Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity

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July 26th 2012

Abstract

We examine the impact of Chinese import competition on broad measures of technical change - patenting, IT, R&D, TFP and management practices – using new panel data across twelve European countries from 1996-2007. In particular, we establish that the *absolute* volume of innovation increases within the firms most affected by Chinese imports. We correct for endogeneity using the removal of product-specific quotas following China's entry into the World Trade Organization. Chinese import competition led to increased technical change *within firms* and reallocated employment *between firms* towards more technologically advanced firms. These within and between effects were about equal in magnitude, and account for about 15% of European technology upgrading over 2000-2007 (and even more when allowing for offshoring to China). Rising Chinese import competition also led to falls in employment, profits, prices and the share of unskilled workers. By contrast, import competition from developed countries had no effect on innovation. We develop a simple "trapped factor" model that is consistent with these empirical findings.

JEL No. O33, F14, L25, L60,

Keywords: China, technical change, trade, firm survival, employment

Acknowledgements: This is a revised version of Centre for Economic Performance Working Paper No. 1000. We would like to thank the Economic and Social Research Council, Anglo-German Foundation, the European Commission, the Alfred Sloan Foundation, and the National Science Foundation for their financial support. Helpful comments have been received from Steve Redding, our formal discussants (Oriana Bandiera, Natalie Chen, Allan Collard-Wexler, Francesco Daveri, Fritz Foley, Andrei Levchenko, Marc Melitz, Ralph Ossa, Peter Schott and Reinhilde Veugelers) and from seminar audiences in Aarhus, AEA, Brussels, Berkeley, Boston University, Brown, CEMFI, Colorado, Duke, Georgetown, Harvard, Houston, LSE, Mannheim, Maryland, Minnesota, MIT, NBER, NYU Stern, OECD, Penn State, Princeton, PSE, Queen's, San Francisco Fed, Sciences Po, SITE, Stanford, Southampton, Texas, Toronto, UC Davis, UCLA, UCSC, Venice, Warwick, World Bank, Yale, ZEW and Zurich. Charles Wang and Dinesh Cheryan provided excellent research assistance.

I. INTRODUCTION

A vigorous political debate is in progress over the impact of globalization on the economies of the developed world. China looms large in these discussions, as her exports have grown by over 15% per year over the last two decades. One major benefit of Chinese trade had been lower prices for manufactured goods. We argue in this paper that increased Chinese trade has also induced faster technical change from both innovation and the adoption of new technologies, contributing to productivity growth. In particular, we find that the *absolute* volume of innovation (not just patents per worker or productivity) increases *within* the firms more affected by exogenous reductions in barriers to Chinese imports.

Several detailed case studies such as Bartel, Ichinowski and Shaw (2007) on American valve-makers, Freeman and Kleiner (2005) on footwear or Bugamelli, Schivardi and Zizza (2008) on Italian manufacturers show firms innovating in response to import competition from low wage countries. A contribution of our paper is to confirm the importance of low wage country trade for technical change using a large sample of over half a million firms and exploiting China's entry into the World Trade Organization (WTO) to identify the causal effect of trade.

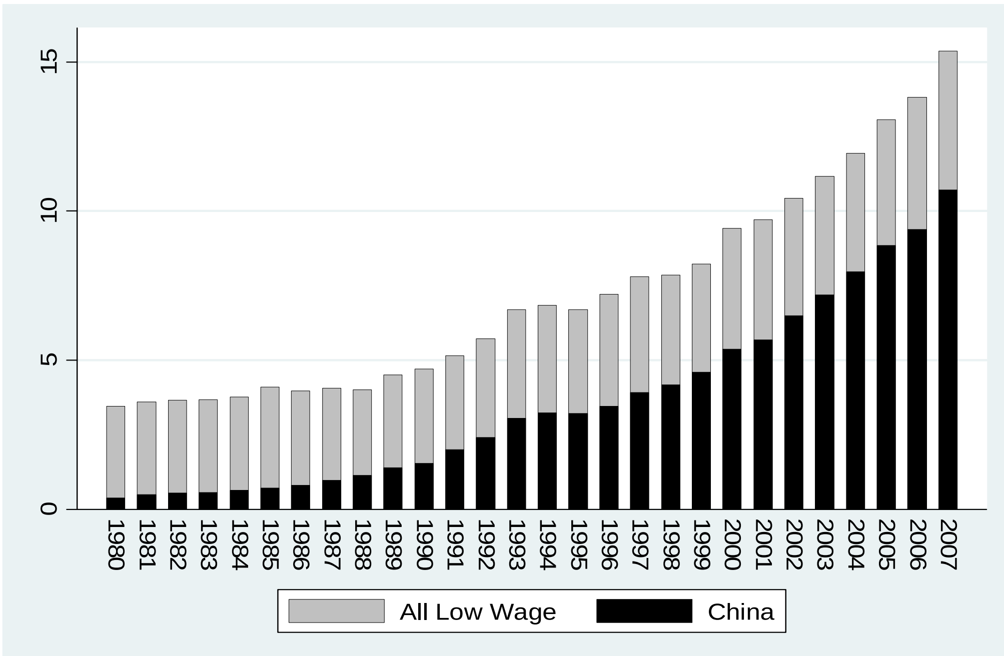
The rise of China and other emerging economies such as India, Mexico and Brazil has also coincided with an increase in wage inequality and basic trade theory predicts such South-North integration could cause this. Despite this, the consensus among most economists was that trade was less important than technology in explaining these inequality trends.[1] There are three problems with this consensus, however. First, most of this work used data only up to the mid 1990s, which largely predates the rise of China (see Figure 1).[2] Note that we end our sample in 2007 prior to the Great Recession to avoid conflating the effect of China with that of the financial crisis and subsequent huge fall in trade. Second, Feenstra and Hansen (1999) points to an impact of trade through offshoring rather than final goods. Third, an emerging line of theory has pointed to mechanisms whereby trade can affect the incentives to develop and adopt new technologies. Thus, the finding

[1] See, for example, Acemoglu (2002), Autor, Katz and Kruger (1998), Machin and Van Reenen (1998) and DiNardo, Fortin, and Lemieux (1996).

[2] In the 1980s China only accounted for about 1% of total imports to the US and EU and by 1991 the figure was still only 2%. However, by 2007 China accounted for almost 11% of all imports and Krugman (2008) emphasises this in his re-evaluation of the older literature. Note that Figure 1 may overestimate China's importance as import growth does not necessarily reflect value added growth. For example, although IPods are produced in China, the intellectual property is owned by Apple. However, our identification relies on *differences* in Chinese imports over time and industries, and our results are stronger when we use quota abolition as an instrumental variable, so using import value (rather than value added) does not appear to be driving our results.

that measures of technical change are highly correlated with skill upgrading does not mean trade has no role. What may be happening is that trade is stimulating technical progress, which in turn is increasing the demand for skilled labor.

FIGURE 1: Share of all imports in the EU and US from China and all low wage countries



Notes: Calculated using UN Comtrade data. Low wage countries list taken from Bernard, Jensen and Schott (2006) and are defined as countries with less than 5% GDP/capita relative to the US 1972-2001.

Our paper addresses these three problems. First, we use data from the last decade to examine the recent role of trade in affecting technical change in developed countries. Second, we will examine offshoring to China. Third, we analyze the impact of imports on patents, information technology (IT), research and development (R&D), total factor productivity (TFP) and management practices. We distinguish between the impact of import competition on technology through a within firm effect and a between firm (reallocation) effect and find that *both* matter.

A major empirical challenge in determining the causal effect of trade on technical change is the presence of unobservable technology shocks. To tackle this endogeneity issue we implement three alternative identification strategies. Our main approach is to use China's entry into the World Trade Organization (WTO) in 2001 and the subsequent elimination of most quotas in the ensuing years under the Agreement on Clothing and Textiles (formerly the Multi Fiber Agreement). These sectors are relatively low tech, but were still responsible for over 22,000 European patents in our sample period. Second, we exploit the fact that the exogenous liberalization policies in China had differential effects on imports into Europe across industries. In particular, Chinese import growth in Europe was much stronger in the sectors where China had some comparative advantage. Third, we control for differential industry-specific time trends. All three identification strategies support our main finding that Chinese trade stimulates faster technical change.

We present two core results. First, on the intensive margin, Chinese import competition increases innovation, TFP and management quality *within* surviving firms. Firms facing higher levels of Chinese import competition create more patents, spend more on R&D, raise their IT intensity, adopt more modern management practices, and increase their overall level of TFP. Second, Chinese import competition reduces employment and survival probabilities in low-tech firms - e.g. firms with lower levels of patents or TFP shrink and exit much more rapidly than high-tech firms in response to Chinese competition. Thus, our paper jointly examines the effects of trade on survival/selection and innovation. The combined impact of these within firm and between effects is to cause technological upgrading in those industries most affected by Chinese imports. An additional set of results shows that Chinese imports significantly reduce prices, profitability and the demand for unskilled workers as basic theory would suggest.

We focus on China both because it is the largest developing country exporter, and because China's accession to the WTO enables us to plausibly identify the causal effects of falling trade barriers. However, we also show results for imports from all other developing countries, and find a similar impact on technical change. In contrast, imports from developed countries appear to have no impact on technology.

We also offer some back of the envelope quantification of Chinese import effects on technical change. Over 2000-2007 China appeared to account for almost 15% of the increase in patenting, IT and productivity. Furthermore, this effect has grown in recent years and is up to twice as large when incorporating offshoring. These results suggest that trade with emerging nations such as China may now an important factor for technical change and growth in richer countries.

To motivate the empirical framework we discuss a model, further developed in Bloom, Romer, Terry and Van Reenen (2012), that explains how trade from China drives innovation in exposed firms. The intuition relies on "trapped-factors" – that is factors of production which are costly to move between firms because of adjustment costs and sunk investment (e.g. firm-specific skills and capital). Chinese imports reduce the relative profitability of making low-tech products but since firms cannot easily dispose of their "trapped" labor and capital, the shadow cost of innovating has fallen. Hence, by reducing the profitability of current low-tech products and freeing up inputs to innovate, Chinese trade reduces the opportunity cost of innovation. In addition to Chinese import competition stimulating innovation, we find support for two other predictions of the model. First, import competition from low wage countries like China has a greater effect on innovation than imports from high wage countries. This occurs because Chinese imports have a disproportionate effect on the profitability of low-tech products, providing greater incentives to innovate new goods. Second, firms with more trapped factors (as measured by industry-specific human capital, for example) will respond more strongly to import threats.

Our paper relates to several literatures. First, for labor economics we find a role for trade with low wage countries in increasing skill demand (at least since the mid-1990s) through inducing technical change.[3] Second, although many papers have found that trade liberalization increases aggregate industry productivity[4], the precise mechanism is unclear. This evidence tends to be indirect since explicit measures of technical change are generally unavailable at the micro-level.[5] The literature focuses on the reallocation effects (e.g. Melitz, 2003) even though within plant productivity growth is typically as large as the between-plant reallocation effect. Our paper uses new patenting, IT, R&D, management and productivity data to establish that trade drives out low-tech firms (reallocation) and increases the incentives of incumbents to speed up technical change.

Third, there is a large theoretical literature on trade and technology.[6] Our paper supports theories arguing for an important role of trade on technical change. In particular, our finding that (i) the positive trade effect is on *innovation* (rather than just compositional effects on productivity via offshoring or product switching) and (ii) is much stronger from lowering import barriers against low-wage countries rather than high-wage countries is different from the mechanisms emphasized in other theories (e.g. market size or learning).

Finally, there is a large empirical literature examining the impact of competition on innovation, but a major challenge is finding quasi-experiments to identify the causal impact of competition on innovation (e.g. Aghion et al, 2005). Our paper extends this work by using China's

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[3] Technological forces also have an effect on trade. For example, better communication technologies facilitate offshoring by aiding international coordination. This is another motivation for addressing the endogeneity issue. Additionally, there is the direct impact on local employment and welfare (e.g. Autor, Dorn and Hansen, 2012).

[4] See, for example, Pavcnik (2002), Trefler (2004), Eslava, Haltiwanger and Kugler (2009), and Dunne, Klimek and Schmitz (2008).

[5] For low-wage countries, Bustos (2011) finds positive effects on innovation from lower export barriers for Argentinean firms and Teshima (2008) finds positive effects on process R&D from lower output tariffs for Mexican firms. The only study of Southern trade on Northern innovation is LeLarge and Nefussi (2008), who find that the R&D of French firms reacts positively to low wage country imports, although they have no external instrument.

[6] Theoretical analysis of trade and innovation is voluminous from the classic work by Grossman and Helpman (1991, 1992) and recent important contributions by Yeaple (2005) and Atkeson and Burstein (2010).

trade growth, and particularly its entry into the WTO, as an exogenous shift in competition.

The structure of the paper is as follows: Section II sketches some theoretical models, Section III describes the data and Section IV details the empirical modeling strategy. Section V describes our results and Section VI discusses their magnitudes. Some extensions and robustness tests are contained in Section VII and Section VIII concludes.

II. THEORY

There are a large number of theories of how reducing import barriers against low wage countries (like China) could affect technical change in high wage countries (like Europe or the US). We first outline a simple "trapped factor" model that predicts a positive effect of such liberalization on *innovation*, and two ancillary predictions. We contrast this with other perspectives on innovation (where trade expands the menu of products in the world economy) and *composition* where trade alters the distribution of products without changing the number of quality of products.

A. The "Trapped Factor" model of Trade-induced innovation

In Bloom, Romer, Terry and Van Reenen (2012) we develop a stylized model of trade-induced innovation (see Appendix A for a more detailed summary). The basic assumption is that firms can allocate a factor of production either to produce old goods or innovate and produce new goods. China can produce old goods, but cannot (as easily) innovate and produce new goods. At the beginning of the period there are factors of production employed in "Northern" firms making old goods (protected by trade barriers). These factors are "trapped" in the sense that there is some human or fixed capital that is specific to the old good that is lost for a period if the firm chooses to reallocate the factor from producing the old good to innovating a new good. The magnitude of the firm-specific capital determines the opportunity cost of innovation and if it is sufficiently high the firm optimally chooses not to innovate.

When import barriers are lowered, Chinese exports increase and the profitability of making old goods falls. Therefore, the opportunity cost of using the trapped factors for innovating (rather than producing the old good) falls, making innovation more attractive[7]. Not only do we expect

[7] In the model we make the simplifying assumption that the firms who innovate also produce the good while it is on patent. When it comes off patent the good is produced in the home country if protected by trade barriers or in the South if not protected. If we extend the model to allow for offshoring, then the innovation could still occur in the rich country but production of the new good could occur in the low wage country (e.g. the R&D for the I-Pod is in the US, but it is produced in China). In this case, reducing trade barriers with China will make the costs of *producing* the new good cheaper and this could be an additional reason why incentives to innovate on new goods increase.

falling import barriers against China to generate more innovation in rich countries, but it should also occur within the same firms due to the firm-specific capital. In terms of welfare, this model suggests a benefit of lowering trade barriers against low wage countries is that it stimulates innovation, which is likely to be too low in equilibrium.[8]

In addition to predicting a within firm increase in innovation in response to a fall in import barriers against China, the trapped factor approach has two other empirical implications that we will examine. First, integration with a high wage country will have a much less positive impact on innovation. This is because imports from high-wage countries will not reduce the price of old goods relative to potential new goods as other rich countries have no comparative disadvantage in the production of new goods. In our data imports from other high wage countries do not appear to stimulate innovation, consistent with the model. A second implication of the model is that all else equal firms who have more trapped factors will respond more positively to the China shock. Using different proxies for such trapped factors (e.g. our estimates of product-specific human capital, see Appendix A) we also find support for this second prediction. There may be other theories that can also rationalize the results so we do not want to over-claim for our simple model. Nevertheless, we believe it may capture some features of the stylized facts in our data and the prior case studies[9].

