Innovation Responses to Import Competition

INCOMPLETE AND PRELIMINARY

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Abstract
How does trade liberalization that raises a country's import competition affect the innovative activity of its firms? We exploit the strong growth of Chinese exports resulting from China's entry into the World Trade Organization in 2001 as a competitive shock to, specifically, Mexican manufacturing firms. Innovation is captured through information on the adoption of detailed firm level production techniques such as just in time inventory methods, quality control measures, and job rotation among the Mexican firms. Our results indicate that China's rise in global trade did not affect by much Mexico's rate of innovation, which contrasts with the substantial gains that others have found in the case of bilateral liberalizations. At the same time, there is a striking heterogeneity in the responses across firms for different productivities, with productive firms innovating more and less productive firms innovating less, which leads to positive selection in that initial differences in firm performance are sharpened by the advent of new competition. We discuss the implications of these findings for theories of trade and innovation.[1]

[1] The authors thank Swati Dhingra, Amit Khandelwal, Mark Roberts, Andres Rodriguez-Clare, Jon Vogel, Stephen Yeaple, and participants at the LACEA September 2010 (San Jose) conference as well as participants at Columbia, Georgetown, Penn State, Princeton and NBER seminars for comments. The financial support of the World Bank's Research Support Budget is gratefully acknowledged.

1 Introduction

Trade liberalization in form of foreign market access improvements rarely encounters domestic political opposition because it means higher exports and employment for domestic firms. Economists have long supported the dismantling of trade barriers on efficiency grounds, noting additional gains recently through the reallocation of firms' market shares and increased incentives to innovate, among others (Pavcnik 2002, Melitz 2003, Bernard et al. 2003, Aw, Roberts, and Winston 2007, Costantini and Melitz 2008, Verhoogen 2008, Lileeva and Treer 2010, Bustos 2010). Given these benefits from improved foreign market access, it is natural to ask how they compare with the benefits from improving domestic access to foreign firms.

This paper addresses this question by examining innovation of Mexican firms in response to increased competition from China between the years 1998 to 2004. China's entry into world trade was the largest trade shock during the last 30 years.[2] By becoming a member of the World Trade Organization (WTO) in 2001, China gained new market access, and her already high rates of export growth accelerated. Figure 1 shows the increasing presence of China on the world markets, with a particular steep slope in the years after 1998. Mexico was among the countries most strongly affected, because Mexico had substantial overlap with China in terms of product range, and the location of Mexico next to the United States has made it particularly vulnerable to competition from China. In comparison to its imports from China, Mexico's exports to China over this period were trivial.

[2] See Krugman (2008), Bloom, Draca, and Van Reenen, and Winters and Yusuf (2007).

