NAICS industry. ***, **, * mark significance at the 1, 5, and 10 percent level, respectively.

As Table 5 shows, Chinese competition led to a sustained and significant increase in firm exit. Indeed, we find large negative effects on firm exit that are statistically significant in our IV specification. The coefficient implies that the 4-percentage-point increase in Chinese import share between 1999 and 2005 led to the exit of 4.2% of the firms sampled in 1999 over that period, which is very large relative to the 17% overall exit rate of these firms. On the profit side, IV specifications are consistent with negative effects of rising import competition on profits of surviving firms, even as the standard errors are too large to reject a zero effect. This is likely due to selection effects: survivors are likely to be the best-performing firms, which would lead to an upward bias that could partially offset the negative effect of increased Chinese import competition. This is even more plausible given the fact that Chinese competition had a large effect on perceived non-US international competition at the same firms, as we documented in the last section. These important selection effects are also why our baseline theory features endogenous exit.

The second half of Table 5 shows the impact of Chinese competition on product and process innovation. Our IV results for process innovation are consistent with our theory, in that they show a strongly negative response of process innovation. There are very strong and robust negative effects of Chinese import competition on process innovation of surviving firms. The average surviving firm innovated almost 4 times out of a possible 12 innovation counts in the 6 years between 1999 and 2005, but the average effect of Chinese import competition lowers this by about 0.6.

However, the empirical results for product innovation do not confirm the theory, which would have predicted a positive response. We find a much weaker effect of Chinese import competition on product innovation, where the Chinese import coefficient is not significant in the IV specification (and only marginally in the OLS) and the magnitude of the effect is only about a tenth of the size for product innovation as compared to process innovation. One possible explanation is that in the data, a large fraction of product innovators also pursue process innovation. While in our conditional analysis we are able to simultaneously control for the effects of product and process innovation strategies, our measures of reported innovation as a dependent variable do not allow for this separation. As a result, it is possible that some of the variation in product innovation is driven by the strong negative response of process innovation to Chinese competition.

Table 6: Strategy responses

	Continuing firms (firm level) 1999-2005		All firms (including entry, sector-level) 2001-2012	
	Process	Product	Process	Product
Dependent variable	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Chinese share of imports	-0.360	0.079	-1.677*	-0.950
	(1.578)	(1.927)	(0.936)	(0.623)
Observations	863	863	151	151
R-squared	0.001	-0.004	0.012	-0.007

Notes: Robust standard errors in parentheses are clustered by 4-digit NAICS industry. ***, **, * mark significance at the 1, 5, and 10 percent level, respectively.

Table 6 reports the impact of Chinese competition on strategy priorities, in particular process and product innovation strategies. Our baseline specification focuses on continuing firms from 1999 to 2005 in the WES. In general, we do not find evidence of any statistically significant impact of Chinese competition on strategy. While the signs of the estimates are both consistent with our baseline theory, it seems that firms' strategic responses to Chinese competition were too heterogeneous to lead to a common pattern.

Even as we do not find any effects on strategic priorities for continuing firms from 1999 to 2005, there are two ways in which this might understate possible strategic effects. First, the same firms might change their strategies several years later. Second, even if incumbent firms do not adjust their strategies, it is possible that new entrants would optimally adjust their strategies. Together with selective exit of firms with innovation strategies, this could lead to a change in strategic orientation within an industry without much of a change within continuing firms. To allow for both of these channels and to maximize our chances of detecting a strategic response, we move to a sector-level analysis, which allows us to add more data from the SIBS dataset on strategic behavior. Since the SIBS does not ask firms for all the detailed strategic dimensions of the WES, we had to adjust the WES strategy measures to focus on whether product or process innovation were considered important. With this industry-level variation in the strategy measure over the 2001–2012 period, we estimated whether the number of firms that considered process or product innovation important for their strategy was affected by Chinese competition.[9] Columns 3 and 4 of Table 6 document the results. Process and product innovation strategies both appear to have declined, with process innovation strategy falling almost twice as much with a decline that is statistically significant at the 10% level. Overall, our results are consistent with strategic orientation changing through selection, including entrants adjusting their strategy optimally, while incumbent firms might have trouble changing strategies.