B. Alternative Innovation models

There are several alternative models of how reducing trade barriers against low wage country goods could induce Northern innovation. First, lowering import barriers in general increases competition and competitive intensity can increase innovation. However, the effects of competition on innovation are theoretically ambiguous in general. Competition may foster innovation because of reduced agency costs (e.g. Schmidt, 1997), "higher stakes" (Raith, 2002) or lower cannibalization of existing profits.[10] However, there is a fundamental Schumpeterian force that competition lowers price-cost margins, thereby reducing the quasi-rents from innovation. We will examine competition

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[8] In standard growth models this arises because of both knowledge externalities and the distortions induced by R&D being produced by monopolistically competitive firms. Of course, a first best solution would be to directly subsidize R&D, but in the absence of such a policy, increased trade may be a second best solution. In the model underinvestment occurs because the differentiated good sector is produced under monopolistic competition.

[9] The idea of falling opportunity costs stimulating innovation has parallels to some theories of business cycles that suggest that "bad times" can generate greater productivity enhancing activities (e.g. Aghion and Saint-Paul, 1998, or Barlevy, 2007).

[10] This is the Arrow (1962) "displacement effect". It shows up in different guises in Grossman and Helpman (1992), Aghion et al (2005)'s "escape competition" effect and the "switchover costs" of Holmes et al (2008).

emanating from high wage countries and show that the main effect we identify is through low wage country competition, consistent with the trapped factor model.

A second class of models stresses the importance of trade in increasing market size that will generally foster innovation incentives (e.g. Schmookler, 1966; Krugman, 1980; Acemoglu, 2008). Lower trade costs generate a larger market size over which to spread the fixed costs of investing in new technologies[11]. We will investigate these effects by examining whether European firms' *exports to China* are associated with changes in innovation activity and show that this is not driving the imports effect we identify.

Finally, imports could enhance innovation by enabling domestic firms to access better overseas' knowledge (e.g. Coe and Helpman, 1995 or Acharya and Keller, 2008). This may occur through the imports of intermediate inputs and supply networks (e.g. Goldberg, Khandelwal, Pavcnik and Topalova, 2010a,b)[12]. These mechanisms do not seem appropriate in the Chinese context however, as European firms have (currently) a large technological lead over China[13].

C. Compositional models

Perhaps an even simpler approach is to consider a framework where we keep the menu of products fixed in the economy. When trade barriers fall between the EU/US and China, the high-tech industries will grow relatively faster than low-tech industries in the EU/US. The opposite will occur in China. On empirical grounds, this simple framework is unsatisfactory, as most of the aggregate changes we observe following trade liberalization have occurred *within* rather than *between* industries. This could be explained, however, by firms operating in more finely disaggregated industries and we will show that there are strong reallocation effects whereby low-tech firms tend to shrink and exit because of China. Bernard, Jensen and Schott (2006) show a similar result for US plants using indirectly proxies for technologies such as capital intensity.

But we also report that China induces faster technical change *within firms* and *plants,* a finding that goes beyond the existing results. In principle, firm TFP increases could be accounted for by two factors: changes in a firm's product portfolio or offshoring. First, on product switching,

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[11] Recent work by Lileeva and Trefler (2010) has shown market size effects on Canadian firms of joining NAFTA.

[12] A related literature typically finds that productivity rises when exporting increases (e.g. Verhoogen, 2008).

[13] Eaton and Kortum (1999, 2001 and 2002) combine competition, market size and learning in a quantifiable general equilibrium trade model. For example, in Eaton and Kortum (2001) a fall in trade costs increases effective market size (which encourages innovation) but also increases competition (which discourages innovation). In their baseline model, these two forces precisely offset each other so the net effect of trade on innovation is zero. Although the Eaton-Kortum framework is powerful, it does not deal easily with one of our key results: that there is a strong effect on innovation for incumbent firms in the same sector where trade barriers fell.

Bernard, Redding and Schott (2010) investigate the impact of trade liberalization in heterogeneous multi-product firms. In the face of falling trade costs with a low wage country like China, Northern firms shift their product mix towards more high-tech products (see Bernard, Redding and Schott, 2007). We will investigate this mechanism by examining how plants change their product classes, and find some evidence for this. Second, a fall in trade costs with China will mean that producers of goods that can use Chinese intermediate inputs will benefit. For example, firms may slice up the production process and offshore the low-TFP tasks to China (see for example Grossman and Rossi-Hansberg, 2008). This will have a compositional effect if the remaining activities in the home country are more technologically advanced. To investigate this mechanism we will look explicitly at offshoring to China using a method introduced by Feenstra and Hansen (1999).

Although we will show evidence that both product switching and offshoring are important in our data, neither can fully explain our core findings. In particular, about half of the China-induced increase in innovation comes from expanding the volume of patents within firms. This implies that changing composition can only be part of the story.

III. DATA

We combine a number of rich datasets on technical change (see Appendix B). Our base dataset is Bureau Van Dijk's (BVD) Amadeus that contains close to the population of public and private firms in 12 European countries. Firms in Amadeus have a list of primary and secondary four-digit industries which we use to match in the industry level trade data (the average firm had 2 primary codes, but some had as many as 10 primary and 11 secondary codes). In our main results we use a weighted average of Chinese imports across all industries that the firm operates in, but we also present robust results where we allocate the entire firm's output to a single industry.

A. Patents

We combined Amadeus with the population of patents from the European Patent Office (EPO) through matching by name. Patent counts have heterogeneous values so we also use future citations to control for patent quality in some specifications. We consider both a main sample of "patenters" – Amadeus firms filing at least one EPO patent since 1978 – and a wider sample where we assume that the firms unmatched to the EPO actually had zero patents.

B. Productivity and Research and Development (R&D)

Amadeus contains accounting information on employment, capital, materials, wage bills and sales. We calculate TFP using firms in France, Italy, Spain and Sweden because of their near population firm coverage and inclusion of materials which is needed to estimate "four-factor" TFP (materials is not a mandatory accounting item in other countries), although the results are similar using the data for all 12 countries. We estimate TFP in a number of ways, but our core method is to use a version of the Olley Pakes (1996) method applied by de Loecker (2011) to allow for trade and imperfect competition. In a first stage, we estimate production functions separately by industry across approximately 1.4 million observations to recover the parameters on the factor inputs.[14] We then estimate TFP and, in the second stage regression relate this to changes in the trade environment. As a robustness test we also allowed the production function coefficients to be different by country and industry as well as estimated at a finer level of industry aggregation which show similar results. Details of this procedure are contained in Appendix C. R&D data comes from BVD's Osiris database that provides data on publicly listed firm in Europe, covering around 4,000 manufacturing firms. Of these, 459 firms report performing R&D for 5 years or more so can be used for some of the regressions.

C. Information technology

Harte Hanks (HH) is a multinational company that collects IT data to sell to large IT firms (e.g. IBM, Cisco and Dell). Their data is collected for roughly 160,000 establishments across 20 European countries. HH surveys establishments annually on a rolling basis which means it provides a "snapshot" of the IT stock. The data contain detailed hardware and software information. We focus on using computers per worker (PCs plus laptops) as our main measure of IT intensity because this: (i) is a physical quantity measure which is recorded in a consistent way across sites, time and countries, and (ii) avoids the use of IT price deflators which are not harmonized across countries. In robustness tests we also use alternative measures of IT such as Enterprise Resource Planning software, Groupware and Database software.

The fact that HH sells this data on to firms who use this for sales and marketing exerts a strong discipline on the data quality, as errors would be quickly picked up by clients in their sales calls. HH samples all firms with over 100 employees in each country. Thus, we do lose smaller

[14] The number of observations in the second stage is smaller than 1.4 million because we are estimating in five-year differences.

firms, but since we focus on manufacturing the majority of employees are in these larger firms, and we find no evidence this sampling rule biases our results.[15]

D. Management Practices

The management data was collected in multiple telephone survey waves between 2002 and 2010 from the London School of Economics using a team of 126 MBA-type student interviewers. Firms were interviewed for 45 minutes on average, with this interview targeted at the plant manager at the largest establishment within each firm. Management practices were scored using the Bloom and Van Reenen (2007) methodology, which scores firms on a 1 to 5 scale across 18 questions. These 18 questions span three key areas of management: *monitoring* (do firms continuously collect, analyze and use information), *targets* (do firms have balanced, well-understood and binding targets) and *incentives* (do firms reward high-performers and retrain and/or sanction poor performers). This scoring grid was developed by a leading international consulting firm based on the practices of Lean Manufacturing, the management system developed by Toyota in the 1960s and 1970s which is now becoming widely adopted across Europe, the US and Asia.

Firms were randomly sampled from the population of all manufacturing firms with 100 to 5000 employees, with a sample response rate of 44% on average (see Bloom and Van Reenen, 2010). In each wave we also resurveyed all firms from earlier survey waves to help build a management panel. In this paper we used all 579 European firms with repeat survey data.

E. UN Comtrade data

The trade information we use is sourced from the UN Comtrade data system. This is an international database of six-digit product level information on all bilateral imports and exports between any given pairs of countries. We aggregate from six-digit product level to four-digit US SIC industry level using the Pierce and Schott (2010) concordance. For firms that operate across multiple four digit industries we use a weighted average of imports across all sectors a firm produces in (see Appendix B)[16].

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[15] We find no systematic differences in results between firms with 100 to 250 employees and those above 250 employees, suggesting the selection on firms with over 100 employees is unlikely to cause a major bias. We also find no differences in our patenting results – where we have the full population of firms – between firms with less than and more than 100 employees. It is also worth noting that in the countries we study firms with over 100 employees account for over 80% of total employment in manufacturing.

[16] Te results are similar when we allocate firms to a single primary sector (compare Tables 1 and 5B, for example).

We use the value of imports originating from China (M^{China}) as a share of total world imports (M^{World}) in a country by four-digit industry cell as our key measure of exposure to Chinese trade, following the "value share" approach outlined by Bernard, Jensen and Schott (2002, 2006); i.e. we use $IMP^{CH} = M^{China} / M^{World}$. As two alternative measures we also construct Chinese import penetration by normalizing Chinese imports either on domestic production (M^{China} / D) or on apparent consumption (domestic production less exports plus imports), M^{China} / C. For domestic production we use Eurostat's Prodcom database. Compared to Comtrade, Prodcom has no data prior to 1996, so this restricts the sample period. An additional problem is that some of the underlying six-digit product data is missing (for confidentiality reasons as the industry-country cells are too small), so some missing values for domestic production had to be imputed from export data. Although we obtain similar results with all measures (see Tables 7 and A7) we prefer the normalization on world imports which does not have these data restrictions.

F. Descriptive statistics

The rise of China's share of all imports to the US and the 12 European countries in our sample is remarkable. In 2000 only 5.7% of imports originated in China, but by 2007 this had more than doubled to 12.4%. This increase also varies widely across sectors, rising most rapidly in industries like toys, furniture and footwear (see Table A1). Some basic descriptive statistics are shown in Table A2. With the exception of the survival and worst-case bounds analyses, the regression samples condition on non-missing values of our key variables over a five year period. The exact number of observations (and average firm size) differs between samples. In the sample of firms who have patented at least once since 1978 the mean number of patents per year is one and median employment is 100. When we use the entire sample of firms with accounting data the mean number of patents falls to 0.019 and median employment to 17. R&D reporting firms are the largest of all sub-samples with 2,054 employees at the median with an average R&D intensive of 15% (recall these are all publicly listed firms whereas the other samples also include private firms). For plants with IT data, median employment is 140 and the average IT intensity is 0.58 computers per worker.

IV. EMPIRICAL MODELING STRATEGY

Our empirical models analyze both the *within* firm margin of technological upgrading and the *between* firm margin of upgrading through selection effects. To investigate these we examine five broad indicators of "technology" – IT, patents, R&D, TFP and management practices.

A. *Technical change within surviving plants and firms*

Consider a basic firm-level equation for the level of technology (*TECH*) in firm *i* in industry *j* in country *k* at time *t* as:

$$\ln TECH_{ijkt} = \alpha IMP_{jkt-l}^{CH} + \beta x_{ijkt} + \varepsilon_{ijkt} \tag{1}$$

TECH will be interpreted broadly and measured using a number of indicators such as patented innovations[17], R&D spending, IT, TFP and management practices. We measure IMP_{jkt}^{CH} mainly as the proportion of imports (*M*) in industry *j* and country *k* that originate from China $(M_{jk}^{China} / M_{jk}^{World})$ and the x_{ijkt} are a set of control variables such as country dummies interacted with time dummies to absorb macro-economic shocks. The trade-induced technical change hypothesis is that $\alpha > 0$. Note that we allow for a dynamic response in equation (1) depending on the lag length indicator *l*. Our baseline results will use $l = 0$ to be consistent with the other technology equations, but we show the differences in results to alternative lag lengths in sub-section V.C.[18]

Since there may be many unobservables that are correlated with the firm (and industry's) level of technology and imports that different across firms but broadly constant over time, we will control for these by including a fixed effect and estimate:

$$\Delta \ln TECH_{ijkt} = \alpha \Delta IMP_{jkt-l}^{CH} + \beta \Delta x_{ijkt} + \upsilon_{ijkt} \tag{2}$$

We use Δ to denote the long (usually five year) difference operator. Rapid growth in the Chinese import share is therefore used as a proxy for a rapid increase in trade competition from low wage countries. The growth of Chinese imports may still be related to unobserved shocks, υ_{ijkt} so we consider instrumental variables such as the removal of quotas when China joined the WTO to evaluate potential endogeneity biases. We maximize the use of the data by using overlapping five-

[17] Because of the zeros in patents when taking logarithms we use the transformation *PATENTS* = 1 + *PAT* where *PAT* is the count of patents. The addition of unity is arbitrary, but equal to the sample mean of patents. We also compare the results with fixed effect Negative Binomial count data models below which generated similar results (see Table 6).

[18] For patents, the largest effects appear after three years (see Table A6) which is consistent with the idea that most firms take a few years to obtain innovations from their increased R&D spending.

year differences (e.g. 2005-2000 and 2004-1999) but since we cluster at the country-industry pair level (or sometimes just industry level) this is innocuous. We report some results using non-overlapping five-year differences and specifications in levels (e.g. fixed effect Negative Binomial models).

B. Technological upgrading through reallocation between plants and firms

In addition to examining whether Chinese import competition causes technological upgrading *within* firms we also examine whether trade affects innovation by reallocating economic activity *between* firms by examining employment and survival equations. As discussed in the Section III, compositional models would predict that China would cause low-tech plants to shrink and die, as they are competing most closely with Chinese imports. Consequently, we estimate firm employment growth equations of the form:

$$\Delta \ln N_{ijkt} = \alpha^N \Delta IMP^{CH}_{jkt} + \beta^N \Delta x^N_{ijkt} + \gamma^N (TECH_{ijkt-5} * \Delta IMP^{CH}_{jkt}) + \delta^N TECH_{ijkt-5} + \upsilon^N_{ijkt} \tag{3}$$

where the coefficient α^N reflects the association of jobs growth with the change in Chinese imports, which we would expect to be negative (i.e. α^N <0) and *TECH* is the relevant technology variable (e.g. patenting). We are particularly interested in whether Chinese import competition has a larger effect on low-tech firms, so to capture this we include the interaction of ΔIMP^{CH}_{jkt} with the (lagged) technology variables. If Chinese trade has a disproportionately negative effect on low-tech firms we would expect γ^N > 0.