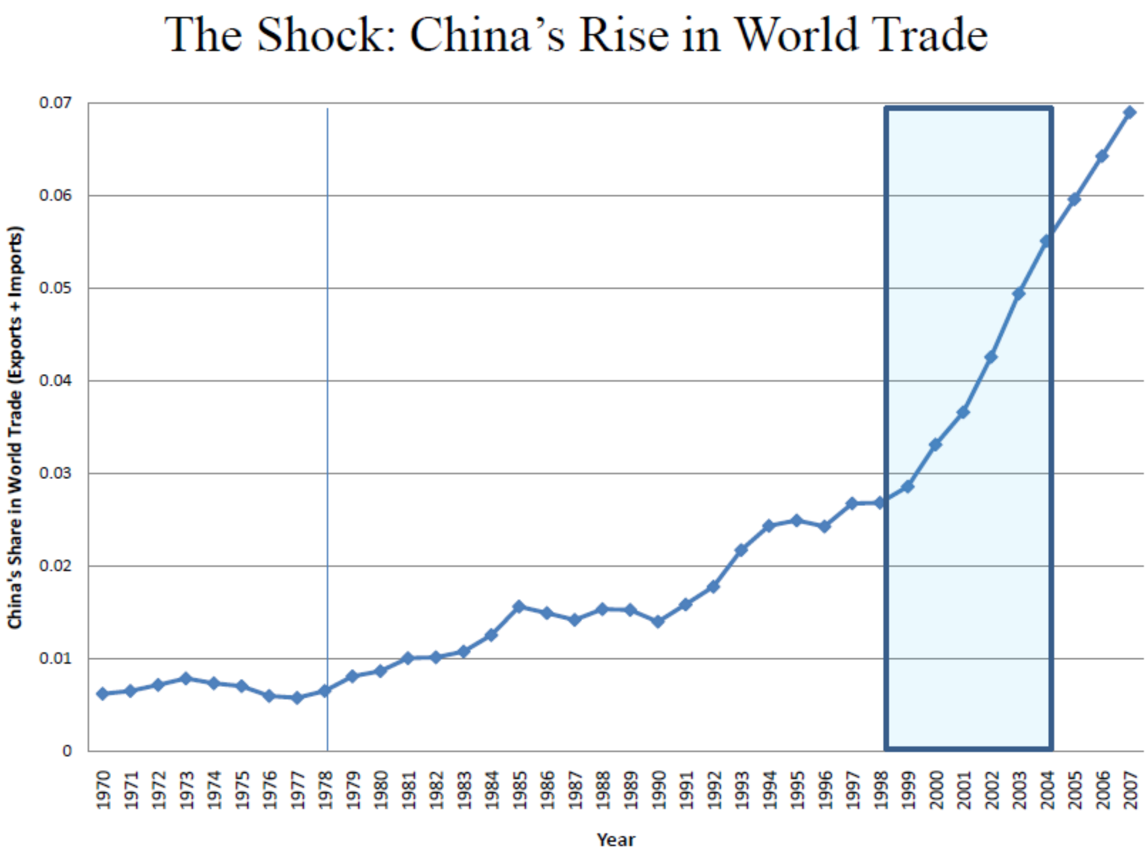

Figure 1: Chinese exports over time

This setting yields an unparalleled opportunity to examine the innovative behavior of firms under the threat of competition. Innovation has many dimensions, and relatively little is known on which ones are most important. Some emphasize inventory management while others the control of the production process, other observers see workers as the crucial element while a fourth group focuses on computers and equipment. This paper provides evidence on this and other specific forms of innovation by Mexican firms as they faced new import competition from China. This affords us a new look into the black box of firm-level innovation in response to competitive shocks.[3]

[3] The terms firm and plant are used interchangeably in this paper; the evidence below is on plants.

Our main findings are as follows. First, the aggregate level of innovation of Mexican manufacturing firms did not change much with the new import competition from China. In contrast, earlier studies have often found substantial overall effects (Pavcnik 2002, Bloom, Draca, and Van Reenen 2009, Lileeva and Treer 2010). Our second, and related finding is that the aggregate effect masks a striking heterogeneous response across firms of different productivity. We find that relatively productive firms innovate more in response to the China trade shock while less productive firms innovate less. Import competition sharpens the difference between strong and weak performing firms because it leads to innovation that amplifies the initial difference. This is a positive dynamic selection finding.

Third, there is little evidence that the innovation strategies of Mexican firms can be explained by market size reallocations. The sales growth of the firms that innovate during the period of China's entry into the WTO is similar to the sales growth of firms that do not innovate. While a market-size explanation of firm-level innovation is not supported by our results, they are consistent with productive firms having relatively more to gain from innovation than less productive firms, as, for example, in the model of Aghion, Harris, Howitt, and Vickers (2001).[4] We also find that a high degree of intermediate good imports from Asia, foreign ownership, and a skilled labor force is conducive to innovation in the face of import competition.

The gains from trade liberalization is a central question in international economics, and this paper sheds new light on innovation gains in this context. It has long been

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[4] In Aghion, Harris, Howitt, and Vickers (2001), competition will provide greater incentives to innovate for high- compared to low-productivity firms because conditional on innovation, a high-productivity firm can win out against the foreign competitor in a limit pricing contest whereas the low-productivity firm cannot.

argued that trade liberalization can affect a country's rate of innovation, and analysis of the detrimental impact of import substituting trade strategies adopted by many less developed countries after World War II was early evidence of this (Krueger 1975, Bhagwati 1978). Our work builds on and extends this research by emphasizing heterogeneity as a determinant of firms' innovation choices (see surveys by Tybout 2003 and Redding 2010).

Our approach is distinct in two ways. First, we examine innovation in the sense of particular organizational forms and production techniques. The specific way in which a firm controls product quality, optimizes its inventory, and manages its operations more generally explain much of the variation in economic performance across firms, a finding emphasized in the business literature and more recently also by economists (Womack, Jones, and Roos 1991 and Bloom and Van Reenen 2007, Syverson 2010, respectively). In the context of trade liberalization, studies on the adoption of specific firm techniques are extremely rare; an exception is Schmitz (2005) who presents a case study on the abolition of restrictive work practices among North American iron ore producers. Information on the introduction of computer systems needed for Just-in-Time techniques is presented in Lileeva and Treer (2010), while Dhingra (2011) employs direct evidence on production process innovations in analyzing trade-offs faced by multi-product firms.

Comparatively little is known on how firms change their organizational structure and their operations management in response to new sources of competition. The main advantage of analyzing specific innovations is its potential for better understanding the factors determining overall firm performance. When firm innovation is broken down into its constituent parts, this will provide more information on which are the truly crucial elements, and it also sheds new light on how individual choices fit together to form the overall firm strategy. This information should prove valuable in understanding the import and export behavior of _rms. In addition, particular innovations may have quite different implications of trade liberalization on labor markets and the economy as a whole. If innovation is mainly in form of improved inventory management we would expect labor demand to become less skill biased than if innovation is mostly in form of machinery replacing unskilled labor, for example. In contrast, a focus on productivity changes does not give as much information, also because the productivity changes that can be measured in practice pick up changes in market power (Foster, Haltiwanger, and Syverson 2008), product mix (Bernard, Redding, and Schott 2010, Mayer, Melitz, and Ottaviano 2010), and factor market distortions (Hsieh and Klenow 2010) as well.