5. Conditional moments: Heterogeneous performance impact of competition, conditional on strategy

5.1 Predetermined initial strategies

As described in section 3.3, identifying firm performance moments in response to a competition shock conditional on initial strategy requires that initial strategy choices be predetermined. In this context, a key question is whether firms in 1999 did in fact anticipate rising Chinese competition and therefore chose their strategy in 1999 to reflect these competitive perceptions.

Table 7: Initial strategies and perceived international competition

Dependent variable	**perceived non-US, international competition** (in 1999)	(in 2005)
Proc. Innovation strategy (in 1999)	0.521	0.312
	(0.370)	(0.204)
Prod. Innovation strategy (in 1999)	0.146	0.346
	(0.400)	(0.294)
Low cost strategy (in 1999)	-0.146	-0.111
	(0.173)	(0.197)
Observations	1,370	1,239
R-squared	0.015	0.013

Notes: Standard errors clustered by 4 digit NAICS

To ensure that this is not a concern, we exploit the data on perceptions of competition by location of competitors. Importantly, due to the panel nature of the WES data, we can go beyond checking whether there is a correlation of initial strategies in 1999 with contemporary competitive perceptions in 1999. We can also analyze whether initial strategy choices in 1999 are correlated with the level of future competitive perceptions in 2005. It is useful to remember that these competitive perceptions correctly reflect the rise in Chinese competition, as documented earlier in Table 4. However, Table 7 shows that perceived non-US international competition for the firm is not systematically correlated with its initial strategic choices in 1999.

[9] For this long-run specification, we used three non-overlapping time differences from 2001–2005, 2005–2009, and 2009–2012 and estimated effects with industry and year fixed effects.

5.2 Performance, conditional on strategy

With respect to performance, conditional on strategy, our theory made two unambiguous predictions, as shown in Table 1 and equations (7) and (8a,b). First, in response to competitive shocks, exit should increase for firms pursuing process innovation strategies. Second, in response to competitive shocks, profits should increase for firms pursuing product innovation strategies. Table 8 shows that these two unambiguous predictions of the theory do hold in the data. Overall, the pattern of conditional moments is consistent with predictions in Table 1.

Table 8: Exit and performance, conditional on survival

Dependent variable	Future exit	Profits
	(1)	(2)
	IV	IV
Chinese share of imports	5.040**	-3.200
	(2.212)	(4.750)
Chinese share of imports x(Process innovation strategy)	**1.675*** **	**3.078** **
	(0.628)	**(1.265)**
Chinese share of imports x(Product innovation strategy)	**-0.176**	**3.079*** **
	(0.476)	**(1.100)**
Chinese share of imports x(Low-cost strategy)	1.103	-4.182
	(0.891)	(3.227)
Chinese share of imports x(initial size)	-0.328**	0.196
	(0.148)	(0.339)
Main effects (Process innovation strategy, Product innovation strategy, Low-cost strategy, Initial size)	YES	YES
Observations	1,320	840
R-squared	0.024	0.009

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth.

But the theory is even more helpful to interpret the remaining coefficients, for which the theory made ambiguous predictions. To understand why, note that each of these ambiguous predictions was the result of two opposing forces. While endogenous selection would pull the predictions in one direction, endogenous innovation would pull it the opposite way. We can therefore interpret the net effect on the remaining coefficients as reflecting the relative strength of selection vs. innovation investment effects.

Let us start with process innovation strategies and the impact of competition on profits for surviving firms. The theoretical prediction in Table 1 is ambiguous, since investment effects would predict that firms reduce process innovation investment in response to competition, which will then reduce the probability of successful process innovations, thereby reducing average profits ex-post. But at the same time, selection forces should tend to increase observed average profits, conditional on survival, as the most unprofitable firms – often failed innovators – will tend to exit. Our empirical result of systematically higher average profits of surviving firms with initial process innovation strategy therefore tells us that selection forces dominate the investment effects for process innovation strategies. Taken together, the results for process innovation strategies suggest that such strategies are risky, as process innovators are more likely to exit but do perform better conditional on survival.