Equations (2) and (3) are estimated on surviving firms. However, one of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate:

$$SURVIVAL_{ijkt} = \alpha^S \Delta IMP^{CH}_{jkt} + \beta^S \Delta x^S_{ijkt} + \gamma^S (TECH_{ijkt-5} * \Delta IMP^{CH}_{jkt}) + \delta^S TECH_{ijkt-5} + \upsilon^S_{ijkt} \tag{4}$$

which is defined on a cohort of firms (or establishments) who were alive in a base period and followed over the next five years. If these establishments (or firms) survived over the subsequent five years we define $SURVIVAL_{ijkt}$ = 1 and zero otherwise. If Chinese imports do reduce survival probabilities, we expect α^S < 0 and if high-tech plants are more protected we expect γ^S > 0.

To complete the analysis of between firm effects we would also need an entry equation. The fundamental problem is that there is no "initial" technology level for entering firms. We cannot use the current observed technology level ($TECH_{ijkt}$) as this is clearly endogenous (in equations (3) and (4) we use lagged technology variables under the assumption that technology is weakly exogenous).

We can address the issue of entry indirectly, however, by estimating an industry-level version of equation (2):

$$\Delta TECH_{jkt} = \alpha^{IND} \Delta IMP_{jkt}^{CH} + \beta^{IND} \Delta x_{jkt} + \upsilon_{jkt}^{IND} \tag{5}$$

where the coefficient on Chinese imports, α , in equation (5) reflects the combination of within firm effects from equations (1) and (2), the reallocation effects from equations (3) and (4), and the unmodelled entry effects. In examining the magnitude of the Chinese trade effects, we will simulate the proportion of aggregate technical change that can be accounted for by Chinese imports using equations (2)-(4) and break this down into within and between components. We will also compare the micro and industry estimates of equation (5) which give an alternative estimate of the within and between effects, including entry.

V. RESULTS

A. Within firm and within plant results

Table 1 presents our core results: within firm and within plant measures of technical change. All columns control for fixed effects by estimating in long-differences and country-specific macro shocks by including a full set of country dummies interacted with a full set of time dummies. Our key measure of innovation, patents, is the dependent variable in column (1). The coefficient suggests that a 10 percentage point increase in Chinese import penetration is associated with a 3.2% increase in patenting. Since jobs fell in those industries affected by Chinese imports (see Table 3) we underestimate the growth in patent intensity (patents per worker) by not controlling for (endogenous) employment. If we also include the growth of employment in column (1), the coefficient (standard error) on imports is slightly larger at 0.387 (0.134).[19] Note that our pooling across multiple overlapping years to construct five-year differences is largely innocuous as we are clustering the standard errors by country-industry pair. For example if we use only the last five year difference the qualitative results are similar. In this experiment the coefficient (standard error) is 0.591(0.201) for patents; 0.314(0.077) for IT; and 0.400 (0.079) for TFP.

[19] The coefficient (standard error) on employment in the patents equation was 0.015(0.008) implying that larger firms have a higher volume of patents. If we include the ln(capital/sales) ratio as well as ln(employment) in the regression this barely shifts the results (the coefficient on Chinese imports is 0.370 with a standard error of 0.125). Thus, the correlation with Chinese trade is not simply an increase in all types of capital, but seems related specifically to technical change. The other results in the table are all robust to controlling for employment growth – see Table 5 below for more analysis controlling for firm and industry size.

A concern with patenting as an innovation indicator is that firms may simply be taking out more patents to protect their existing knowledge in the face of greater Chinese competition. To test this “lawyer effect” we also look at citations per patent – if firms are now patenting more incremental knowledge for fear of being copied by the Chinese, the average quality of their patents should fall, so citations per patent should drop. The results on citations per patents in Table A3 show, in fact, that Chinese competition does not lead to a fall in citations. The coefficient on Chinese imports is actually positive (but insignificant).

In column (2) of Table 1 we examine IT intensity and find a positive and significant coefficient on Chinese imports. We use computers per employee as our main measure of IT diffusion as this is a good indicator of a general-purpose technology used widely across industries. However, in Table A4 we investigate other measures of IT – the adoption of Enterprise Resource Planning, database software, and groupware tools – and also find positive coefficients on Chinese imports.

Column (3) of Table 1 uses R&D as the outcome and also shows a large and significant increase in firm-level R&D expenditure when Chinese imports rise, which is more evidence that the increase in innovation observed in column (1) is not due to firms merely taking out more intellectual property protection. Column (4) uses a wider measure of technical change as the dependent variable, TFP growth, and again establishes a positive and significant association with Chinese imports growth. The final column delves uses the latest version of the management practices data first described by Bloom and Van Reenen (2007).[20] Hence, Chinese trade competition also appears to stimulate the rapid adoption of modern (Lean) management practices.

As we discuss in Section VI below the magnitudes are economically significant: a 10 percentage point increase in Chinese imports is associated with a 3.2% increase in patenting, a 3.6% increase in IT, a 12% increase in R&D, a 2.6% increase in TFP and a 0.8 (1.38 standard deviation) increase in the management index. Note that the latter is an extremely large change given that that the average gap between US and Indian management practices is 0.85.

B. Endogeneity: the problem of unobserved technology shocks

An obvious problem with estimating these equations is the potential endogeneity of Chinese imports due to unobserved technology shocks correlated with the growth of Chinese imports. To address

[20] We have up to three panel data observations per firm between 2010 and 2002 across the European countries considered here (see Appendix B) so can only use shorter (three year) differences.

this we consider three alternative strategies to control for these unobserved shocks: (i) using the natural experiment of China joining the WTO, (ii) constructing an IV from initial conditions and (iii) controlling for industry time trends. The smaller size of the datasets for R&D and management makes it infeasible to implement these identification strategies so we focus mainly from this point forwards on the three large-sample technology measures: patents, IT and TFP.

China joining the WTO as a quasi-experiment - One identification strategy is to use the accession of China to the WTO in 2001, which led to the abolition of import quotas on textiles and apparel. We discuss this in detail in Appendix D, but sketch the idea here. The origin of these quotas dates back to the 1950s when Britain and the US introduced quotas in response to import competition from India and Japan. Over time, this quota system was expanded to take in most developing countries, and was eventually formalized into the Multi-Fiber Agreement (MFA) in 1974. The MFA was itself integrated into GATT in the 1994 Uruguay round, and when China joined the WTO in December 2001 these quotas were eliminated in two waves in 2002 and 2005 (see Brambilla, Khandelwal and Schott, 2010). Since these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s in preparation for the Uruguay Round, it seems plausible to believe their level in 2000 was exogenous with respect to future technology shocks. The level of quotas also varied quasi-randomly across four-digit industries[21] – for example, they covered 77% of cotton fabric products (SIC 2211) but only 2% of wool fabric products (2231), and covered 100% of women's dresses (2334) but only 5% of men's trousers (2325). This variation presumably reflected the historic bargaining power of the various industries in the richer countries in the 1950s and 1960s when these quotas were introduced, but are now uncorrelated to any technology trends in the industries as we show below.

When these quotas were abolished this generated a 240% increase in Chinese imports on average within the affected product groups. In fact, this increase in textile and apparel imports was so large it led the European Union to re-introduce some limited quotas after 2005.[22] Since this re-introduction was endogenous, we use the initial level of quotas in 2000 as our instrument to avoid using the potentially endogenous post-2005 quota levels. Although the quota-covered industries are

[21] The quotas were actually imposed at the six-digit level that we aggregated up to the four-digit industry level weighting by their share of world imports calculated in the year 2000 (the year before WTO accession).

[22] The surge in Chinese imports led to strikes by dock workers in Southern Europe in sympathy with unions from the apparel industry. The Southern European countries with their large apparel sectors lobbied the European Union to reintroduce these quotas, while the Northern European countries with their larger retail industries fought to keep the quota abolition. Eventually temporary limited quotas were introduced as a compromise, which illustrates how the abolition of these quotas was ex ante uncertain, making it harder to pick up anticipation effects.

considered low-tech sectors, European firms in these industries generated 21,638 patents in our sample. In Appendix D we give several examples of such patents taken out by European firms.

Panel A of Table 2 uses this identification strategy of China's accession to the WTO.[23] Since this is only relevant for textiles and clothing, we first present the OLS results for these sectors for all the technology indicators in columns (1), (4) and (7). In column (1) there is a large positive and significant coefficient on the Chinese trade variable, reflecting the greater importance of low wage country trade in this sector. Column (2) presents the first stage using the (value-weighted) proportion of products covered by quotas in 2000. Quota removal appears to be positively and significantly related to the future growth of Chinese imports. Column (3) presents the IV results that show a significant effect of Chinese imports on patents with a higher coefficient than OLS (1.86 compared to 1.16).

Columns (4)-(6) repeats the specification but uses IT intensity instead of patents as the dependent variable. Column (4) shows that the OLS results for IT are also strong in this sector and column (5) reports that the instrument has power in the first stage. The IV results in column (6) also indicate that the OLS coefficient appeared downward biased.[24] The final three columns repeat the specification for TFP showing similar results to patents and IT. So overall there is a large OLS coefficient for patents, IT and TFP, but an even larger IV coefficient and certainly no evidence of upward bias for OLS.[25]

There are several issues with the specification. First, the regressions all use the actual flow of Chinese imports to reflect the threat of import competition. However, an advantage of the IV estimates is that by replacing the actual flow of imports by the predicted flow based on quota relaxation, this more accurately reflects the *threat* of Chinese competition.[26] Second, one could argue that firms will be adjusting their innovation efforts earlier in response to *anticipation* of quota relaxation. However, at the time there was considerable uncertainty over whether the liberalization would actually take place. A common view was that even if there was an abolition of quotas this

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[23] In Panels A and B of Table 2 we cluster by four-digit industry as the instruments have no country-specific variation. We also drop years after 2005 so the latest long difference (2005-2000) covers the years before and after China joined the WTO.

[24] If we repeat the IV specification of column (6) but also condition on employment growth the coefficient on Chinese imports is 0.687 with a standard error of 0.373. Dropping all the four-digit sectors that had a zero quota in 2000 uses only the continuous variation in quotas among the affected industries to identify the Chinese import effect. Although this regression sample has only 766 observations, this produces a coefficient (standard error) under the IV specification of 2.688(1.400) compared to an OLS estimate of 1.238(0.245).

[25] The Hausman tests fail to reject the null of the exogeneity of Chinese imports for the patents and IT equations, but does reject for the TFP equation (p-values of 0.342, 0.155 and 0.001 respectively).

[26] In the reduced forms the coefficient (standard error) on Chinese imports was 0.201(0.091), 0.163(0.038) and 0.129(0.018) in the patents, IT and TFP equations. Regressions include country dummies times year dummies.

would be temporary, as to some extent it was with the temporary reintroduction of some quotas in 2006. We discuss this issue in more detail in Appendix D where we show that there is no significant correlation of the quota instrument with technical change or Chinese imports *prior* to the 2001 WTO accession.[27] This placebo experiment also addresses the concern that quota intensity is proxying some other trend correlated with Chinese import growth.

To further examine this issue we include lagged Chinese import growth (1995-2000) as an additional control in Table 2. The coefficients are robust to this.[28] The most rigorous test is to include lags of both technology and Chinese imports in the regression, which we do in Table A5. We use the TFP specifications as we have the largest time series of data in order to condition on the pre-policy variables. Column (1) of Table A5 repeats the specification from the final column of Table 2 Panel A. Column (2) conditions on the balanced panel where we observe firms for 10 years and shows that the results are robust even though we have only two-thirds of the industries. Column (3) includes the two pre-policy variables, the lagged growth of imports and the lagged growth of TFP. The coefficient on lagged imports is insignificant, but lagged TFP is negative and significant. Importantly, the coefficient on current Chinese import growth remains positive and significant, actually rising from 1.49 to 1.61. The negative coefficient on the lagged dependent variable is expected due to mean reversion, so we also report the results of instrumenting this with the firm's 1996 level of TFP. This reverses the sign of the coefficient on the lag, suggesting a positive relationship between past and present TFP. Again the coefficient on Chinese imports is essentially unchanged, suggesting that the significant impact of imports instrumented by WTO quota abolition is not proxying for pre-existing industry trends.

Initial conditions as instrumental variables - A disadvantage of the quota-based instrument is that we can only construct the instrument for the affected industries (textiles and clothing), so we consider a second identification strategy. The overall increase in Chinese imports is driven by the exogenous liberalization being pursued by Chinese policy makers. The industries where China exports grew more depended on whether the industry is one in which China had a comparative advantage. For example, if we consider the growth of Chinese imports in Europe between 2000 and 2005, sectors in which China was already exporting strongly in 1999 are likely to be those where

[27] For example, to test for anticipation effects we regressed the level of the imports quota on the growth of technology 1996-2000 *prior* to WTO accession in 2001. All the coefficients on technology were small and insignificant suggesting no anticipation effects. The coefficient (standard error) was 0.096(0.177) for patents and 0.024(0.031) for TFP. We do not have IT data before 2000 so cannot implement this placebo test.

[28] For example in column (6) the coefficient on lagged imports is positive (0.168) but insignificant and the coefficient on Chinese import growth remains positive and significant (1.792 with a standard error of 0.421).

China had a comparative advantage – such as textiles, furniture and toys – and are also the sectors which experienced much more rapid increase in import penetration in the subsequent years (see Table A1). Consequently, high exposure to Chinese imports in 1999 can be used (interacted with the exogenous overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($IMP^{CH}_{jt-6} * \Delta M_t^{China}$) as an instrument for ΔIMP^{CH}_{jkt} where IMP^{CH}_{jt-6} is the Chinese import share in industry j in the EU and US. Note that we do not make IMP^{CH}_{jt-6} specific to country k to mitigate some of the potential endogeneity problems with initial conditions.[29] A priori, the instrument has credibility. Amiti and Freund (2010) show that over the 1997 to 2005 period at least three quarters of the aggregate growth of Chinese imports was from the expansion of existing products rather than from adding new products. Similarly, Brambilla et al (2010) find this was true when focusing on textiles and clothing after 2001.[30]

Column (1) of Table 2 panel B re-presents the basic OLS results for patents. Column (2) presents the first stage for the instrumental variable regressions. The instrument is strongly correlated with the endogenous variable, the growth of Chinese import intensity. Column (3) presents the second stage: the coefficient on Chinese imports is 0.495 and significant.[31] Columns (4) through (6) repeat the experiment for IT. In column (6) the coefficient on Chinese imports is positive and significant and above the OLS estimate. In the final column (9) for TFP, the IV coefficient is again above the OLS estimate.[32] Taking Panels A and B of Table 2 as a whole, there is no evidence that we are under-estimating the effects of China on technical change in the OLS estimates in Table 1. If anything, we may be too conservative.[33]

Controlling for technology shocks using industry trends. A third way to control for unobservable technology shocks is to include industry trends. We do this in Panel C of Table 2 by including a set of three-digit industry dummies in the growth specifications. In column (1) we reproduce the baseline specification for patents and column (2) includes the industry trends. We

[29] This identification strategy is similar to the use of "ethnic enclaves" by papers such as Card (2001) who use the proportion of current immigrants in an area as an instrument for future immigrants.

[30] This appears to be common in several countries- e.g. Mexico after NAFTA (e.g. Iacovone and Javorcik, 2008).