Second, we examine innovation responses to trade liberalization when the size of the market is shrinking. There is a large literature on how an expanding market size might increase innovation because innovation is complementary to the firm's decision to export (Yeaple 2005, Verhoogen 2008, Costantini and Melitz 2008, Atkeson and Burstein 2008, Lileeva and Treer 2010, and Bustos 2010)[5], but this argument does not apply in the case of new import competition because market size is generally shrinking. Innovation in the face of new import competition must be driven by something other than increases in firm scale, and in this respect our research relates to research on the impact of changes in domestic competition and FDI entry (see Holmes and Schmitz 2010 and Aghion, Blundell, Griffith, Howitt, and Prantl 2009, respectively). Arguably, from a policy perspective the innovation response to

[5] Similar market size effects are seen in the case of FDI; in particular, technology spending of firms that decide to supply Wal-Mart in Mexico (which increases the market size of the supplier) goes up relatively that of non-Wal-Mart suppliers (Iacovone, Javorcik, Keller, and Tybout 2010).

unilateral trade liberalization at home is just as important as the response to bi- or multilateral liberalizations.

A recent contribution on the impact of import competition from China is Bloom, Draca, and Van Reenen (2009).[6] These authors emphasize that the contribution of trade in generating wage inequality in rich countries is larger than generally presumed by showing that this competition induced European firms to increase spending on computers, which had a positive effect on the skill premium. Our work differs because instead of technology investments we analyze specific organizational changes of the firms, and moreover, in contrast to Bloom, Draca, and Van Reenen (2009) we find strong heterogeneity in firms' innovation responses to competition, increasing for some and decreasing for other firms.

The remainder of the paper is as follows. We start out by introducing the empirical approach in section 2. The various forms of innovation analyzed in this paper are introduced in section 3. This section also covers their basic features in our sample of Mexican firms, which guides the empirical analysis. A description of our other data is also in section 3. All empirical results are discussed in section 4, while section 5 provides some concluding discussion.

2 Estimating the relationship between innovation and competition

[6] Other research on the impact of China's recent entry into global trade includes Utar and Torres Ruiz (2010) and Iacovone, Rauch, and Winters (2010). The latter examine the impact of China's trade on the market shares of firms and products in Mexico, which is complementary to our emphasis on innovation. Utar and Torres Ruiz (2010) study productivity changes among Mexican export processing firms (maquiladoras) using familiar methods. Maquiladoras are also included in our sample below.

The empirical approach is this paper is straightforward. We relate firm-level innovation to a variable that captures the change in import competition faced by Mexican plants after China's entry into the World Trade Organization:

$$y_{i(j)t} = \beta_0 + \beta_1 \Delta comp_{jt} + \gamma X + u_{i(j)t}. \qquad (1)$$

Here, $y_{i(j)t}$ denotes a specific type of innovation of firm i, for example the adoption of Just-in-Time (JIT). Firm i is observed in year t, and each firm belongs to a particular six-digit industry j, the variable $\Delta comp_{jt}$ is the change in competition for industry j at time t, the term X is a vector of other observable determinants of $y_{i(j)t}$, and $u_{i(j)t}$ is an error term. Our sample is a balanced panel of firms with two years of observations, for 1998 and for 2004, which in equation (1) is estimated as a long-difference regression. In the case of JIT as the dependent variable, for example, $y_{i(j)t}$ is equal to one if the firm has introduced JIT between the years 2000 and 2004, and zero otherwise.[7] The goal is to consistently estimate β_1 as the impact of competition changes on innovation.

There are reasons to believe that $\beta_1 < 0$; for example because increased competition dissipates rents that are necessary to sustain innovation (Schumpeter), and there are other reasons that would give $\beta_1 > 0$; for example because increased competition increases managerial effort (Schmidt 1997) or it may lower product line switching

[7] We choose the years 2000 to 2004 because by the end of the year 1999 it had started to become clear that China would enter the WTO soon (official accession was in the year 2001).

costs (Holmes, Levine, and Schmitz 2008).[8] At this point we are agnostic about the sign of β_1, the competition effect on innovation.

We will also generalize equation (1) by letting the impact of competition on innovation depend on characteristics of the firm. Denoting a specific firm characteristic by $q_{i(j)t}$, the extended estimating equation becomes:

$$y_{i(j)t} = \beta_0 + \beta_1\ \Delta comp_{jt} + \beta_3\ q_{i(j)t} + \beta_3(q_{i(j)t} \text{ x } \Delta comp_{jt}) + \gamma X + u_{i(j)t}. \qquad (2)$$

Equation (2) includes the linear term in $q_{i(j)t}$ so that β_3 captures only the differential effect from changes in competition. The parameter β_3 is of key interest, because β_3 not equal to 0 would indicate that the competition effect on innovation varies with the firm characteristic. Several firm characteristics are prime candidates for $q_{i(j)t}$. In line with a large body of trade research emphasizing exogenous heterogeneity in productivity, we will begin with the productivity of the firm in the year 1998, prior to China's entry into the WTO.