A similar logic applies to product innovation strategies, i.e. these strategies turn out to be risky, even as the impact of Chinese competition on exit rates is statistically insignificant. To see why, remember that the prediction of the theory about exit rates in the product innovation strategy case is ambiguous. On the one hand, selection forces imply that exit rates should increase in response to more Chinese competition. On the other hand, this is countered by the investment effect, which says that firms should increase their product innovation investments to attempt to shield themselves from Chinese competition. This increased innovation investment in turn should increase the fraction of successful innovators, which would tend to reduce exit rates. Our empirical results of no systematic impact of Chinese competition on exit rates for firms with initial product innovation therefore shows that selection and investment effects are of similar magnitudes for product innovators. But this means that selection and therefore bankruptcy risk must have increased. If bankruptcy risk would not have changed, then we should have observed a decline in exit rates, which would be driven by the increase in innovation investments in the case of product innovations. The absence of such a decline indicated that there is considerable bankruptcy risk associated with product innovation strategies, as captured by our theory.

Finally, we note that the signs on the interaction coefficients for low-cost strategies are consistent with the view that low-cost firms consistently underperformed in response to Chinese competition. This is important to note, as process innovations are sometimes argued to mainly reflect cost-saving innovations. Our results are consistent with firms pursuing low-cost strategies and process innovation strategies together, but they also highlight that both strategies have their own distinct effects.

For low-cost strategies, neither the exit effect nor the effect on profits is significant, which may partly reflect the possibility of low-cost firms partially benefiting from Chinese trade in the form of outsourcing. We will return to this issue in section 6.2.

6. Robustness

This section provides additional evidence to better connect our analysis to the literature in at least two respects. First, although our results on the negative impact of Chinese competition on process innovation are consistent with similar findings by Autor, Dorn, Hanson, Pisano, and Shu (2016), Bena and Simintzi (2015), Gong and Xu (2017), and Li and Zhou (2017) for the US, they are somewhat different from the findings of Bloom, Draca, and Van Reenen (2015) for Europe. The question here is whether there is evidence that could help us understand how and why the North American results differ from the European results of Chinese competition.

Second, a number of studies, such as Bena and Simintzi (2015) and Branstetter, Chen, Glennon, Yang, and Zolas (2017), have used China's entry into the WTO as an outsourcing shock, rather than as a direct competitive shock. The outsourcing channel has potentially different implications for firm performance and welfare, which is why separating competitive effects in product markets from outsourcing effects seems important.

6.1 Size effects of innovation

One basic question about the negative impact of Chinese competition on process innovation is whether these effects might generally be driven by the contraction of firms. For example, if Chinese competition leads to a general contraction of firms and innovation expenditures are proportional to firm size, then in absolute terms innovation might fall, even as innovation intensity stays constant.

To investigate these size effects, we use revenue as a measure of firm size. A simple approach would be to scale our process innovation measures by revenues. However, since the innovation outcomes are not measured in expenditure terms, we prefer a more general approach. In particular, we flexibly control for a third-order polynomial of revenue growth to allow for a general relation between revenue and process innovations. Table 9 shows that despite this general strategy to control for size effects, Chinese competition has a strongly negative effect on process innovation.

Table 9: Long differences (1999-2005): Chinese import and innovation (Size effects)

Dependent variable	Process innovation
	IV
Chinese share of imports	-6.415**
	(3.257)
$\Delta revenues$	1.582***
	(0.398)
$(\Delta revenues)^2$	0.329
	(0.207)
$(\Delta revenues)^3$	-0.289***
	(0.101)
Observations	859
R-squared	0.091

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth.

6.2 Outsourcing and processing trade

In this section, we analyze whether outsourcing effects are an alternative mechanism that can explain the negative process innovation effects in response to Chinese trade. Outsourcing would have different implications in terms of firm profits and welfare. If firms optimally outsource activities to China, then the fall in process innovation would not capture competitive effects, but would instead reflect the fact that outsourcing is a substitute for process innovations. The implications for firm profits under the outsourcing mechanism would be very different, as outsourcing firms would just replace cost-saving process innovation with cost-saving outsourcing practices. Hence, firm profits might still increase, even under intensive use of outsourcing.