[31] Unsurprisingly the results are more precise if we combined the initial conditions and quota instruments together. For example in column (3) the coefficient (standard error) on patents is 2.322 (0.990). Furthermore, we cannot reject the null that the instruments are valid using a Hansen over-identification test. The p-values for rejection of instrument validity are 0.438 for the patent equation, 0.330 for the IT equation and 0.948 for the TFP equation.

[32] If we use the initial conditions estimator for R&D following the column (9) specification we find a point estimate (standard error) of 1.179 (0.582).

[33] The downward bias on OLS of trade variables is also found in Auer and Fisher (2010) who examine the impact of trade with less developed countries on prices. They use a variant of an initial conditions estimator based on the industry's labor intensity. Like them, we also find important import effects on prices (see sub-section VI.B).

repeat this for each of the technology variables. Although the magnitude of the coefficient on Chinese imports is smaller in all cases, it remains significant at the 10% level or greater across all three specifications. Note that the industry trends are jointly insignificant in all three cases. It is unsurprising that the coefficient falls as we are effectively switching off' much of the useful variation and exacerbating any attenuation bias. Furthermore, although including these industry dummies may deal with omitted trends, they do not deal with reverse causality, which, as argued above will cause a downward bias on the coefficient of interest. The WTO instrument is superior in this respect as in principle it deals with both reverse causality and omitted variables.

The results are generally robust to even tougher tests. If we include four digit industry trends the coefficient (standard errors) in the patent, IT and TFP regressions are 0.185(0.125), 0.170(0.082) and 0.232(0.064). If we include three digit dummies interacted with country dummies the results are: 0.274(0.101); 0.176(0.08) and 0.167(0.052). Hence, the primary source of identification is (i) multi-product firms who face differential industry effects in addition to their primary sector and (ii) the acceleration of import growth and technology. The continued importance of the trade variable even after this tough test is remarkable.

Summary on endogeneity - The main concern in interpreting the technology-trade correlation in Table 1 as causal is that there are unobserved technology shocks. The evidence from Table 2 is that controlling for such potential endogeneity concerns in a variety of ways does not undermine a causal interpretation of the impact of Chinese imports on technical change in the North.

C. Reallocation effects: jobs and survival

Table 3 examines reallocation effects by analyzing employment growth in Panel A and survival in Panel B. We first examine the basic associations in column (1) of Panel A, which suggests a strong negative effect of Chinese imports - a 10 percentage point increase in imports is associated with a 3.5% fall in employment. In addition, high-tech firms (as indicated by a high level of lagged patents per worker) were more likely to grow. Most importantly, the interaction of Chinese trade and lagged patent stock enters with a positive and significant coefficient in column (2). This suggests that more high-tech firms are somewhat shielded from the effects of Chinese imports. In columns (3) and (4) we repeat the estimates but for the “patenters” sample rather than all firms (i.e. those firms who had at least one patent since 1978) and find a similar result: firms with a high lagged patent stock had less job falls following a Chinese import shock.[34] In columns (5) and (6) we run similar employment estimations using the initial level of IT and TFP and again find similar positive interaction terms, suggesting high-tech firms are somewhat protected from the effects of Chinese import competition.

We also examined the dynamic effects of Chinese imports on employment and compared this to the impact on technology. Table A6 explores the timing for patents by moving from a lag-length of 5 years in column (1) to a lag-length of zero years in column (6) as in our baseline model. Chinese imports appear to have the largest impact on patents after about three years. Panel B of Table A6 shows the same results for employment, where we see the largest impact for Chinese imports is contemporaneously. This is consistent with the idea that firms respond to Chinese imports by cutting employment while also initiating innovative projects. These innovation projects appear to take around three years on average to produce innovations that are sufficiently developed to be patented.

Panel B of Table 3 examines survival. We consider a cohort of firms and plants alive in 2000 and model the subsequent probability that they survived until 2005 as a function of the growth of industry-wide Chinese imports and the initial technology levels. Column (1) shows firms facing higher rates of Chinese import growth are less likely to survive - a ten percentage point increase in Chinese imports decreases the survival probability by 1.2 percentage points. Since the mean exit rate in our sample period is 7-percentage point this represents a 17% increase in exit rates. Column (2) analyzes the interaction term between Chinese import growth and lagged patents and finds again a positive "shielding" effect – firms with a low initial patent stock have a significantly higher change of exiting when faced by an influx of Chinese imports. In columns (3) and (4) we re-estimate these specifications using only patenting firms and again find a significant positive interaction between lagged patent stocks and Chinese imports[35]. Columns (5) and (6) shows that there are also positive interaction effects when we use IT or TFP as alternative measures of technology, although these are not significant at the 5% level. Further investigation reveals that the main effect is coming from firms in the bottom quintile of the technology distribution who were

[34] Furthermore, this result is not driven by the inclusion of employment in our patent stock measure. To test this we estimated both a model where employment was removed from the denominator (that is, a simple patent stock measure) and a model that include lagged employment and its interaction with Chinese imports. The estimate of our technology-imports interaction terms for these models were 0.192(0.086) and 0.160(0.083) respectively.

[35] We have re-estimated all these results with the IV strategies discussed in the previous section and, as with the technology equations, all results are robust.

significantly more likely to exit because of Chinese import competition.[36] These findings on the impact of low wage country imports on reallocation is consistent with those found in US manufacturing establishments in Bernard, Jensen and Schott (2006) using indirect measures of technology (capital intensity and skills) for the pre-1997 period in the US.

VI. MAGNITUDES: INDUSTRY-LEVEL RESULTS, SELECTION AND GENERAL EQUILIBRIUM EFFECTS

Taking all these results together we have a clear empirical picture of the role of Chinese imports in increasing technological intensity both within firms (Tables 1 and 2) and between firms by reallocating output to more technologically advanced firms (Table 3). We now turn to the economic magnitude of these effects.

A. Magnitudes

We can use the regression coefficients to perform some partial equilibrium calculations to quantify how much of the aggregate change in technology China could account for and to gauge the relative importance of within and between firm effects (details in Appendix E). In summary, for patents per employee we apply the coefficients from all our regressions with the empirical growth of Chinese imports to predict growth in patent intensity and then divide this by the actual growth in aggregate patent intensity in our sample. For IT and TFP we follow a similar exercise, again applying our regression coefficients to get a predicted increase from China and dividing by the total increase in aggregate data.

In Table 4 we see that over the 2000-2007 period Chinese imports appear to have accounted for about 14.7% of the increase in aggregate patenting per worker, 14.1% of the increase in IT intensity and 11.8% of TFP growth in European manufacturing. The predicted impact of Chinese imports appears to increase over this period. For example, we estimate that Chinese imports accounted for 13.9% of the increase in patents per employee over the 2000-04 period but 18.7% over the 2004-2007 period. The reason for this acceleration is clear in Figure 1, where Chinese import growth has rapidly increased over this period. Table 4 also shows for patents the contributions of the within and between components are roughly equal which is consistent with the

[36] For example, estimating column (5) but using the lowest quintile of the IT intensity distribution rather than the linear IT intensity gave a coefficient (standard error) of 0.214 (0.102) on the interaction.

literature on trade liberalization (e.g. Pavcnik, 2002). For IT and productivity, the within component is larger which may be because the adjustment costs are lower in response to the more gradual growth of Chinese imports over the 2000's compared to the "shock" trade liberalizations examined in places like Chile and Columbia.

B. Industry level results

In Table 5 we re-estimate our technology regressions at the industry level in Panel A and at the firm level in Panel B.[37] This provides another approach to comparing the within firm and between firm magnitudes of the impact of trade with China, since the industry level magnitudes capture both effects while the firm level magnitudes capture only the within effects. In addition to being a cross check on the magnitudes as estimated from the full set of equations, the industry-level estimates include any effect of China on entry.[38] For example, if Chinese competition discourages entry of innovative firms within an industry, then the calculations in Table 4 will over-estimate the impact of trade on technical change. By contrast, the industry level aggregates are the stock of firms so include all growth from entrants as well as survivors.

Table 5 starts by examining outcomes where we expect Chinese trade to have a negative impact: prices, employment and profitability. We use producer prices as a dependent variable in column (1) of Panel A (there is no firm-level price data) and observe that Chinese imports are associated with large falls in prices in the most affected industries, consistent with Broda and Romalis (2009). Column (2) uses employment as the dependent variable and shows a larger negative effect at the industry level (Panel A) than the firm level (Panel B) consistent with the evidence from Table 3 that there is a trade effect on exit probabilities.[39] Column (3) contains the results for profitability (profits before tax, interest and dividends divided by revenue) and shows that industry and firm profits have fallen significantly (the smaller firm-level coefficient is the usual selection effect due to the least profitable firms being the first to exit). This negative profitability effect is important, as it is consistent with the idea that Chinese imports are causing an increase in competitive pressure in the industry (as assumed in the "trapped factor" model). If Chinese import

[37] The firm-level results are identical to those in Table 1 for IT and R&D. The patents and TFP results differ somewhat from Table 1 because we exploited the multi-industry information at the firm level to construct a weighted average of Chinese imports in the main results. By contrast, in Table 5 we allocate a firm to its primary four-digit industry (Panel B) for comparability to the industry level results (Panel A). See Appendix B for details.

[38] Atkeson and Burstein (2010) stress this as one of the main problems with firm-level analysis of trade. See also Arkolakis, Costinot and Rodríguez-Clare (2010).

[39] Interestingly, Autor, Dorn and Hansen (2012) looking at US labor markets find Chinese import competition not only reduces employment and wages, but also increases transfer payments for disability and unemployment.

share was instead only proxying some greater ability to offshore (which if properly measured it should not as these are Chinese imports in the firm's *output* market not its *input* market), then we would expect the coefficient to be positive as this should enhance rather than inhibit profitability. We discuss offshoring in more detail in sub-section VII.D below.

In columns (4) to (10) of Table 5 we show results for our technology measures - patents, IT, R&D and TFP. At the industry level (Panel A) we find that Chinese import competition is significantly associated with increases in all of these measures of technology. Note that these industry-level results are based on data that includes all firms and plants at a given point in time, rather than just survivors. In Panel B columns (4) to (10) confirm that the firm level results show similar strong associations between Chinese import growth and technology, but with magnitudes between one-half to two-thirds of those at the industry level, broadly consistent with the share of the within firm component shown in the Table 4 magnitude calculations. This suggests that any entry effects omitted from the firm-level results, but included in the industry level results, must be relatively small given the similarity of the magnitudes.[40]

C. Dynamic Selection bias

A concern with our finding of positive effects of Chinese imports competition on within firm technical change is that it reflects dynamic selection bias. For example, it may be that firms who know that they are technologically improving are less likely to exit in the face of the Chinese import shock. This could generate our positive coefficients in Table 1. Note that our industry-level results in Table 5A are robust to this problem as it examines aggregate innovation. Dynamic selection bias would mean, however, that we allocate too much of this aggregate industry effect to the within firm component and too little to the reallocation component in the calculations of Table 4.

Appendix F gives a formal statement of the dynamic selection problem and suggests two ways of tackling it by (i) bounding the selection bias and (ii) a control function approach. First, we can place an upper bound on the magnitude of the dynamic selection effects by exploiting the fact that the number of patents can never fall below zero. We create pseudo observations for firms who exit and give them a value of zero patents for all post exit periods until the end of the sample in 2005. This is a "worst case bounds" bounds approach (see Manski and Pepper, 2000 or Blundell et al, 2007) as the effect of trade could never be less than this lower bound.

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[40] For example, the magnitude of the within industry level effects 2000-2007 for patents, IT and TFP are 12.5%, 10.8% and 16.1%, very similar to the equivalent firm-level values of 14.7%, 14.1% and 11.8% as shown in Table 4.

Table 6 implements this method. We first report the baseline results of Table 1 column (1) and then report the results for the worst-case lower bounds in column (2). Note that as well as additional observations on our existing 8,480 firms we also obtain additional firms as we now can construct a five-year difference even for firms with less than five years of actual patenting data by given them zeros for the years after they exit. Dropping firms with less than five years of data is another possible source of selection bias that is addressed by this method.[41] Our results appear to be robust to these potential selection bias problems as the coefficient on Chinese imports in column (2) remains positive and significant and has fallen only by less than one-sixth, from 0.321 to 0.271.

Since patents are counts we also consider a Negative Binomial model. It is less straightforward to deal with fixed effects in such models than in our baseline long-differences models, especially with weakly exogenous variables like Chinese imports (e.g. the Hausman, Hall and Griliches, 1984, fixed effect Negative Binomial model requires strict exogeneity). We use the Blundell et al (1999) method of controlling for fixed effects through pre-sample mean scaling for the baseline model. This estimator has proven attractive in the context of patent models and exploits the long pre-sample history of patents to control for the fixed effect (we have up to 23 years of pre-sample patent data). More details of the estimation technique are in Blundell et al (2002) and the textbook by Cameron and Trevidi (2005).

Column (3) implements the Negative Binomial model and shows that the coefficient on imports is similar to the baseline results with a positive and significant coefficient that is if anything slightly higher than the long differenced results. Column (4) shows that the worst-case lower bounds are again not much lower than the baseline, with the effect falling from 0.397 to 0.389.

We conclude from Table 6 that the dynamic selection problem is not causing us to substantially overestimate the impact of Chinese competition causing a within firm increase in the volume of innovative activity.

This worse case bounds approach will not work for TFP as it does not have a lower bound of zero. However, the approach that we have taken to calculate TFP already includes a control function approach to remove the bias associated with selection in production functions following Olley and

[41] A total of 658 firms some history of patenting exited to bankruptcy in our sample. 406 of these were already in the main sample of 8,480 firms and 30,277 observations (Table 1, column (1)). The additional 252 of the 658 exiting firms were outside the main sample because they reported less than five consecutive observations so that a five-year difference in patenting could not be defined. The increase in observations from 30,277 in column (1) to 31,272 in column (2) are the additional observations on these 658 exiting firms.

Pakes (1996). Details of this are in Appendix C. Thus, our TFP estimates should be robust to this selection problem.

D. General equilibrium and Welfare

We cannot prematurely jump to aggregate welfare conclusions from the results in the paper. Atkeson and Burstein (2010) argue that lowering trade costs may lead to the exit of low productivity domestic firms, but it will deter product innovation through new entry. In Ossa and Hsieh (2010) the reduction of barriers to Chinese imports raises average European firm productivity (as we find), but lowers the average quality of Chinese exporters to the EU. While Arkolakis et al (2008, 2010) argue that the standard gains to trade summarized in the ratio of exports to GDP are not fundamentally altered in a wide class of models that allow for heterogeneous firms. More subtly, the innovation response in rich countries in sectors where China has comparative advantage (like textiles), might reduce the standard Ricardian gains from trade (Levchenko and Zhang, 2010).[42]

Our empirical models are partial equilibrium and do not capture all of the complex welfare effects of trade with China. Therefore, what they directly estimate is the impact of increasing trade on innovation on an industry-by-industry basis. This is directly relevant for typical trade policy question, such as the costs of putting quotas on imports in any particular industry.

Nevertheless, we think that our results are also suggestive of a positive aggregate effect of Chinese trade on innovation as implied by standard endogenous growth models (such as the trapped factor model of Bloom et al, 2012, building on Romer and Riviera-Batiz, 1992)[43]. First, the within firm effects of Chinese imports on innovation is at least as large as the between firm-reallocation effects (see Table 4). Second, any possible falls in innovation through lower entry within the same industry cannot offset our main results. For example, the net effect of China (including all entry effects) is on average positive in the industry-level analysis of Table 5 Panel B.