Going beyond productivity, the analysis will be extended to other initial (year-1998) determinants, such as the skill composition of the firm's labor force. Moreover, we will also examine whether contemporaneous changes in firm characteristics between 1998 and 2004 are related to specific firm innovation between the years 1998 and 2004. On the one hand, it might be that the introduction of specific innovation and, say, the training of the labor force are complementary activities. On the other, if both activities eat up firm resources (and the firm is partially credit constrained), or

[8] The theoretical literature of the impact of competition on innovation is covered in Bloom, Draca, and Van Reenen (2009) and Holmes and Schmitz (2010).

innovation and labor training are alternative ways of tackling new import competition, the relationship between innovation and other contemporaneous firm changes may be negative.

Consistent parameter estimation in (1) and (2) requires that a number of issues are addressed. There is the possible endogeneity of the change-in-competition variable $\Delta comp_{jt}$ as well as measurement error in our dependent variables, $y_{i(j)t}$: Moreover, several of our dependent variables, for example Just-in-Time (JIT), take on only the value of zero and one. We will therefore estimate the equations not only with linear probability models using least squares but also with probit models using maximum likelihood. These issues will be discussed below.

The following section discusses the data sources and the definition of the innovation variables.

3 Data

This paper employs data provided by Instituto Nacional de Estadística y Geografía (INEGI), a Mexican statistical agency. We use surveys of manufacturing firms from the years 2005 and 1999, which cover information for the years 2004 and 1998. These surveys of the Encuesta Nacional de Empleo, Salarios, Tecnología y Capacitación (ENESTyC), provide information on a large range of characteristics in the area of technology, employment, and labor training salaries, in addition to basic information on sales, investment, and age of the firm. The survey includes all Mexican firms with more than 100 employees, and uses a sampling procedure that ensures representativeness to include smaller firms. The data attaches a unique identified to each firm that remains the same over time, which allows us to follow firms over time.

In the section on firm organization, the ENESTyC questionnaires ask about the existence (and in 2005 also the year of introduction) of a number of firm techniques. These techniques define key elements of the operations management of the firm, which is the business function responsible for planning, coordinating, and controlling the resources needed to produce a firm's product (Reid and Sanders 2005). Most of the specific techniques that we will study are part of operations management concepts that became known in the 1980s and are sometimes collectively referred to as lean manufacturing. These ideas originated mostly in Japan, specifically with the car maker Toyota. They gained rapidly influence in business circles, and it is reasonable to expect that these concepts were well-known in Mexican firms towards the end of the 1990s.

While the concepts are related, each of them defines a particular aspect of the techniques firms are employing. The following gives a list of techniques, followed by a brief description of the key elements of each technique: (1) Total Quality Management, (2) Statistical Quality Control, (3) Quality Control, (4) Just-in-Time System, (5) Re-organization, (6) Job Rotation, (7) Worker Participation and (8) Process Re-engineering.[9]

[9] The following descriptions draw on a number of sources on operations management, mainly the INEGI manuals, but also in particular Reid and Sanders (2005).

(1) **Total Quality Control**: Total Quality Control, or Total Quality Management (TQM), is an integrated effort designed to improve quality performance at every level of the organization. TQM focuses on proactively identifying root causes of reoccurring problems, correcting them at the source, where customers ultimately determine what is important (customer-driven quality). Key methods include continuous improvement, employee empowerment, understanding quality control tools, and the formation of work groups acting as problem-solving teams (so-called quality circles).

(2) **Quality Control of Production**: The question whether product quality is meeting the pre-established standards. Quality Control uses a number of statistical methods, in particular (i) Descriptive statistics, (ii) Statistical process control, which is to determine whether a process is performing as expected, and (iii) Acceptance sampling, where entire batches of products are accepted or rejected by only inspecting a few items.

(3) **Just-in-Time** System: The goal is to get the right quantity of goods to the right place exactly when they are needed. Key ideas are (i) to eliminate unsynchronized production, unstreamlined layouts, and unnecessary material handling (referred to as waste); (ii) to take a broad view of operations so that the system, not individual tasks, are optimized; (iii) to make operations simpler, with fewer steps (also less error prone); and (iv) to improve visibility so that waste can be detected. Methods include so-called Kanbans and pull production systems, quick setups and small lots, uniform plant loading, and exible resources such as general-purpose equipment and multi-trained workers.

(4) **Re-Organization**: The re-organization of the work facility in terms of equipment, machinery, and installations. Re-organization can improve the

physical arrangement of resources within a facility. Standard forms of facility layout are (i) process layouts, which groups similar resources together, and (ii) product layouts, which is designed to produce a specific product efficiently. It is central to have workstations in close physical proximity to reduce transport and movement as well as streamline the ow of material. A key method is so-called cellular manufacturing. Improved work facility layout also reduces the probability of work risks, thereby reducing downtime.

(5) **Job Rotation**: Job rotation is a central part of the worker-related aspects of modern operations management. It recognizes that in addition to the advantages that labor specialization brings, it can also carry high costs in terms of high absenteeism, high turnover rates, and high number of employee grievances _led, at the same time when workers are dissatisfied because they see little growth opportunity, control over work, room for initiative, and intrinsic satisfaction in their work. Job rotation aims at changing that by shifting the worker through several jobs to increase understanding of the total process, together with the necessary skill training. This may also lead the worker to make better decisions at their own departments and to increased communication across various different departments of the firm.