To analyze whether our results are indeed driven by outsourcing, we utilize aggregate trade data on processing trade. If outsourcing is indeed a major factor for manufacturing, then one would expect this to be related to trade of intermediates, or processing trade. Before moving to the formal analysis, it is worthwhile to inspect the general time trends in overall Chinese trade to Canada, as well as processing trade, in Figure 3.

As the figure shows, overall Chinese exports to Canada accelerated sharply after China's WTO entry at the end of 2001. The dashed line captures China's processing trade, which also accelerated, but at a slower pace. In fact, the share of processing trade in China's exports to Canada has been systematically falling since China's entry into the WTO. These aggregate trends already foreshadow some of our empirical analysis.

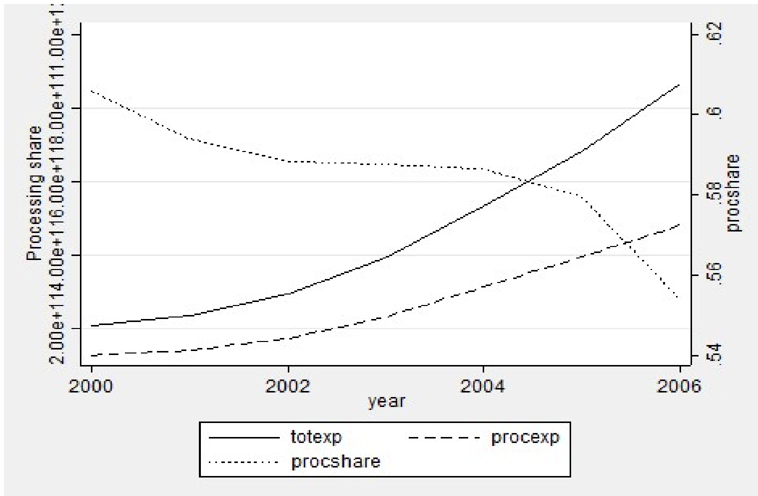

Figure 3: Time series of total Chinese exports to Canada, processing exports and the share of processing trade from 2000 to 2006.

Table 10a summarizes our analysis of the influence of processing trade, as captured by the processing trade share, on process innovation. As the table shows, controlling for processing trade share does not substantially affect the negative impact of Chinese competition on process innovation.

Table 10a: Long differences (1999-2005): Chinese import and innovation (Outsourcing)

Dependent variable	Process innovation	Process innovation
	(1)	(2)
	IV	IV
Chinese share of imports	-12.012***	-11.290***
	(3.799)	(3.547)
Chinese processing trade share		1.400
		(1.191)
Observations	908	908
R-squared	0.0311	0.037

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth.

Table 10b: Exit and performance, conditional on survival with processing trade controls

Dependent variable	Future exit	Profits
	(1)	(2)
	IV	IV
Chinese share of imports	5.390***	-2.642
	(1.915)	(4.530)
Chinese share of imports x(Process innovation strategy)	**1.970*** **	**3.262** **
	(0.584)	**(1.656)**
Chinese share of imports x(Product innovation strategy)	**0.139**	**2.448**
	(0.481)	**(1.814)**
Chinese share of imports x(Low-cost strategy)	1.415***	-2.152
	(0.536)	(1.917)
Chinese share of imports x(initial size)	-0.358***	0.156
	(0.122)	(0.323)
Chinese processing trade share	-0.141	-1.850
	(0.471)	(1.504)
Chinese processing trade share x(Process innovation strategy)	0.144	0.597
	(0.264)	(0.965)
Chinese processing trade share x(Product innovation strategy)	-0.368**	0.025
	(0.156)	(0.362)
Chinese processing trade share x(Low-cost strategy)	-0.569***	-1.323
	(0.159)	(1.013)
Chinese processing trade share x(Initial size)	0.012	0.138
	(0.033)	(0.107)
Main effects (Strategies, Initial size)	YES	YES
Observations	1,320	840
R-squared	0.053	0.025

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth.