[42] Another argument is that increased innovation from Chinese trade drives up the wages of R&D scientists leading to no net increase in innovation, We believe this fully offsetting increase in R&D prices is unlikely. First, much of the improvements we identify do not require large increases in R&D scientists – the incremental changes in IT, TFP, management practices and patenting may require more skilled workers, but not more scientists. Second, it is unlikely the supply curve of R&D scientists is completely vertical – workers for innovation-related tasks can be imported from overseas and redeployed from other activities. Bloom, Griffith and Van Reenen (2002), for example, showed that the number of R&D employees rose in countries that introduced fiscal incentives for R&D even in the short-run.

[43] It may be that there is "too much" innovation of course, so slowing down innovation has positive welfare effects. However, most empirical estimates have found that there is a socially sub-optimal level of R&D and innovation (e.g. Jones and Williams, 1998).

VII. EXTENSIONS AND ROBUSTNESS

In Section II we discussed several models of trade induced technical change. The trapped factor model, amongst others, suggested that innovation should rise when faced by greater import competition and should occur for firms facing the largest trade shock. The trapped factor model also implies that the innovation response (i) should be weaker for import competition from high wage countries, (ii) larger for firms more subject to the trapped factor problem. We investigate these further implications in the next two sub-sections, examine skills as another outcome in sub-section C and finally examine three alternative theories of Section II relating to offshoring, product switching and export-led innovation in sub-sections VII.D to VII.F.

A. Low wage vs. high wage country trade

Our key measure of Chinese import competition is the share of total imports originating in China. An alternative approach is to normalize Chinese imports by a measure of domestic activity such as production or apparent consumption. These alternative normalizations are presented in Table A7. Although the magnitude of the coefficients changes as the mean of the imports variable is different, the qualitative and quantitative results are remarkably similar.[44]

Using these alternative definitions of Chinese imports also allows us to separately distinguish the impact of Chinese imports from all other low wage country imports and high wage country imports. We define low wage countries as those countries with GDP per capita less than 5% of that in the US between 1972 and 2001. On this definition, the increase in non-Chinese low wage imports (as a proportion of all imports) 1996-2007 was close to zero (0.005), whereas China's growth was substantial (see Figure 1).

Table 7 presents some analysis of using measures of Chinese imports normalized by domestic production. The dependent variable is the change in patents in Panel A, the change in IT in Panel B and the change in TFP in Panel C. Column (1) simply shows what we have already seen – Chinese import penetration is associated with significantly greater technical change. Column (2) includes the non-Chinese low wage country import penetration measure. The coefficient is insignificantly different from the Chinese imports coefficient in all panels. When we include all low

[44] For example, a one standard deviation increase in the import share in Table 1 column (1) is associated with a 10% increase in patenting. By contrast, a one standard deviation increase in the import share in column (1) of Panel B in Table A7 is associated with a 14% increase in patenting.

wage country import penetration instead of just China in column (3) we obtain similar coefficients to those in column (1), with a positive and significant coefficient for all three technology measures. We conclude that China is qualitatively no different from other low wage countries - it is just the largest trade shock from low wage countries in recent decades.

Column (4) of Table 7 includes the growth of imports from high wage countries. The coefficient is positive in all panels, but insignificant. High wage imports are also easily dominated by Chinese imports when both are included in column (5). Column (6) uses total import penetration that is positive but again dominated by China in column (7). One concern is that the endogeneity bias may be greater for high wage country imports than Chinese imports. We followed Bertrand (2004) and used trade-weighted exchange rates as an instrument that, although generally significant in the first stages, did not qualitatively change any of our results.[45]

Taken as whole Table 7 strongly suggests that China is a good example of a low wage country trade shock. Import competition from low wage countries appears to stimulate faster technical change, whereas import competition from richer countries does not. According to our model, this is because imports from the South make the production of low-tech goods less profitable and increases incentives to move up the quality ladder. Rich country imports are more likely to be higher tech goods that for Schumpeterian reasons shrink profit margins and offset any pro-innovation effects of competition.

B. Heterogeneity: The effect of Chinese imports on innovation is stronger when there are more "trapped factors"

In Section II we suggested that firms with "trapped factors" (e.g. due to firm-specific human capital) may be less likely to innovate until a shock such as the reduction of trade barriers against Chinese goods lowers the opportunity cost of innovating. To test this idea we allow the effect of Chinese imports to be heterogeneous with respect to environments where we might think that trapped factors are more important.

[45] For example in column (6) of Table 7 the coefficient (standard error) on trade weighted exchange rates was 0.391(0.178) in the first stage for IT and the coefficient on imports in the second stage remained insignificant (actually falling to -0.095 with a standard error of 0.172). For TFP the first stage coefficient (standard error) was 0.819(0.220) and the imports variable remained significant and positive in the second stage with a coefficient (standard error) of 0.210(0.081). For patents the first stage was very weak due to much fewer degrees of freedom with a coefficient (standard error) on the instrument of 0.082. The second stage coefficient on imports was negative but very imprecisely determined: -2.310(4.392).

Our first simple test is to construct a measure of the industry-specific wage premia that our model suggests is the product-specific human capital following an innovation (see Appendix A). We estimate these three digit inter-industry wage differentials in the standard way (e.g. Krueger and Summers, 1988) from a Mincerian wage equation using individual-level data. We do this for the UK as (i) there is abundant publicly available micro-data and (ii) we want to avoid conflating institutional constraints (like unions and minimum wages) with the underlying technology of the industry and the UK has the least regulated labor market of our European countries[46].

In column (1) of Table 8 we repeat our basic patents equation. In column (2) we include our proxy for trapped factors, the measure of the industry-specific wage premium. This has a negative and significant correlation with innovation as the model would suggest as the opportunity cost of innovating is higher for firms with more trapped factors. Column (3) includes the key term: an interaction of the growth of Chinese imports and the industry wage premium. The coefficient on this term is positive and significant implying that the effect of Chinese competition is greater when there is more industry-specific human capital as the model predicts.

Using industry wage premium interprets the theory quite literally and it may be that trapped factors are a more general phenomenon. An alternative measure of trapped factors is to use measured TFP ("MFP") as a higher value of this term will reflect the fact that some firms have higher TFP than others (see Appendix A). The advantage of this measure is that it is firm specific, but a disadvantage is that we can only construct TFP for a sub-sample of the data. Column (4) of Table 8 presents the patent equations for this sub-sample. Even though the sample is smaller, the effect of Chinese import competition on patents is similar to that in the overall sample in Table 1 (0.284 vs. 0.321). We then include the firm's initial TFP in column (5) which, in line with the trapped factor model, is negatively correlated with subsequent patent growth. Column (6) includes the key interaction term between import growth and initial TFP. There is a significant and positive interaction suggesting that high TFP firms are more likely to respond by innovating when faced by a Chinese import shock than low productivity firms. This result has the same flavor as Aghion et al (2005) that the innovation in firms nearer the technology frontier responds more positively to competition, than low TFP firms. Unlike Aghion et al, however, we find no evidence of an inverted

[46] For example, the OECD (2009) index of "strictness of employment protection in 2008" gives the UK the lowest score (i.e. highest flexibility) of 1.1 (on a scale of zero to 6) of all 30 developed countries with the exception of the US. By contrast, Portugal had the greatest degree of job protection with a score of 4.2.

"U" which may be because we focus on competition from less developed countries who are near the bottom of the quality ladder, rather than an increase in general competition.[47]

We could not find any evidence that larger firms responded more to Chinese imports. But Holmes and Stevens (2010) argue that size is not an adequate proxy for productivity, finding that small plants actually do relatively better than larger plants following an increase in Chinese import competition. In their model, small firms survive by operating in product niches rather than the standardized products competing with China. Like Holmes and Stevens (2010) we find that size *per se* is an inadequate proxy for productivity, but document a new result that firms endogenously create niche products through innovation when faced by Chinese competition.

In summary, Table 8 as a whole suggests some heterogeneity of the effect of trade on innovation in a direction consistent with our simple trapped factor model.

C. Skill demand

To examine skill demand we use the UK Labor Force Survey, as none of our micro datasets has plant or firm level skills measures. We create a three-digit panel on the share of the college-educated workers in the total wage-bill. Since the impact of China is relatively common across Europe, we think the UK results should be broadly representative.

In column (1) of Table 9, we see that Chinese imports are associated with an increase in the wage-bill share of college-educated workers, suggesting Chinese trade raises the demand for skills. In column (2) we see the standard result that IT is also associated with an increase in the share of wages for college workers. Including both variables into the regression in column (3) shows that both IT and Chinese imports are significant, although both have lower coefficients, suggesting part of the association of IT with skilled workers may be a proxy for the impact of developing country trade[48]. In column (4) we re-estimate this specification by OLS using the textile and apparel sample, and in column (5) report the IV results that support a causal impact of Chinese import competition on the demand for skilled workers. This is consistent with the model that Chinese trade leads firms to switch from producing older low-tech goods to the design and manufacture of new goods, which is likely to increase the demand for skilled workers.

[47] In a similar vein, Amiti and Khandelwal (2010) find stronger effects of trade on quality upgrading for firms closer to the quality frontier. Following Khandelwal (2010) we tried interacting imports with his average length of a quality ladder in the industry. The interactions typically went in the expected direction, but were insignificant.

[48] When disaggregating the wage bill share in relative wages and relative employment we find a positive association of Chinese imports with both components, but the strongest impact is on relative employment rather than relative wages.

D. Offshoring

We have focused on China's effect through competition in the final goods market, but an alternative way in which China could affect technical progress is through allowing Western firms to buy cheaper intermediate inputs and offshore low value added parts of the production chain.[49] We investigate this by adapting the offshoring measure of Feenstra and Hansen (1999) for China, which uses the input-output tables to measure for each industry the share of Chinese inputs in total imported inputs[50]. Column (1) of Table 10 includes this China offshoring measure in the patent equation. It enters with a positive but insignificant coefficient. Interestingly, in columns (2) and (3) we look at IT and TFP and *do* find a significant positive impact of offshoring. Throughout Table 10, the share of Chinese imports in the final goods market (our baseline measure) remains positive and significant with only slightly lower coefficients.[51]

We also investigated using the WTO quasi-experiment of Table 2 to construct "input quotas" using the input-output tables to calculate predicted falls in the barriers to using Chinese inputs. Looking at the reduced forms for the technology equations (i.e. simply regressing the five year growth of each technology measure on input quotas and country dummies interacted with time dummies), removal of input quotas had no significant impact on patents, but significantly increased IT intensity and TFP (see Table 10). When output quotas were also included in this specification, input quotas remained significant at the 5% level for the TFP equation, but were only significant at the 10% level for the IT equation.[52] Output quotas remained positive and significant in all three specifications.

Together these results suggest that while offshoring does not increase overall innovation (as measured by patents) it does increase IT intensity and productivity, presumably since offshoring moves the less IT intensive and lower productivity parts of the production process overseas to China.

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[49] Intermediate inputs are stressed (in a developing country context) by Amiti and Konings (2006) and Goldberg et al, 2010b).

[50] See Appendix B for details. We also considered the share of total imported inputs in all inputs (or all costs) like Feenstra-Hansen, but as with our analysis of total imports in the final goods market, it is the Chinese share (reflecting low wage country inputs) that is the dominant explanatory factor.

[51] This is compared to the baseline results in columns (1), (2) and (4) in Table 1 for patents, IT and TFP. The coefficient estimates in Table 10 imply a one standard deviation increase in offshoring has a similar marginal effect on IT and TFP (0.014 and 0.008 respectively) to a one standard deviation increase in Chinese imports (0.014 and 0.007 respectively).

[52] The coefficients (standard errors) on input quotas were 0.727(0.523), 0.696(0.365) and 0.290(0.136) in the patents, IT and TFP equations. We estimate these equations on industries where at least 0.5% of imported inputs are from China.

We re-estimated all the technology, employment and survival equations including extra terms in Chinese offshoring (see Table A8). As with Table 10, these terms made little difference to the main patents equation but did have some effect on the IT and TFP equations, suggesting more of a role for offshoring in increasing the reallocation effects of China, broadly in line with the compositional models of sub-section IIC. We re-calculated the aggregate magnitudes of the effects of China on technical change including the offshoring terms (see Table A9, the analog of Table 5). Although the overall effects on patents are not much changed (China still accounted for just under 15% of the increase in patenting), the implied effects of China on aggregate IT and TFP more than doubled suggesting that offshoring magnifies the product market competition effects of Chinese trade we have focused on. This implies that if anything, we are *underestimating* the effect of China by focusing on the final goods markets effects.

E. Product and industry switching

A leading compositional theory we discussed in the theory section was that in the face of Chinese import competition European firms change their product mix. To investigate this we examine whether a plant changes its primary four-digit industrial sector in the HH data, which has accurate four-digit industry data going back to 1999 (the other datasets have less reliable information on the changes in industry affiliation). On average 11% of plants switch industries over a five-year period, a substantial number that is consistent with evidence from recent papers.[53]

Table 11 begins by regressing a dummy for switching on Chinese imports and the usual controls, finding plants in industries exposed to China were more likely to switch industries. Column (2) includes a control for lagged IT intensity that reduces the probability of switching, but only slightly reduces the coefficient on Chinese imports. Column (3) includes employment growth, which has little impact. The second half of Table 11 uses IT intensity growth as the dependent variable. Column (4) shows that switching is indeed associated with greater use of IT, but the magnitude of the effect is small: plants who switched industries had a 2.5% faster growth in IT intensity than those who did not. Column (5) displays the standard regression for this sample, showing the positive relationship between IT intensity and Chinese imports for the sub-sample where we have switching data. Most importantly, column (6) includes the switching dummy; this reduces the coefficient on Chinese imports, but only by a small amount. A similar story is evident

[53] For example, Bernard, Redding and Schott (2010) on the US, Goldberg et al (2010a, b). Bernard et al (2006) found that 8% of their sample of US manufacturing plants switched four-digit industries over a five-year period.

when we include employment growth in the final column. So industry switching is statistically significant but cannot account for much of Chinese import effects.

One limitation of this analysis is that our data does not allow us to observe product switching at a more disaggregate level. Bernard et al (2010, Table 5) show, however, that in US manufacturing firms three quarters of the firms who switched (five-digit) products did so across a four-digit industry. If we run column (5) on those plants who did not switch industries, the Chinese imports effect remains strong (0.474 with a standard error of 0.082). This could still conceivably be driven by the small percentage of plants who switched five-digit sector within a four sector, but it seems unlikely given the small effect of controlling for four-digit switching on the Chinese imports coefficient.

F. Exports to China

We have focused on imports from China as driving changes in technology but as discussed in Section II, exports may also have an impact through market size effects. Comtrade allows us to construct variable reflecting exports to China (as a proportion of total exports in the industry-country pair) in an analogous way to imports. Table A10 presents the results, and shows that in every column of results exports are not significant. This is unsurprising as most of the theories of export-led productivity growth focus on exporting to *developed* countries rather than emerging economies, like China. It is unclear what benefit there is to learning, for example, from China that is usually thought of as being behind the European technology frontier. And in terms of market size, China's share of the total world exports produced by European manufacturers is still relatively small at around 1.3%, so is not likely to drive technology change in the North.

VIII. CONCLUSIONS

In this paper we have examined the impact of trade on technical change in twelve European countries. Our motivation is that the rise of China which constitutes perhaps the most important exogenous trade shock from low wage countries to hit the "Northern" economies. This helps identify the trade-induced technical change hypothesis. We use novel firm and plant level panel data on innovation (patents and R&D), information technology, TFP and management practices combined with four-digit industry-level data on trade.