(6) **Statistical quality control**: The questionnaires by INEGI specify that in this question the surveyor asked for the installation of any system of quality assurance, by which products are cross checked along certain check points on the production chain if their quantity and quality matches predefined standards.

(7) **Worker participation**: Surveyors were asked to determine if there was regular communication with workers or if workers were directly involved in decision making processes.

(8) **Process re-engineering:** This variable measures mayor changes to the production change, that may involve new or improved equipment, or streamlined production processes.

In Table 1 we provide summary statistics on these innovation measures before 1998, and in the period from 1998 to 2004. 8 percent of plants in our sample introduced Just in Time before 1998, and 21 more percent of the remaining plants introduced this system in the years 1998-2004, making Just in Time the least adopted innovation in our analysis. More firms had adopted Quality Control or Statistical Control, which were used by 36 and 29 percent of plants respectively before 1998, with new introductions of around 40 percent of the remaining plants from 1998 to 2004. There is generally a positive correlation between these measures of innovations, although with a range of 0.18 to 0.42 this correlation is not particularly strong.

	Nr of firms with innovation in 1998	Nr of firms that adopt innovation between 1998-2004	Percent of firms with innovation in 1998	Percent of firms that adopt innovation between 1998-2004
Just in time	184	488	0.08	0.21
Quality control	834	790	0.36	0.34
Job rotation	289	604	0.13	0.26
Participation	238	566	0.10	0.25
Re-engineering	251	644	0.11	0.28
Re-ordering	336	804	0.15	0.35
Statistical control	659	774	0.29	0.34

Total quality control	447	875	0.19	0.38

Table 1: Innovation frequency in 1998 and innovation adoption from 1998 to 2004.

In addition to these variables, the ENESTyC surveys also include variables that are relevant for innovation strategies of firms, in particular whether a firm exports, what fraction of its sales it exports, whether a firm imports part of its materials and intermediates, and if so from where, whether a firm is foreign owned, and at what percentage; the skill composition of the firm's labor force, as well as the extent of worker training that was performed. In addition, the surveys cover variables that measure technology investment inputs, such as R&D expenditures and other activities affecting the technological capabilities of the firm (such as technology purchases, equipment purchases, and indicators of process and product innovation). Our analysis will focus mainly on the adoption of specific firm techniques such as Just-in-Time, for reasons laid out above.

Our measure of import competition is based on the actual market share gains of Chinese exporters between the years 1998 and 2004.[10] While we are interested in the response of Mexican firms to Chinese competition, we recognize that Chinese market share gains in Mexico are potentially endogenous to the performance of the Mexican firms themselves. To address this issue, we employ information on Chinese market share gains in the United States instead of Chinese gains in Mexico over this period. By exploiting evidence on the competitive strength of China in a different,

[10] We are in the process of adding policy measures--the change in tariffs—for a subset of industries as additional measures of changes in import competition.

much larger though closely related market, we are more plausibly examining an exogenous shock to the Mexican manufacturing sector.

The import competition variable is the 1998-to-2004 change in the imports from China in the United States, relative to all US imports, for narrowly defined industries. We merge the survey information with the well known international trade data from COMTRADE employing the concordance of Iacovone, Rauch, and Winters (2010). This links the Mexican plant data at the six-digit level (CMAP 6) to the COMTRADE trade data according to the Harmonized System (HS) classification.

The following section presents our empirical findings.

4 Empirical Results

We now turn to estimating the effect of competition from China on the innovative behavior of Mexican plants. A simple estimation strategy is adopted in which measures of innovation after China's entry into the WTO in 2001 are related to competition from China and a number of control variables. We start with simple, descriptive tables that convey the heterogeneous response of Mexican plants to Chinese competition.

First we ask about characteristics of innovators. In Table 2 we restrict plants to those that did not have a given innovation in the year 1998. We then decompose these firms into those that have above or below median sales, and those that have above or below median labor productivity, where we measure labor productivity as the share of output to the number of all employees. We define both sales and productivity relative to the four-digit industry to ensure that both the high- and the low-productivity firm groups have firms from all industries.[11]

We compute the mean number of innovators for each of these four groups. Again the table highlights that there was substantial innovation in the time period from 1998 to 2004 that we consider. The highest share of innovators is found for all innovations for large and productive firms. It also seems that larger but less productive firms seem to innovate more than productive small firms, possibly due to easier access to funds.

Decomposition of firms by innovation and sales mean number of firms that introduced innovation (number of these firms)			
		Sales low	Sales high
Statistical control	Lab prod low	0.461 (245)	0.468 (556)
	Lab prod high	0.403 (556)	0.625 (283)
Quality control	Lab prod low	0.556 (228)	0.51 (488)
	Lab prod high	0.477 (488)	0.686 (261)
Total quality control	Lab prod low	0.424 (271)	0.498 (637)
	Lab prod high	0.386 (637)	0.642 (307)
Reordering	Lab prod low	0.408 (292)	0.385 (672)
	Lab prod high	0.365 (672)	0.554 (327)
Just in time	Lab prod low	0.165 (309)	0.225 (730)
	Lab prod high	0.178 (730)	0.413 (346)

[11] Lileeva and Trefler (2010) have recently adopted a similar approach.