But even though processing trade and outsourcing does not explain the negative impact of Chinese trade on process innovation, it might have an impact on the performance impact of competition, conditional on strategy. To see this, consider low-cost strategies. Although these low-cost firms might be negatively affected by increased Chinese product market competition, they might at the same time benefit from lower costs of outsourcing. This is indeed what Table 10b shows. Firm with low-cost and product innovation strategies seem to benefit from outsourcing, as captured by processing trade. On the other hand, our main result of increased exit and better performance conditional on survival for firms with process innovation strategies is robust to controlling for processing trade.

6.3 Domestic competition and product homogeneity

In this section, we provide evidence that might explain why Chinese competition could have negative effects on innovation in the US, as shown by Autor, Dorn, Hanson, Pisano, and Shu (2016), while also leading to positive effects on innovation in Europe, as shown by Bloom, Draca, and Van Reenen (2015). The basic idea follows the insight of Aghion, Bloom, Blundell, Griffith, and Howitt (2005) that the impact of competition on innovation might follow an inverted U relationship. In particular, if the initial level of competition in Europe was relatively low, then one would expect increased Chinese competition to lead to increased innovation. In contrast, the initial level of competition in the US and Canada might be considered relatively high, so that a further competitive shock from China leads to a negative effect on innovation.

Table 11a: Long differences (1999-2005): Chinese import and innovation (initial competition sample splits)

Dependent variable	Process innovation						Future exit	
	Perceived domestic competition		Herfindahl index		Product homogeneity		Product homogeneity	
	high	low	low	high	high	low	high	low
	(1)	(2)	(3)	(4)	(5)	(6)	(5)	(6)
	IV	IV	IV	IV	IV	IV	IV	IV
Chinese share of imports	-5.956***	-12.127	-9.479**	-3.501	-8.661***	-14.511*	1.231***	-0.795*
	(2.021)	(7.630)	(3.965)	(16.262)	(3.220)	(8.658)	(0.314)	(0.462)
Observations	465	343	452	456	480	428	675	679
R-squared	0.012	0.013	0.011	0.013	0.039	0.010	0.043	0.003

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth.

A full cross-country investigation of this hypothesis is beyond the scope of this paper. However, we can analyze the implications of the inverted U hypothesis within Canada. Specifically, if correct, the inverted U hypothesis would predict that firms or sectors with more intense initial competition should exhibit significantly more negative effects of Chinese competition on innovation. We investigate this hypothesis using three different measures of competition. First, we use the previously discussed measure of perceived competition. This has the advantage of being available at the firm level and therefore allows for variation within sectors. Second, we use a Herfindahl index of industry concentration, where low values reflect greater competition. Third, we use measures of product homogeneity, based on elasticities of substitution from Broda and Weinstein (2006). High homogeneity (high elasticity) may be related to greater competition.

Table 11a shows that all three of these measures of competition are potentially consistent with an inverted U hypothesis. The table shows that more initially competitive industries and firms that perceived higher initial levels of competition indeed exhibited more negative process innovation effects in response to Chinese competition. This evidence is only suggestive, as most of these coefficients are not statistically significant from each other.

Since our results on product homogeneity might suggest that the impact of Chinese competition was stronger in low-product-homogeneity sectors, we also add results for firm exit for our product homogeneity sample splits. These show that firms in high-homogeneity sectors were more likely to exit in response to Chinese competition, suggesting that high initial product homogeneity resulted in a stronger competitive impact of Chinese competition.

Table 11b: Exit and performance, conditional on survival

Dependent variable	Product homogeneity			
	HIGH		LOW	
	Future exit	Profits	Future exit	Profits
	(1)	(2)	(3)	(4)
	IV	IV	IV	IV
Chinese share of imports	6.617***	-1.364	-3.065	-12.530
	(2.151)	(5.071)	(4.309)	(15.359)
Chinese share of imports x(Process innovation strategy)	1.944***	5.749***	1.508	0.507
	(0.607)	(1.250)	(2.896)	(5.043)
Chinese share of imports x(Product innovation strategy)	-0.614	2.609***	1.036	4.296
	(0.386)	(0.836)	(2.797)	(4.745)
Chinese share of imports x(Low-cost strategy)	0.747	-7.296	2.192	0.208
	(0.687)	(5.393)	(1.372)	(2.942)
Chinese share of imports x(initial size)	-0.413***	0.079	0.114	0.812
	(0.137)	(0.361)	(0.331)	(1.081)
Main effects (Strategies, Initial size)	YES	YES	YES	YES
Observations	656	447	664	393
R-squared	0.126	0.037	0.004	0

Notes: Standard error clustered at the 4 digit NAICS level. Sector level Chinese import share is instrumented with initial import share in 1999 interacted with aggregate Chinese import growth. Sample splits are based on Broda-Weinstein estimates of elasticities of substitution for US industries. Results are similar to CAN based product homogeneity measures.