The results are easy to summarize. Our primary result is that the absolute volume of innovation as measured by patenting (and R&D) rose *within* firms who were more exposed to increases in Chinese imports. A similar large within firm effect is observe for other indicators of technical change such as TFP, IT intensity and management quality. Second, in sectors more exposed to Chinese imports, jobs and survival rate fell in low-tech firms (e.g. lower patenting intensity), but high-tech firms were are relatively sheltered (the between firm effect). Both within and between firm effects generate aggregate technological upgrading.

These results appear to be robust to many tests, including treating imports as endogenous using China's accession to the World Trade Organization in 2001. In terms of magnitudes, China could account for around 15% of the overall technical change in Europe between 2000 and 2007. This effect appears to be increasing over time and may even be an underestimate as we also identify a similar sized role for offshoring to China in increasing TFP and IT adoption (although not for innovation). This suggests that increased import competition with China has caused a significant technological upgrading in European firms in the affected industries through both faster diffusion and innovation. In terms of policy, our results imply that reducing import barriers against low wage countries like China may bring important welfare gains through technical change, subject to the caveats over general equilibrium effects discussed in sub-section VI.D.

There are several directions this work could be taken. First, we would like to investigate more deeply the impact of low wage countries on the labor market, using worker level data on the non-employment spells and subsequent wages of individuals most affected by Chinese trade. Much of the distributional impact depends on the speed at which the reallocation process takes place. Second, we want to complement our European analysis with a similar exercise in the US and other countries. Thirdly, we would like to further develop our trapped factor model, to see how important it is in explaining trade effects compared to the more conventional market size and competition effects. Finally, it would be helpful to more structurally extend the analysis to properly take into account general equilibrium effects. These areas are all being actively pursued.

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TABLE 1: TECHNICAL CHANGE WITHIN INCUMBENT FIRMS AND PLANTS

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(R&D)**	**ΔTFP**	**ΔMANAGEMENT**
Estimation method	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**	**3 year diffs**
Change in Chinese Imports	0.321***	0.361**	1.213**	0.257***	0.814***
ΔIMP_{jk}^{CH}	(0.102)	(0.076)	(0.549)	(0.072)	(0.314)
Sample period	2005-1996	2007-2000	2007-1996	2005-1996	2010-2002
Number of Units	8,480	22,957	459	89,369	1,576
Number of country by industry clusters	1,578	2,816	196	1,210	579
Observations	30,277	37,500	1,626	292,167	3,607

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses (except columns (3) and (5) which are three-digit industry by country). All changes are in five-year differences, e.g. ΔIMP_{jk}^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair (except column (5) which is in three-year long differences). All columns include a full set of country by year dummies. *Δln(PATENTS)* is the change in *ln(1+PAT), PAT* = count of patents. *IT/N* is the number of computers per worker. *R&D* is expenditure on research and development. TFP is estimated using the de Loecker (2011) version of the Olley-Pakes (1996) method separately for each industry based on 1.4m underlying observations (see Appendix C) and *Management* is the average score on the 18 Bloom and Van Reenen (2007) management questions around monitoring, targets and incentives. The 12 countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK for all columns except (4) which only includes France, Italy, Spain and Sweden (the countries where we have good data on intermediate inputs) and column (5) which covers France, Germany, Italy, Ireland, Sweden and the UK. Dummies for establishment type (Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch) are included in column (2). Standard survey noise controls such as interviewer dummies and interview/interviewee controls (e.g. tenure in firm) are included in column (5) as in Bloom and Van Reenen (2007). Units are firms in all columns except (2) where it refers to plants.

TABLE 2: CONTROLING FOR UNOBSERVED TECHNOLOGY SHOCKS

PANEL A: USING CHANGES IN QUOTAS AS AN IV (TEXTILE AND APPAREL INDUSTRIES ONLY)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PATENTING ACTIVITY			INFORMATION TECHNOLOGY			TOTAL FACTOR PRODUCTIVITY		
Dependent Variable:	**Δln(PATENTS)**	**ΔIMP^{CH}**	**Δln(PATENTS)**	**Δln(IT/N)**	**ΔIMP^{CH}**	**Δln(IT/N)**	**ΔTFP**	**ΔIMP^{CH}**	**ΔTFP**
Method:	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**
Change Chinese Imports	1.160***		1.864*	1.284***		1.851***	0.620***		1.897**
	(0.377)		(1.001)	(0.172)		(0.400)	(0.100)		(0.806)
Quotas removal		0.108***			0.088***			0.068***	
		(0.022)			(0.019)			(0.026)	
Sample period	2005-1999	2005-1999	2005-1999	2005-2000	2005-2000	2005-2000	2005-1999	2005-1999	2005-1999
Number of units	1,866	1,866	1,866	2,891	2,891	2,891	55,791	55,791	55,791
Number industry clusters	149	149	149	83	83	83	187	187	187
Observations	3,443	3,443	3,443	2,891	2,891	2,891	55,791	55,791	55,791

PANEL B: USING "INITIAL CONDITIONS" AS AN INSTRUMENTAL VARIABLE (ALL INDUSTRIES)

Dependent Variable	**Δln(PATENTS)**	**ΔIMP^{CH}**	**Δln(PATENTS)**	**Δln(IT/N)**	**ΔIMP^{CH}**	**Δln(IT/N)**	**ΔTFP**	**ΔIMP^{CH}**	**ΔTFP**
Method:	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**
Change in Chinese Imports	0.321***		0.495**	0.361***		0.593***	0.257***		0.507*
	(0.117)		(0.224)	(0.106)		(0.252)	(0.087)		(0.283)
Chinese imports in SIC4*US		0.167***			0.124***			0.078***	
&EU Chinese import growth		(0.017)			(0.002)			(0.021)	
Sample period	2005-1996	2005-1996	2005-1996	2007-2000	2007-2000	2007-2000	2005-1996	2005-1996	2005-1996
Number of Units	8,480	8,480	8,480	22,957	22,957	22,957	89,369	89,369	89,369
Number of industry clusters	304	304	304	371	371	371	354	354	354
Observations	30,277	30,277	30,277	37,500	37,500	37,500	292,167	292,167	292,167

PANEL C: INCLUDE INDUSTRY TRENDS (OLS, ALL INDUSTRIES)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(IT/N)**	**ΔTFP**	**ΔTFP**
Change in Chinese Imports	0.321***	0.191*	0.361***	0.170**	0.257***	0.128**
	(0.102)	(0.102)	(0.076)	(0.082)	(0.072)	(0.053)
Three Digit Industry trends?	No	Yes	No	Yes	No	Yes
Sample period	2005-1996	2005-1996	2007-2000	2007-2000	2005-1996	2005-1996
Number of Units	8,480	8,480	22,957	22,957	89,369	89,369
Number of clusters	1,578	1,578	2,816	2,816	1,210	1,210
Observations	30,277	30,277	37,500	37,500	292,167	292,167

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. In all panels we use the same specifications as Table 1 columns (1), (2) and (4) but estimate by instrumental variables (IV). In Panel A the IV is "Quota removal" is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the four-digit industry that were covered by a quota restriction on China in 2000 (prior to China's WTO accession) that were planned to be removed by 2005 (see the Appendix D for details). Sample only includes textiles and apparel industries. In **Panel B** the IV is the share of Chinese imports in all imports in an industry across the whole of the Europe and the US (6 years earlier) interacted with the aggregate growth in Chinese imports in Europe. The base year is (t-6). **Panel C** reproduces the baseline OLS regressions in columns (1), (3) and (5) and then includes a full set of three-digit dummies in columns (2), (4) and (6). Since these specifications are in long differences this is equivalent to including three digit trends in the levels specification. The number of units is the number of firms in all columns except the IT specification where it is the number of plants. All columns include country by year effects. Standard errors for all regressions are clustered by four-digit industry in parentheses in panels A and B and by four-digit industry by country pairs in Panel C.

TABLE 3: EMPLOYMENT AND EXIT

PANEL A: EMPLOYMENT

Dependent Variable: Employment Growth, $\Delta \ln N$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable (TECH)		Patent stock	Patent stock	Patent stock	IT	TFP
Sample	All Firms	All Firms	Patenting firms	Patenting firms	IT sample	TFP sample
Change in Chinese Imports	-0.349***	-0.352***	-0.361***	-0.434***	-0.379***	-0.382***
ΔIMP^{CH}_{jk}	(0.067)	(0.067)	(0.134)	(0.136)	(0.105)	(0.093)
Change in Chinese imports*technology at t-5		1.546**		1.434**	0.385**	0.956**
ΔIMP^{CH}_{jk} *$TECH_{t-5}$		(0.757)		(0.649)	(0.157)	(0.424)
Technology at t-5	0.513***	0.469***	0.389***	0.348***	0.230***	0.256***
$TECH_{t-5}$	(0.050)	(0.058)	(0.043)	(0.049)	(0.010)	(0.016)
Number of Units	189,563	189,563	6,335	6,335	22,957	89,369
Number of country by industry clusters	3,123	3,123	1,375	1,375	2,816	1,210
Observations	581,474	581,474	19,844	19,844	37,500	292,167

PANEL B: EXIT

Dependent Variable: *SURVIVAL*	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable		Patent stock	Patent stock	Patent stock	IT	TFP
Sample	All Firms	All Firms	Patenting firms	Patenting firms	IT sample	TFP sample
Change in Chinese Imports	-0.122***	-0.122***	-0.065	-0.089	-0.182**	-0.189***
ΔIMP^{CH}_{jk}	(0.036)	(0.036)	(0.047)	(0.050)	(0.072)	(0.056)
Change in Chinese imports*technology at t-5		0.391**		0.261**	0.137	0.097
ΔIMP^{CH}_{jk} *$TECH_{t-5}$		(0.018)		(0.114)	(0.112)	(0.076)
Technology at t-5	0.052***	0.040***	-0.006	-0.014	-0.002	-0.003
$TECH_{t-5}$	(0.008)	(0.011)	(0.007)	(0.009)	(0.006)	(0.004)
Survival Rate for Sample (mean)	0.929	0.929	0.977	0.977	0.886	0.931
Number of country by industry clusters	3,369	3,369	1,647	1,647	2,863	1,294
Observations (and number of units)	490,095	490,095	7,985	7,985	28,624	268,335

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four-digit industry pair) in parentheses. ΔIMP^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. In columns (1) to (4) *TECH* is ln[(1+ the firm's patent stock)/employment]. In column (5) *TECH* is computers per employee *(IT/N)* and in column (6) *TECH* is *TFP*. 12 Countries in all columns except column (6) which is for four countries. In columns (3) and (4) only "patenting firms" (defined as a firm that had at least one European patent between 1978 and 2007) included. Sample period is 2005-1996 for all except column (5) which is 2007-2000. Number of units is the number of firms in all columns except (5) where it is the number of plants. All columns include country by year effects. **In Panel A** the dependent variable is the five year difference of ln(employment). **In Panel B** the dependent variable (*SURVIVAL*) refers to whether an establishment that was alive in 2000 was still alive in 2005 for the HH sample in column (5). In the other columns it is based on Amadeus company status (Appendix B) and is defined on the basis of whether a firm alive in 2000 was dead by 2005.

TABLE 4: APPROXIMATE MAGNITUDES

PANEL A: Increase in Patents per employee attributable to Chinese imports (as a % of the total increase over the period)

Period	Within	Between	Exit	Total
2000-07	5.8	6.3	2.5	14.7

PANEL B: Increase in IT per employee attributable to Chinese imports (as a % of the total increase over the period)

Period	Within	Between	Exit	Total
2000-07	9.8	3.1	1.2	14.1

PANEL C: Increase in Total Factor Productivity attributable to Chinese imports (as a % of the total increase over the period)

Period	Within	Between	Exit	Total
2000-07	8.1	3.4	0.3	11.8

Notes: Panel A reports the share of aggregate IT intensity accounted for by China, Panel B the increase in patents; and the Panel C the increase in total factor productivity. This is calculated by multiplying the regression coefficients and the observed Chinese import share growth to generate a predicted change in IT/Employee, Patents/Employee and TFP 2000 to 2007 inclusive. This aggregate predicted growth in IT/Employee is then divided by the average annual change in IT/employee between 1999 to 2007 (2.5%). The aggregate predicted change in Patents/Employee is then divided by 3.5% (the aggregate annual growth rate of patents from 1986 to 2006 in the USPTO) and the aggregate predicted growth in TFP is divided by 2% (the average TFP growth in manufacturing).

TABLE 5: COMPARING INDUSTRY LEVEL REGRESSIONS TO FIRM LEVEL REGRESSIONS

PANEL A. INDUSTRY-COUNTRY LEVEL

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	**Δln(Prices)**	**Δln(Employment)**	**Δln(Profits /Sales)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(IT/N)**	**Δln(R&D)**	**Δln(R&D)**	**Δln(TFP)**
Change in Chinese Imports	-0.447**	-0.422***	-0.112**	0.368 *	0.368*	0.399***	0.354***	2.145*	1.791**	0.326***
ΔIMP_{jk}^{CH}	(0.216)	(0.148)	(0.052)	(0.200)	(0.200)	(0.120)	(0.120)	(1.186)	(0.829)	(0.072)
Change in employment					0.005		-0.088***			
					(0.012)		(0.013)			
Change in ln(Production)									-0.297	
									(0.403)	
Sample period	2006-2000	2005-1996	2007-2000	2005-1996	2005-1996	2007-2000	2007-2000	2007-2000	2007-2000	2005-1996
Country by industry clusters	131	2,990	2,295	1,646	1,646	2,902	2,902	151	151	1,140
Observations	262	11,800	5,372	6,888	6,888	7,409	7,409	322	322	5,660

PANEL B. FIRM LEVEL EQUIVALENT (ALLOCATING FIRM TO A SINGLE FOUR-DIGIT INDUSTRY)

Dependent Variable:	**Δln(Prices)**	**Δln(Employment)**	**Δln(Profits /Sales)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(IT/N)**	**Δln(R&D)**	**Δln(R&D)**	**Δln(TFP)**
Change in Chinese Imports	*No firm- level price data available*	-0.280****	-0.043***	0.171**	0.215**	0.361**	0.195***	1.213**	1.545***	0.164***
ΔIMP_{jk}^{CH}		(0.066)	(0.008)	(0.082)	(0.098)	(0.076)	(0.067)	(0.549)	(0.330)	(0.051)
Change in employment					0.015*		-0.617***			
					(0.009)		(0.010)			
Change in ln(Production)									0.558***	
									(0.043)	
Years		2005-1996	2007-2000	2005-1996	2005-1996	2007-2000	2007-2000	2007-2000	2007-2000	2005-1996
Country by industry clusters		2,814	2,259	1,578	1,464	2,816	2,816	196	196	1,018
Observations		556,448	214,342	30,277	22,938	37,500	37,500	1,626	1,626	241,810

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Panel A uses data aggregated to the industry by country level and panel B is the firm level equivalent specification with firms allocated to a single industry (except columns (6) and (7) which are plant level). Coefficients estimated by OLS in five-year differences with standard errors (clustered by industry-country pair) in parentheses below coefficients. Chinese imports are measured by the value share of Chinese imports in total imports. There are 12 countries in all columns except (10) which only includes France, Italy, Spain and Sweden (where we have good data on intermediate inputs) and (3) which is based on Germany, France, Finland, France, Spain and Sweden (where gross profit information is available). All columns include country-year effects. The dependent variable in column (1) is producer prices and is measured at the two-digit level. In column (3) the dependent variable is (pre-tax and interest) profits rates. Columns (8) and (9) in Panel A use industry R&D data from the OECD STAN database and includes Germany, Denmark, Spain, Finland, France, the UK, Italy, Norway and Sweden, and is run at the two-digit level. In column (10) productivity is estimated using the de Loecker (2011) version of the Olley-Pakes method separately for each two-digit industry (see text). All firms are allocated to a single four-digit industry unless otherwise stated (i.e. we do not use the multiple-industry information exploited in the other tables) in order to make the two Panels comparable.