Re-engineering	Lab prod low	0.282 (294)	0.329 (712)
	Lab prod high	0.235 (712)	0.485 (330)
Job rotation	Lab prod low	0.283 (300)	0.259 (688)
	Lab prod high	0.263 (688)	0.479 (334)
Particip	Lab prod low	0.259 (305)	0.247 (709)
	Lab prod high	0.226 (709)	0.45 (338)

Table 2: In this table we consider firms that did not have the corresponding innovation in 1998. We decompose these firms by above/below median sales and labor productivity, measured as output per worker. For each of the four groups we display the mean number of firms that innovated in that group, and the number of firms in that group in brackets.

In Table 3 we repeat the exercise, but replace the measure of labor productivity by our measure of Chinese competition in the decomposition. This table demonstrates the main findings of this paper. First, firms that face more competition from China seem to innovate more, although this effect is not universal, and can be rather small. Second, larger firms innovate more. This second effect is stronger and more robust than the first. Plants that are both, large and that face a high degree of competition from China innovate most. This finding holds for all innovations separately.

Decomposition of firms by innovation and sales mean number of firms that introduced innovation (number of these firms)			
		Chinese competition low	Chinese competition high
Statistical control	Sales low	.432 (374)	.409 (427)
	Sales high	.479 (427)	.563 (412)
Quality control	Sales low	.521 (336)	.492 (380)

	Sales high	.515 (380)	.629 (369)
Total quality control	Sales low	.381 (417)	.411 (491)
	Sales high	.523 (491)	.566 (453)
Reordering	Sales low	.379 (440)	.375 (524)
	Sales high	.437 (524)	.444 (475)
Just in time	Sales low	.194 (483)	.156 (556)
	Sales high	.259 (556)	.312 (520)
Re-engineering	Sales low	.259 (452)	.239 (554)
	Sales high	.361 (554)	.398 (488)
Job rotation	Sales low	.263 (451)	.273 (537)
	Sales high	.307 (537)	.356 (485)
Particip	Sales low	.240 (468)	.231 (546)
	Sales high	.280 (546)	.347 (501)

Table 3: In this table we consider firms that did not have the corresponding innovation in 1998. We decompose these firms by above/below median sales and Chinese competition, measured as share of Chinese in total imports. For each of the four groups we display the mean number of firms that innovated in that group, and the number of firms in that group in brackets.

To determine statistical significance, we now turn to a regression analysis of these findings. To keep the number of regressions manageable, we aggregate the eight innovations into one innovation index, which is a count of innovations that a firm introduced in the years 1998-2004. We exclude 67 firms that had all eight innovations in 1998, and therefore cannot by construction contribute any meaningful variation to the analysis. We use fixed effects to control for the initial number of innovations that a firm has.

Throughout the reported results we apply robust standard errors, which we cluster at six digit industry level (the level at which competition varies). As noted above, we are concerned that the observed degree of import penetration of China in Mexico is endogenous. One possibility is that Chinese firms make greater inroads into the Mexican market whenever the Mexican competitors are particularly weak. Therefore, the change in the Chinese import share in the United States is employed as our main measure of competition. China's export success in the US market Chinese exports to the US are positively correlated with Chinese exports to Mexico, but the US imports are less likely to be subject to reverse causality.

Baseline table: Pooled innovations

	(1)	(2)	(3)	(4)	(5)	(6)
	Innovation	Innovation	Innovation	Innovation	Chinese comp	Chinese comp
					in Mexico	in Mexico
	OLS	OLS	IV	IV	First stage	First stage
Chinese comp Mex	-1.427	-1.447	-3.131	-3.350		
	(1.028)	(1.003)	(2.348)	(2.358)		
Sales	0.263*	0.265*	0.196	0.191	-0.0313***	-0.0314***
	(0.138)	(0.139)	(0.163)	(0.164)	(0.00442)	(0.00444)
Interaction	3.389**	3.360**	4.945**	5.094**	0.747***	0.746***
	(1.514)	(1.497)	(2.506)	(2.506)	(0.0532)	(0.0533)
Age 5		-0.413**		-0.405**		0.00533
		(0.180)		(0.181)		(0.00544)
Age 10		-0.274		-0.286		-0.00251
		(0.181)		(0.181)		(0.00229)
Chinese comp EU					0.602***	0.601***
					(0.120)	(0.120)
Chinese comp world					0.0482	0.0477
					(0.0330)	(0.0329)
Chinese comp rest of world					0.00475***	0.00478***
					(0.00151)	(0.00150)

Observations	2080	2080	2080	2080	2080	2080
F statistic					119.09	112.2

Table 4: Pooled innovations. We use fixed effects for 2 digit industries, and cluster at the level of six digit industries. The sales variable is a dummy variable that takes a value of one for above median size.