Table 11b documents the results of sample splits according to product homogeneity for the performance effects of Chinese competition, conditional on initial strategy. We focus on the product homogeneity results due to space constraints, but results with perceived competition and Herfindahl indexes are similar. The table shows that our baseline results of the effects of Chinese competition on innovation strategy firms are driven by sectors with high product homogeneity.

6.4 Controlling for long-run trends

In this section, we address the issue of unobservable long-run trends that could be correlated with initial trade exposure to China and might therefore invalidate our identification strategy. Since we lack data on strategy and innovation outcomes before 1999, we instead use additional data after 2006 to estimate long-run trends. To this end, we use the Survey of Innovation and Business Strategy (SIBS), which was conducted by Statistics Canada in 2009 and 2012. As mentioned before, this survey is a repeated cross section and therefore does not allow us to conduct any of the firm-level panel data analysis we used in the core results, especially in the moments conditional on strategy. However, we can use this data to validate our results for our unconditional moments by adjusting the SIBS and WES datasets to ensure comparability. Specifically, the SIBS only includes firms with at least 20 employees, so we adjust the WES sample to be comparable. There are also some differences in the phrasing of questions, which forces us to use slightly different measures of innovation. To generate a consistent dataset for innovation, we follow the SIBS and construct a measure from the WES consisting of the share of firms that report an improved or new process or product in the last three years in each 4-digit NAICS industry. We then run industry-level panel regressions of innovation on Chinese import competition.

Table 12: Innovation results, controlling for long run trends

	Process innovation	Product innovation
Dependent variable	(1)	(2)
	IV	IV
Chinese share of imports	-1.594***	-0.021
	(0.498)	(0.411)
Industry fixed effects	YES	YES
Observations	151	151
R-squared	0.003	0.000

Notes: Sample combines data from the WES and the SIBS. The overall time horizon is 2001 to 2012 with non-overlapping sample periods of 2001-2005, 2005-2009, 2009-2012. Robust standard errors in parentheses are clustered by 4-digit NAICS industry. ***, **, * mark significance at the 1, 5, and 10 percent level, respectively.

We analyze a long difference specification with 3 non-overlapping time windows of 2001–2005, 2005–2009. and 2009–2012. The use of these separate time windows allows us to include industry fixed effects, which will capture unobservable long-run trends, while still leaving enough variation for our IV estimator to be identified. The instrument interacts the 2001 Chinese import share in Canada for each sector with the log of total Chinese imports to Canada. Table 12 reports our results, which are broadly consistent with the unconditional moments reported in Table 6. Note that we estimated a similar specification on the sector level for the unconditional strategy responses and previously reported it in Table 6.

7. Conclusion

Motivated by the recent emergence of China as a major international competitor, we empirically analyzed the implications of this competitive shock for firm dynamics in the Canadian manufacturing sector. Our baseline results for average firms, including small and young companies, are consistent with US studies of large, publicly traded Compustat firms. In particular, we document a strong decrease in process innovations in response to more Chinese competition, which contrasts with a more muted response of product innovation.

Furthermore, initial heterogeneity in business strategy turns out to be important for understanding performance in response to Chinese competition. Our findings indicate that business strategies pursuing either product or process innovation leave firms systematically exposed to higher risk.

These empirical results add a more nuanced perspective to recent studies of the response of developed country firms to increased competition from emerging markets. Additionally, they suggest that adding risk-return trade-offs to models of international trade and innovation significantly enhances our understanding of firm dynamics and competitiveness. Note that this additional risk margin is directly related to an aggregate competitive shock. This means that it will influence common, non-diversifiable risks and might therefore influence risk pricing. Such a model might therefore link international trade, innovation, and asset pricing. This is a topic that we leave for future research.