TABLE 6: ASSESSING DYNAMIC SELECTION BIAS IN THE PATENTS EQUATION

	(1)	(2)	(3)	(4)
Estimator	**5 year long differences**	**5 year long differences**	**Fixed effects Negative Binomial**	**Fixed effects Negative Binomial**
Method	**Baseline**	**Worst case Lower Bound**	**Baseline**	**Worst case Lower Bound**
Change in Chinese Imports	0.321***	0.271***		
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	(0.102)	(0.098)		
Level of Chinese Imports			0.397***	0.389***
$\left(M_{jk}^{China} / M_{jk}^{World}\right)$			(0.168)	(0.165)
Number of Clusters	1,578	1,662	1,578	1,662
Number of Firms	8,480	8,732	8,480	8,732
Number of Observations	30,277	31,272	74,038	75,463

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 1996-2005 for all columns. Estimation in columns (1) and (2) by OLS in long-differences and by Negative Binomial count data model with fixed effects using the Blundell et al (1999) technique in columns (3) and (4). Standard errors (clustered by country by four-digit industry pair) in parentheses. "Worst case lower bounds" impute a value of zero to all observations through 2005 where a firm dies (death is defined as in Table 3B). There are more observations for the Negative Binomial than five year long differences as we are using observations with less than five continuous years. All columns include a full set of country by year dummies. 12 countries included in all samples.

TABLE 7: LOW WAGE COUNTRY AND HIGH WAGE COUNTRY IMPORTS

PANEL A: DEPENDENT VARIABLE IS CHANGE IN LN(PATENTS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports	0.182**	0.063			0.182**		0.178**
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$	(0.074)	(0.125)			(0.073)		(0.077)
Change in Non-China Low Wage Imports		0.152					
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$		(0.128)					
Change in All Low Wage Imports			0.106***				
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$			(0.040)				
Change in High Wage Imports				0.004	0.003		
$\Delta\left(M_{jk}^{High} / D_{jk}\right)$				(0.019)	(0.019)		
Change in World Imports						0.017	0.004
$\Delta\left(M_{jk} / D_{jk}\right)$						(0.018)	(0.018)
Number of Firms	8,364	8,364	8,364	8,364	8,364	8,364	8,364
Number of industry-country clusters	1,527	1,527	1,527	1,527	1,527	1,527	1,527
Number of Observations	29,062	29,062	29,062	29,062	29,062	29,062	29,062

PANEL B: DEPENDENT VARIABLE IS CHANGE IN IT INTENSITY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports	0.129***	0.126***			0.128***		0.120***
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$	(0.028)	(0.029)			(0.028)		(0.029)
Change in Non-China Low Wage Imports		0.018					
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$		(0.051)					
Change in All Low Wage Imports			0.127***				
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$			(0.025)				
Change in High Wage Imports				0.014	0.002		
$\Delta\left(M_{jk}^{High} / D_{jk}\right)$				(0.009)	(0.009)		
Change in World Imports						0.024***	0.007
$\Delta\left(M_{jk} / D_{jk}\right)$						(0.009)	(0.009)
Number of Units	20,106	20,106	20,106	20,106	20,106	20,106	20,106
Number of industry-country clusters	2,480	2,480	2,480	2,480	2,480	2,480	2,480
Number of Observations	31,820	31,820	31,820	31,820	31,820	31,820	31,820

PANEL C: DEPENDENT VARIABLE IS CHANGE IN TOTAL FACTOR PRODUCTIVITY

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports	0.065***	0.092**			0.071***		0.062**
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$	(0.020)	(0.048)			(0.021)		(0.022)
Change in Non-China Low Wage Imports		-0.026					
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$		(0.041)					
Change in All Low Wage Imports			0.050***				
$\Delta\left(M_{jk}^{Low} / D_{jk}\right)$			(0.014)				
Change in High Wage Imports				0.007	-0.006		
$\Delta\left(M_{jk}^{High} / D_{jk}\right)$				(0.006)	(0.007)		
Change in World Imports						0.014**	0.002
$\Delta\left(M_{jk} / D_{jk}\right)$						(0.006)	(0.007)
Number of Firms	89,369	89,369	89,369	89,369	89,369	89,369	89,369
Number of industry-country clusters	1,210	1,210	1,210	1,210	1,210	1,210	1,210
Number of Observations	293,167	293,167	293,167	293,167	293,167	293,167	293,167

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Estimation is by OLS with standard errors clustered by four-digit industry pair. $\Delta\left(M_{jk}^{China} / D_{jk}\right)$ represents the 5-year difference in Chinese imports normalized by domestic production (D). is the 5-year difference in All Low Wage Country imports normalized by domestic production (D) $\Delta\left(M_{jk}^{High} / D_{jk}\right)$ is the 5-year difference in total World Imports normalized by domestic production (D). Production data is from Eurostat's Prodcom database (no Swiss data). All specifications include country-year dummies. In Panel B we include site-type dummies and employment growth as additional controls. Sample period is 2000-2007 for Panel B and 1996-2005 for Panels A and C. 12 countries.

TABLE 8: HETEROGENEITY - THE CHINA EFFECT ON INNOVATION IS GREATER FOR FIRMS WITH MORE "TRAPPED FACTORS"

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Δln(PATENTS)						
Change Chinese Imports	0.321***	0.192***	0.202***	0.284*	0.343**	-2.466***
ΔIMP_{jk}^{CH}	(0.102)	(0.090)	(0.092)	(0.157)	(0.153)	(0.848)
Industry wage premia		-0.343***	-0.411***			
		(0.065)	(0.069)			
Change Chinese Imports			2.467***			
* Industry Wage premia			(1.171)			
Total Factor Productivity					-0.232***	-0.287***
TFP_{t-5}					(0.046)	(0.050)
Change Chinese Imports						1.464***
*TFP_{t-5}						(0.462)
ΔIMP_{jk}^{CH} *TFP_{t-5}						
Number of units	8,480	8,480	8,480	5,014	5,014	5,014
Number of clusters	1,578	1,578	1,578	1,148	1,148	1,148
Number of Observations	30,277	30,277	30,277	14,500	14,500	14,500

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four-digit industry cell in parentheses. 12 countries. Industry wage premia defined as coefficients on three digit industry dummies in a wage regression implemented using the UK LFS pooled cross-sections from 1996-2008 (see Appendix A). The ln(hourly wage) regression includes controls for a quadratic in experience, schooling, region and gender. TFP is calculated in the same way as rest of paper using the de Loecker (201) method (see Appendix C)

TABLE 9: RELATIVE DEMAND FOR COLLEGE EDUCATED WORKERS INCREASES WITH CHINESE IMPORTS

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	**Δ(Wage bill Share of college educated)**	**Δ(Wage bill Share of college educated)**	**Δ(Wage bill Share of college educated)**	**Δ(Wage bill Share of college educated)**	**Δ(Wage bill Share of college educated)**
Sample	**All**	**All**	**All**	**Textiles & Clothing**	**Textile & Clothing**
Method	**OLS**	**OLS**	**OLS**	**OLS**	**IV**
Change in Chinese	0.144***		0.099**	0.166***	0.227***
Imports, ΔIMP_{jk}^{CH}	(0.035)		(0.043)	(0.030)	(0.053)
Change in IT intensity		0.081**	0.050*		
$\Delta \ln(IT/N)$		(0.024)	(0.026)		
F-test of excluded IV					9.21
Industry Clusters	72	72	74	17	17
Observations	204	204	204	48	48

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. The sample period is 1999-2006. The dependent variable is the five-year difference in the wage bill share of college-educated workers. Estimation is by OLS with standard errors clustered by three-digit industry pair in parentheses. This data is a three-digit industry panel for the UK between 2000 and 2007 (based on aggregating up different years of the UK Labor Force Survey). All manufacturing industries in columns (1) - (3) and textiles and clothing industries sub-sample in columns (4)-(5). IV regressions use Quota removal (the height of the quota in the three-digit industry in 2000 prior to China joining the WTO). All regressions weighted by number of observations in the Labor Force Survey in the industry cell. All regressions control for year dummies.

TABLE 10: OFFSHORING

Dependent Variable:	(1) **Δln(PATENTS)**	(2) **Δln(IT/N)**	(3) **Δln(TFP)**
Change in Chinese Imports	0.313***	0.279***	0.189***
ΔIMP_{jk}^{CH}	(0.100)	(0.080)	(0.082)
Change in Chinese Imports in source industries	0.173	1.685***	1.396***
$\Delta OFFSHORE$	(0.822)	(0.517)	(0.504)
Number of units	8,480	22,957	89,369
Number of industry-country clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four-digit industry cell in parentheses. 12 countries except column (3) where there are four countries. "Number of units" represents the number of firms in all columns except (2) where it is plants. Offshoring is defined as in Feenstra and Hansen (1999) except it is for Chinese imports only, not all low wage country imports (see Appendix B).

TABLE 11: INDUSTRY/PRODUCT SWITCHING AND TECHNICAL CHANGE

Dependent Variable:	(1) **SWITCHED INDUSTRY**	(2) **SWITCHED INDUSTRY**	(3) **SWITCHED INDUSTRY**	(4) **Δln(IT/N)**	(5) **Δln(IT/N)**	(6) **Δln(IT/N)**
Change in Chinese imports	0.138***	0.132***	0.131***		0.469***	0.466***
ΔIMP_{jk}^{CH}	(0.050)	(0.050)	(0.050)		(0.083)	(0.083)
IT intensity (t-5)		-0.018**	-0.018**			
$(IT/N)_{t-5}$		(0.007)	(0.008)			
Industry Switching				0.025***		0.023*
				(0.012)		(0.012)
Employment growth			-0.002			
Δ *ln(Employment)*			(0.006)			
Observations	32,917	32,917	32,917	32,917	32,917	32,917

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. The plant-level Harte-Hanks data is used for all regressions reported in the table."Switched Industry" is a dummy variable equal to unity if a plant switched four-digit industry classification over the 5-year period. Estimation is by OLS standard errors clustered by four-digit industry and country. 12 Countries. All regressions include country-year effects and site-type controls. Sample period is 2000 to 2007.

APPENDIX A: TRAPPED FACTOR MODELS: THEORY AND MEASUREMENT

A Theory of Trapped Factors and Innovation

We formulate a simple model to examine the impact in the North of a removal of trade barriers against the South (see Bloom, Terry, Romer and Van Reenen, 2012 for details). We assume that factors of production can be used to produce current goods or be used to innovate (losing a period of production). The basic idea is that there are some factors of production that are partially "trapped" due to sunk costs. With a low wage country trade shock, the opportunity cost of using these factors in innovating new goods falls as demand for the old product has been reduced, so the factors may be redeployed in innovating rather than continuing to produce the old good. As a simple example, if skilled workers are no longer used to make a low-tech product but are partly trapped within firms (for example due to firm specific human capital) they will be cheaper to deploy in designing and building a new high-tech product.

To fix ideas, consider a high wage home economy endowed with unskilled workers (*U*) who can only produce old goods and earn wage *w*, and skilled workers (*S*, who have a productivity level $\underline{\theta}$ higher than unskilled workers, *U*) who can spend their time either producing or innovating. In period 0 all workers produce a competitive generic good. In period 1, skilled workers can form partnerships of size Γ if they choose to innovate. When innovating skilled workers lose a period of production but (i) they earn some profits while the product is on patent and (ii) after a period their firm-specific productivity increases through learning by doing to $\overline{\theta} > \underline{\theta}$. If the present discounted value of innovating is Π, skilled workers will innovate in period 1 if $\underline{\theta} w\Gamma < \Pi$ before they have acquired their specific skills. After innovating and learning by doing, the opportunity cost of innovating rises to $\overline{\theta} w\Gamma$, so they will cease to innovate if $\Pi < \overline{\theta} w\Gamma$. This is because the profits from innovating are less than the opportunity cost of ceasing to produce the old good. It follows that the condition to be in a stationary equilibrium is:

$$\underline{\theta} w\Gamma < \Pi < \overline{\theta} w\Gamma$$

We consider an economy in a stationary equilibrium that has a "China shock": a trade liberalization with a low wage country on a measure of old goods that makes them unprofitable to produce but does not change the value of innovating (as by assumption China is not able to innovate in the new goods). The "China shock" thus lowers the opportunity cost (from $\overline{\theta} w\Gamma$ to $\underline{\theta} w\Gamma$) of the workers with firm-specific skills engaging in innovation. Thus, so long as the equilibrium condition holds, the China shock will induce more innovation.

The model has two further predictions we can take to the data. First, integration with another high wage country will not have the same innovation effect, as workers in these countries are paid a similar wage and old products can still be profitably produced. This is consistent with our results as we do not find any effect of imports from high wage countries on innovation. In terms of welfare, this model suggests a new benefit in addition to the usual consumer benefits of lower prices when integrating with China if there is underinvestment in R&D. [54] A second prediction is that the magnitude of the impact of innovation is increasing in the size of the trapped factor (indexed by $\overline{\theta} > \underline{\theta}$). If we allow this to be heterogeneous across industries or products, then it follows that there will be a larger impact of the trade liberalization for those sectors/firms with a higher level of trapped factors. We test this by interacting the Chinese import effect with proxies for the trapped factor. We turn next to how do we may measure these.

Measured inter-industry wage premia as an indicator of Trapped Factors

The model directly implies that a measure of trapped factors is the degree of product-specific skills which should be reflected in higher wages. So in principle this could be measured by the firm-specific component of a wage equation after all other general human capital and labour market shocks are controlled for. Unfortunately, such matched worker-firm data with human capital characteristics is available for only a tiny sub-sample of our firms. Consequently we turn to the more standard route of estimating a Mincerian wage equation with a full set of three digit industry dummy variables (e.g. Krueger and Summers, 1988, who use more aggregated industry dummies). The coefficients on the industry dummies are the inter-industry wage premia which, in our context will be a measure of the product-specific human capital. To do this we use

[54] In the model, underinvestment occurs even in the absence of knowledge externalities because the differentiated good sector is produced under monopolistic competition. The monopoly distortion implies that rents from innovation are lower than the total surplus as consumer surplus is ignored in the private innovation decision. An R&D subsidy would be the first-best policy, but in the absence of sufficiently high subsidies trade is a second best policy that could help close the gap between private and social rates of return to innovation.

pooled cross sections from the UK Labor Force Survey (LFS), the European equivalent of the US CPS (although unlike the CPS there is luckily no top-coding of the wage data). We chose the UK because it is the least regulated labor market in Europe – we did not want the results to be strongly affected by unions, minimum wages and other country-specific labor market institutions. The UK also has good publicly available quality hourly wage data on representative cross sections 1996-2008 covering our sample period.

To be precise we estimate OLS ln(hourly wage) equations of the form:

$$\ln w_{lt} = \psi' x_{lt} + \sum_j \vartheta_j IND_j + \xi_{lt}$$

Where w_{lt} is the hourly wage of worker *l* in year *t* (1996,….,2007), *IND* is a dummy for each of the $j = 1,\ldots,J$ three digit industries, and x_{lt} is a vector of wage equation controls that includes education level (dummies for four levels), a quadratic in age (for labour market experience), gender, year effects and regional dummies. We also checked the results were robust to conditioning on a sample of male workers only and to dropping all years prior to 2001 (when China joined the WTO). For example, when using the pre-2001 LFS sample, the results for Table 8, column(3) were 2.807(0.960) for the interaction term and 0.394 (0.068) for the linear industry wage premia term.