Table 4 shows results for estimating equation 2 with the pooled innovation measure. The competition variable is again an indicator to show above median change in the import share from China in the United States between 1998 and 2004 (6-digit level). Sales is an indicator for above median sales in the initial year, 1998. Again this measure is computed within four digit industries. The other included variables are, first, the geographical distance of the plant to the United States border which is a determinant of the US orientation (especially the export-processing maquiladoras). We also control for whether a plant is located in Mexico City or not, and a set of age indicators (age greater than 10 years is the excluded category). We also include two-digit industry fixed effects which capture broader industry trends. Estimation method is OLS, with p-values based on robust and clustered (6-digit industry) standard errors reported in parentheses.

Column (1) shows the results of estimating equation 2 in OLS. First, note that the coefficient on initial sales positive, albeit not strongly significant. This gives some weak evidence that strong past performance --which led to high productivity by 1998—may translate into higher rates of innovation.

There is, however, a key distinction between high and low productivity firms in terms of their innovative response in the face of import competition. Innovation rates of low productivity firms fall when they are hit by competition, whereas innovation rates of high productivity firms do not. In fact, since the joint effect of the competition and interaction variable in column (1) is positive, about 1.9, the typical firm with sales in the year 1998 speeds up innovation whereas low productivity firms slow down innovation activities. In column (2) we add the mentioned control variables, which do not alter the effects much.

In columns (3) and (4) we repeat these estimation adopting an instrumental variables approach. We instrument Chinese exports to Mexico by Chinese exports of that same six digit product to the EU, to the world (excluding Mexico, the US and the EU), and Chinese exports of that good to the world excluding Mexico and the US. We take the view that Chinese export decisions concerning exports to the EU are taken independently of behavior of Mexican plants, while reflecting production developments in China. The results of these IV estimations are qualitatively and quantitatively similar to the OLS results.

Columns (5) and (6) show the corresponding first stages. All coefficients show the expected sign of a positive correlation between Chinese exports of products to the EU or the rest of the world and Chinese exports of the same good to Mexico. The first stage F-statistics are both over 100.

In Table 5 we add to the OLS estimation from Table 4 a second interaction term that measures productivity of firms. We use the ratio of white to blue collar workers, and create again a variable that indicates above median competition by that measure. We again find that the larger and the more productive firms innovate more. The competition variable itself, and its interactions with size and productivity are not statistically significant. The triple interaction however is large in magnitude and statistically significant in both specifications. This table demonstrates that within the larger plants, the more productive ones are especially likely to respond to the Chinese competition with innovation.

Multiple interactions		
	(1)	(2)
	Innovation	Innovation
Sales	0.277**	0.281**
	(0.139)	(0.140)
White over blue collar workers	0.393***	0.376***
	(0.140)	(0.142)
Chinese comp Mex	-0.570	-0.574
	(1.371)	(1.355)
Sales x comp	0.118	0.0510
	(1.740)	(1.730)
Collar ratio x comp	-1.147	-1.175
	(1.755)	(1.748)
Collar ratio x sales x comp	4.863**	4.946**
	(2.357)	(2.343)
Age 5		-0.337*
		(0.181)
Age 10		-0.199
		(0.179)
Observations	2143	2143

Table 5: Pooled innovations in OLS. We use fixed effects for 2 digit industries, and cluster at the level of six digit industries. The sales variable is a dummy variable that takes a value of one for above median size. The white over blue collar workers variable is a dummy variable that takes a value of one for above mean collar ratios.

We conduct a number of tests to see if the measure that just considers firms above or below the mean is the appropriate one. In Table 6 we decompose the plants into the bottom, medium and top third by size and generate dummy variables indicating each of these categories. We then interact each of these with the Chinese competition indicator. The table shows some robustness of the findings above. Both in the linear effect, and in the interaction, the largest firms show the strongest response to Chinese competition. Significance of the interaction term is lower than in the previous estimation, but the mean effect for the large firms is stronger.

Three size terciles	
	(1)
	Innovation
Q1	-0.273*
	(0.144)
Q2	Omitted
Q3	0.471***
	(0.155)
Q1 x comp	-1.244
	(1.371)
Q2 x comp	-0.734
	(1.106)
Q3 x comp	2.416*
	(1.369)
Age 5	-0.328*
	(0.181)
Age 10	-0.281
	(0.179)
Observations	2143

Table 6: Pooled innovations. We use fixed effects for 2 digit industries, and cluster at the level of six digit industries. Q1 indicates the third of the smallest firms, Q2 the mid sized firms, and Q3 the largest firms.

Tables 7 and 8 (at the end of this document) exploit the same question by estimating the same equation as in the baseline table in OLS and IV but with different size cutoffs. These tables help us to find at which percentile the discontinuity of Mexican firms rests. We find in both tables that the choice of cutoffs does not alter the significance of the interaction term by much. We find strong and significant interactions in both OLS and IV for the top 10, 15, 25, 33 or 50 percent of firms. Coefficients seem to increase if we consider fewer firms for which we set the size control to one, however we seem to lose some statistical power along the way.

We conclude that the finding that productive firms innovate more in response to the China trade shock while less productive firms innovate less is solid, and seems to be robust to a number of alternative specifications. It means that import competition sharpens the difference between strong- and weak performing firms because it leads to innovation that amplifies the initial difference. We emphasize that we find little evidence that strong firms generally innovate more, but rather that import competition triggers this response leading to positive dynamic selection.