References

Aghion, Philippe and Peter Howitt, "A Model of Growth through Creative Destruction," Econometrica, 1992, 60 (2).

Alfaro, Laura, Maggie Chen, Naercio Filho, Andrea Lucchesi and Monika Schnitzer (2017). Globalization and Organizational Change: Evidence from Brazil, mimeo HBS

Amiti, Mary and Amit K. Khandelwal, "Import Competition and Quality Upgrading," Review of Economics and Statistics, 2013, 95 (2), 476–490.

Atkeson, Andrew and Ariel T. Burstein, "Innovation, Firm Dynamics, and International Trade," Journal of Political Economy, 2010, 118 (3), 433–484.

Atkin, David, Azam Chaudhry, Shamyla Chaudry, Amit Khandelwal, and Eric A. Verhoogen, "Organizational Barriers to Technology Adoption: Evidence from Soccer-Ball Producers in Pakistan," Quarterly Journal of Economics, 2017

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," American Economic Review, 2013, 103 (6), 2121–2168.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Shock: Learning from Local Labor Market Adjustment to Large Changes in Trade," Working Paper, 2016.

Autor, David H., David Dorn, and Gordon H. Hanson, Gary Pisano, and Pian Shu, "Foreign Competition and Domestic Innovation: Evidence from US Patents," Working Paper, 2016.

Bena, Jan and Elena Simintzi, "Labor-Induced Technological Change: Evidence from Doing Business in China," Working Paper, 2015.

Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott, "Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of US Manufacturing Plants," Journal of International Economics, 2006, 68 (1), 219–237.

Bloom, Nicholas, Mirko Draca, and John Van Reenen, "Trade-Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," Review of Economic Studies, 2015.

Bloom, Nicholas, Paul M. Romer, Stephen J. Terry, and John Van Reenen, "Trapped Factors and China's Impact on Global Growth," Working Paper, 2014.

Boldrin, Michele and David K. Levine, "The Case Against Patents," Journal of Economic Perspectives, 2013, 27 (1), 3–22.

Branstetter, Lee, Jong-Rong Chen, Britta Glennon, Chih-Hai Yang, Nikolas Zolas. "Does Offshoring Manufacturing Harm Innovation in the Home Country? Evidence from Taiwan and China", mimeo Carnegie Mellon University 2017

Feenstra, Robert C. and David E. Weinstein, "Globalization, Markups and US Welfare," Working Paper, 2010.

Grossman, Gene M. and Elhanan Helpman, "Quality Ladders and Product Cycles," Quarterly Journal of Economics, 1991, 106 (2), 557–586.

Holmes, Thomas J. and John J. Stevens, "An Alternative Theory of the Plant Size Distribution, with Geography and Intra- and International Trade," Journal of Political Economy, 2014, 122 (2), 369–421.

Hombert, Johan and Adrien Matray, “Can Innovation Help US Manufacturing Firms Escape Import Competition from China?” Working Paper, 2014.

Khandelwal, Amit K., “The Long and Short (of) Quality Ladders,” Review of Economic Studies, 2010, 77 (4), 1450–1476.

Klette, Tor J. and Samuel Kortum, “Innovating Firms and Aggregate Innovation,” Journal of Political Economy, 2004, 112 (5), 986–1018.

Melitz, Marc J., “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” Econometrica, 2003, 71 (6), 1695–1725.

Melitz, Marc J., and Gianmarco I. P. Ottaviano, “Market Size, Trade, and Productivity,” Review of Economic Studies, 2008, 75 (1), 295–316.

Romer, Paul M., “Endogenous Technological Change,” Journal of Political Economy, 1990, 98 (5).

Sutton, John, “Competing in Capabilities: The Globalization Process”, 2012.

Tucker, Catherine, “Patent Trolls and Technology Diffusion: The Case of Medical Imaging,” Working Paper, 2014.

Yang, Mu-Jeung, Lorenz Kueng, and Bryan Hong, “Business Strategy and the Management of Firms,” Working Paper, 2015.