Moreover, the response difference of strong versus weak performing firms can only be explained in a framework that allows for a non-monotonic relationship between innovation and competition. One possibility is the escape-competition effect modeled by Aghion et al. (2001). In contrast, while a Schumpeterian argument may explain why low productivity firms innovate less it is inconsistent with high productivity firms innovating at the same time more. Alternatively, if increased competition increases innovation by reducing agency problems, there must be another explanation for why low productivity firms reduce innovation in the face of import competition from China.

5 Conclusion

The Schumpeterian hypothesis that monopolists have a greater incentive to innovate than firms facing tough competition has been revisited by new theory and empirical results finding that more competition may on balance actually increase the rate of innovation. In our analysis of the impact of China's emergence as a force in international trade, we find that the rate of innovation of Mexican plants seems on average unaffected. This may be specific to the shock we are analyzing, which is extraordinary in many respects. At the same time, there is strong evidence that firms with higher labor productivity tend to innovate more than less productive firms in the face of new competition.

For this investigation, we rely on data from surveys on Mexican plants, that allow us to distinguish various specific measures of innovation, such as the introduction of Just in Time management system, job rotation schemes, quality controls, continuous controls and production re-organizations. We find for all these measures that more productive plants are more likely to introduce them as a response to the unilateral competition from China than less productive plants. This difference is strongest for Just in Time. Import competition is thus a force that sharpens the difference between strong-performing and weak-performing firms, a result that is in line with the more qualitative body of research on countries' foreign trade strategies that has been accumulated since World War II.

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Different size cutoffs												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation
Chinese competition	-1.632	-1.497	-1.305	-1.132	-1.459	-1.253	-1.019	-0.832	-0.870	-0.704	-0.825	-0.678
	(1.288)	(1.247)	(1.099)	(1.070)	(0.943)	(0.919)	(0.912)	(0.893)	(0.855)	(0.835)	(0.807)	(0.787)
Sales	0.333**	0.323**	0.286**	0.281**	0.443***	0.444***	0.605***	0.611***	0.792***	0.796***	0.968***	0.964***
	(0.137)	(0.136)	(0.129)	(0.128)	(0.149)	(0.147)	(0.164)	(0.164)	(0.203)	(0.199)	(0.257)	(0.251)
Interaction	3.027*	2.937*	3.355**	3.157**	4.533***	4.179**	3.606*	3.260*	3.839*	3.467*	4.728**	4.350*
	(1.709)	(1.675)	(1.626)	(1.599)	(1.713)	(1.701)	(1.836)	(1.825)	(2.077)	(2.064)	(2.270)	(2.257)
age5		-0.380**		-0.412**		-0.406**		-0.441**		-0.427**		-0.389**
		(0.183)		(0.183)		(0.186)		(0.186)		(0.189)		(0.186)
age10		-0.322*		-0.318*		-0.309*		-0.321*		-0.317*		-0.306*
		(0.185)		(0.183)		(0.182)		(0.182)		(0.185)		(0.185)
Observations	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143
Cutoff	0.66	0.66	0.5	0.5	0.33	0.33	0.25	0.25	0.15	0.15	0.1	0.1

Table 7: OLS, pooled innovations. We use fixed effects for 2 digit industries, and cluster at the level of six digit industries. The cutoff indicates the percentile of firms for which the sales dummy indicates a value of one.

Different size cutoffs												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation	Innovation
Chinese competition	-4.151	-3.573	-3.375	-2.995	-2.953	-2.627	-2.713	-2.416	-2.153	-1.897	-2.470	-2.228
	(3.312)	(3.298)	(2.349)	(2.359)	(1.965)	(1.982)	(1.854)	(1.874)	(1.661)	(1.674)	(1.559)	(1.565)
Sales	0.231	0.239	0.204	0.209	0.390**	0.395**	0.551***	0.560***	0.707***	0.713***	0.805***	0.800***
	(0.194)	(0.192)	(0.158)	(0.156)	(0.167)	(0.165)	(0.179)	(0.179)	(0.217)	(0.213)	(0.256)	(0.251)
Interaction	5.371	4.861	5.273**	4.884*	5.827**	5.371**	4.987**	4.552*	4.786**	4.346*	6.391**	5.940**
	(3.349)	(3.323)	(2.514)	(2.503)	(2.264)	(2.272)	(2.328)	(2.335)	(2.412)	(2.416)	(2.500)	(2.499)
age5		-0.369**		-0.403**		-0.395**		-0.429**		-0.420**		-0.352*
		(0.186)		(0.185)		(0.188)		(0.189)		(0.192)		(0.185)
age10		-0.332*		-0.328*		-0.317*		-0.331*		-0.327*		-0.327*
		(0.184)		(0.182)		(0.181)		(0.181)		(0.183)		(0.184)
Observations	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143	2143
Cutoff	0.66	0.66	0.5	0.5	0.33	0.33	0.25	0.25	0.15	0.15	0.1	0.1

Table 8: IV, pooled innovations. We use fixed effects for 2 digit industries, and cluster at the level of six digit industries. The cutoff indicates the percentile of firms for which the sales dummy indicates a value of one.