In the LFS the wage information is asked in the first (of five) quarters a respondent is interviewed and in the last quarter. We use both quarters and all years between 1996 and 2007 giving us a total of 107,622 observations for manufacturing industries (which is the sample we use).

Measured TFP as an indicator of Trapped Factors

In the trapped factor model, some firms have firm-specific inputs that generate higher productivity (e.g. workers with firm specific skills). Normalize $\underline{\theta}$=1 so that the labor services, *L*, are $U_i + \overline{\theta}_i S_i$. Assume that we can write the production function as Cobb-Douglas so

$$y_i = a + \alpha_l l_i + \alpha_k k_i + \alpha_m m_i$$

Where Y=value added, L = labor services, K = capital services and lower case letters denote logarithms so y = lnY, etc. "True" TFP is therefore:

$$TFP_i = y_i - \alpha_l l_i - \alpha_k k_i - \alpha_m m_i = \ln Y_i - \alpha_l \ln(U_i + \overline{\theta}_i S_i) - \alpha_k \ln K_i - \alpha_m \ln M_i$$

Denote measured TFP as MFP where

$$MFP_i = \ln Y_i - \alpha_l \ln L_i - \alpha_k \ln K_i - \alpha_m \ln M_i = \ln Y_i - \alpha_l \ln(U_i + S_i) - \alpha_k \ln K_i - \alpha_m \ln M_i$$

Consequently measured TFP will be equal to true TFP plus a term that depends on the importance of the trapped factors:

$$MFP_i = TFP_i + \alpha_l \ln\left(\frac{U_i + \overline{\theta}_i S_i}{U_i + S_i}\right)$$

If there are no trapped factors then $\overline{\theta}_i = 1$ and measured and true TFP are the same. Firms which have more trapped factors, $\overline{\theta}_i > 1$, however, will have a higher level of *MFP*. Thus the level of MFP for a firm is correlated with the magnitude of the trapped factors. This can be generalised to any factor which is trapped. If TFP is calculated based on the shares of the untrapped factor, then MFP will be correlated with the size of the trapped factor.

The advantage of using MFP instead of industry wage premia as a measure of trapped factors is that (i) this is firm specific time varying measure rather than an industry specific non-time varying measure and (ii) it is more general than simply being related to trapped factors in labor. The disadvantage of this measure is that it is more indirect. For example, if there is heterogeneity in the effect of trade by true TFP, then the coefficient on the interaction effect of trade and MFP in the patent equation reflects this effect as well.

APPENDIX B: DATA

Datasources

The basic data sources are described in the text, but we give some more details here.

Amadeus Accounting Data - The Amadeus data is provided by the private sector company Bureau Van Dijk, BVD. It has panel data on all European countries' company accounts. It includes private and publicly listed incorporated firms (i.e. not sole proprietors or partnerships). The accounting data includes variables such as employment, sales, capital, profits, materials and wage bills. The data goes back to the late 1970s for some countries, but is only comprehensive across a range of countries since the mid-1990s. We use successive cohorts of the Amadeus DVDs because although all firms are meant to be kept for at least 10 years after exiting, this rule is sometimes violated. Although Amadeus is a reasonably comprehensive list of names (and locations, industries and owners) for the 12 countries we study, the accounting items listed are limited by national regulations. For example, profits are generally required to be disclosed by all firms, but employment is sometimes a voluntary item for smaller firms; some countries (e.g. France) insist on wider disclosure of data than others (e.g. Germany) and disclosure is greater for public firms than private firms. In the regressions (such as the patents regressions), we consider results without and with these accounting items to check against selection bias. In terms of cleaning the accounts variables are winsorized at the 1st and 99th percentiles. The profit/sales variable winsorized between -1 and +1. Amadeus tracks the number of four digit "primary" and "secondary" four digit sectors that a firm operates in. We give primary sectors a two-third weight and secondary sectors a one third weight (results are robust to alternative weighting schemes) and weight equally within these groups (Amadeus does not report the split of sales across the four digit sectors). Using these firm-specific imports measures gives similar results to allocating all firms to their primary four-digit sector (compare Tables 1 and 5B).

EPO Patents Counts - Patents data is obtained from the electronic files of the European Patent Office (EPO) that began in 1978. We take all the patents that were granted to firms and examine the assignee names (see Belenzon and Berkovitz, 2010). We match these to the population of European firms using Amadeus (i.e. we do not insist that we have any accounting data in Amadeus when doing the matching to obtain the maximum match). The matching procedure was based on names and location. Patents are dated by application year.

In principle, a firm in Amadeus that was not matched to the EPO has taken out no patents. Nevertheless, there is a concern that we may have missed out some of the patenting activity by some firms due to the matching procedure as we were quite conservative (we only made a match if we were quite sure that the patent did belong to the Amadeus firm). We consider a narrow sample where we only keep firms if they have made at least one patent since 1978 ("patenters sample") and a wider sample where we assume that firms who we could not match really did zero patents. The analysis of patenting equations (e.g. Table 1) just uses the patenters' sample (there is no variation in the non-patenters sample) whereas the employment and survival equations (Table 3) consider both samples (see Table A2 for descriptive statistics across different samples). When constructing *PATSTOCK*, the patent stock, (e.g. Table 3) we follow Blundell et al (1999) and estimate these by perpetual inventory methods using a depreciation (δ^P) rate of 15%. $PATSTOCK_{it} = PAT_{it} + (1-\delta^P)PATSTOCK_{it-1}$ where PAT_{it} is the count of patents of firm *i* in period *t* and δ^P=0.15.

EPO Patent Citations- The EPO also provides all the citations to these patents from later EPO patents, so we use this to gauge how important a patent was (all else equal, a more highly cited patent is deemed to be more important). This is used in Table A3.

R&D - Research and Development expenditure are taken from BVD's Osiris database. These are publicly listed firms (so a sub-set of Amadeus) but Osiris contains a wider range of accounting items that Amadeus does not include, such as R&D. R&D is not a mandatory item to disclose for all publicly listed firms in Europe. Typically only the larger firms are required to disclose this item, although rules are stricter in some countries than others (e.g. in the UK under the SSAP(13) Revised accounting standard disclosure of R&D is mandatory for medium sized and larger firms). For the industry level values used in Table 5B we use the OECD's ANBERD database which is more comprehensive than Osiris as it covers all firms in a country-industry pair. We use BERD, the research and development expenditure conducted by all businesses within an industry. The ANBER data is available on a consistent basis since 1987 at a broadly two-digit industry level.

Information Technology (IT) - The IT data is drawn from an entirely different database as companies do not report IT spending except rarely as a voluntary item. Harte Hanks (HH) is a private sector company that surveys establishments in order to obtain indicators of their use of hardware, software and IT personnel. The unit of observation is a "site" which in manufacturing is a plant, so it is more disaggregated than the Amadeus data that is firm level. HH surveys plants in firms with 100 employees or more. This covers about 80% of European manufacturing employees, but obviously misses employees in smaller firms (unlike Amadeus). Each plant has an in-depth report including numbers of PCs and laptops, which we use to construct our basic computers measure. There is also information on a number of items of software such as ERP, Databases and Groupware that we use in Table A4. We have data from Harte Hanks between 2000 and 2007.

Survival - For the HH data we have a plant level measure of survival which is based on exit from the economy (i.e. *SURVIVAL* = 0 only if the plant shuts down). For the Amadeus firm-based measure we have a firm-based measure that includes both exit to bankruptcy and exit to takeover and merger (the data cannot distinguish between these types of exit).

Management data - Our management data was collected in 5 waves between 2002 and 2010. We interviewed plant managers in medium sized manufacturing firms across twenty countries (see Bloom and Van Reenen, 2007, 2010). We used a "double blind" survey tool to assess management quality across 18 questions in the areas of shopfloor operations, monitoring, targets and incentives. Each individual question is scored on a scale of 1 (worst score) to 5 (best practice) and we average across all 18 questions by firm-year observation for an overall management quality score. Each wave has a cross sectional and a panel element, with the panel element growing larger over time. There were 778 interviews in the first major cross-sectional wave in 2004 and 2,311 interviews in the last wave in 2010. Hence, we have a larger sample of data towards the end of the period with a relatively short time-span per firm. To merge the management data into the yearly trade data we linearly interpolated scores between survey waves for the same firm. So, for example, a firm which received a management score of 3.0 in 2008 and 3.2 in 2010 would have an interpolated score of 3.1 in 2009. Since we cluster by industry-country in all regressions, the t-statistics are not inflated through this interpolation procedure. The reason for this interpolation is that it increases the size of the data sample we can use in long differences – for example a firm surveyed in 2006, 2008 and 2010 could not be used in a three-year long-difference estimation without interpolating. Because the industry definitions in the management panel are not available at the four-digit level for all countries, we match industry trade data in at the three digit by country level.

UN Comtrade - Our study uses data at the HS6 product level taken from the UN Comtrade online database. We use standard concordances of HS6-SIC4 (e.g. Pierce and Schott (2010)) to aggregate to the four-digit industry level. We calculate a "value share" measure of import penetration as per Bernard, Jensen and Schott (2006) where the value of Chinese imports for a given country-SIC4 cell is normalized by the value of total world imports flowing into the same cell.

Eurostat Prodcom Production database - In Table A7 we use measures of four-digit industry-level production to normalize our imports variable. This measure of domestic production is constructed from the Eurostat Prodcom dataset. Prodcom is an eight-digit product level database of production across EU members. The first four digits of the Prodcom product code correspond to the four-digit NACE classification system. We construct a concordance between the NACE codes and US SIC, after which we aggregate the production figures to the SIC4 level. In the final step of constructing the data we compare the estimated value of production by industry-country cell to the value of exports reported in Comtrade for the same industry-country cell. In cases where the value of exports exceeds the estimated value of production from Prodcom we use the exports number as our lower bound estimate of production. This problem occurs in a limited number of cases and is due to confidentiality restrictions on the reporting of data for small industry-country cells in Prodcom.

Eurostat Producer Prices - We take two-digit industry producer prices from the online Eurostat Structural Business Statistics (SBS) database. The year 2005 is set as the base year for the price index. In some cases the data extends back to 1990 with good coverage after 1996. The SBS database reports prices in NACE codes and we concord these to the US SIC2 level to facilitate the merging in of other variables. We assemble this information for the 12 countries we focus on across our study.

Offshoring measure - This is calculated by using the US BEA input-output matrix, matched up to the Comtrade at the four-digit industry level. The offshoring variable for each industry-year is the estimated share of Chinese imported inputs in total imported inputs estimated on a similar basis to Feenstra and Hanson (1999). For each industry *j* we consider the input-output weights, $w_{jj'}$, between *j* and every other *j'* industry (note $w_{jj'}$ is from the US so the weights do not vary by country and time period). We define offshoring to China as $OFFSHORE_{jkt}^{CH} = \sum_{j'} w_{jj'} IMP_{j'kt}^{CH}$. We also considered the share of total imported inputs (from China and all other countries) in all inputs (or all costs) like the original Feenstra and Hansen paper (this replaces $IMP_{j'kt}^{CH}$ with $IMP_{j'kt}$ in the offshoring definition). However, as with our analysis of total imports in the final goods market in Table 6, it is the Chinese share (reflecting low wage country imported inputs) that is the dominant explanatory factor.

Trade weighted exchange rate IV - Following Bertrand (2004) we define each four-digit industries' exchange rate as the country-weighted exchange rate based on the source of imports in the industry. For example, an industry in Switzerland, which imported 50% from France and 50% from the UK, would have an industry-weighted exchange rate of 50% from the Euro and 50% from Sterling. This weight is held fixed by industry in the base year, but the country-specific exchange rates fluctuate every year.

Constructing industry codes
The HH plant level data (used for IT) only has a single four-digit SIC code, but this does change between years so can be used to look at product switching. Note that in Table 11 the sample conditions on firms staying within the manufacturing sector if a switch occurs i.e. plants that switch to the service sector are dropped from the sample (approximately 11% of plants switch industry according to this criterion). The Osiris data (used for R&D) only has a primary three-digit code. The Amadeus data (used for the patents, TFP and employment equations) has multiple four-digit industry codes which we can exploit to construct a weighted average of industry level imports variable to compare to the single industry code. Unfortunately, the industry data is not updated regularly so it is not reliable as a time series measure of industry switching.

The analysis of patents and TFP in the baseline specifications is based on these multiple four-digit industries. The underlying data is based on successive cross-sections of "primary" and "secondary" industry codes taken from Amadeus. We extract four cross-sections for each available year between 2003-2006. Our set of cross-sections begins in 2003 because Amadeus only began reporting primary and secondary codes separately at this point in time.

For the multiple industry import measure we use the 2003 cross-section to define a baseline set of primary and secondary four-digit industry codes for each firm. We assign a two-thirds weight to the primary codes and one-third to the secondary codes to calculate a multiple four-digit measure of import penetration (the results are not sensitive to the exact weights used). We take the arithmetic mean within sets of primary and secondary codes, that is, we weight industries equally. We follow the same procedure for calculating import penetration for the alternative normalizations presented in Tables 7 and A7. In our data the median firm had one primary industry, the average firm 1.93 and the maximum was 10, only 19% of firms reported any secondary industry code with a mean of 2.68 and maximum of 11).

When calculating a single industry code we use the most commonly occurring four-digit code pooling across all years in the dataset. We take the lowest four-digit industry value in cases where codes occur an equal number of times. Results using this method are shown in Table 5.

APPENDIX C: PRODUCTION FUNCTION ESTIMATION

The Basic Olley-Pakes Approach
Consider the basic value-added production function as:

$$y_{it} = \alpha_l l_{it} + \alpha_k k_{it} + \gamma X_{jt} + \omega_{it} + \eta_{it} \tag{C1}$$

The efficiency term, ω_{it}, is the unobserved productivity state that will be correlated with both output and the variable input decision, and η_{it} is an independent and identically distributed (i.i.d) error term. X_{jt} are the other exogenous variables in the model which are common to all firms in the industry, such as the level of quotas against Chinese goods. Assume that the capital stock is predetermined and current investment (which will react to productivity shocks) takes one period before it becomes productive, that is:

$$K_{it} = I_{t-1} + (1-\delta)K_{it-1}$$

It can be shown that the investment policy functions are monotonic in capital and the unobserved productivity state.

$$i_{it} = i\ (k_{it}, \omega_{it}, X_{jt}) \tag{C2}$$

The investment policy rule, therefore, can be inverted to express ω_{it} as a function of investment and capital, $\omega_t\ (i_{it}, k_{it}, X_{it})$. The first stage of the OP algorithm uses this invertibility result to re-express the production function as:

$$y_{it} = \alpha_l l_{it} + \alpha_k k_{it} + \gamma X_{it} + \omega_t\ (i_{it}, k_{it}, X_{jt}) + \eta_{it}$$
$$= \alpha_l l_{it} + \phi(i_{it}, k_{it}, X_{jt}) + \eta_{it} \tag{C3}$$

where $\phi(i_{it}, k_{it}, X_{jt}) = \phi_t = \omega_t\ (i_{it}, k_{it}, X_{jt}) + \alpha_k k_{it} + \gamma X_{jt}$. We approximate this function with a series estimator and use this first stage to get estimates of the coefficients on the variable inputs. The second stage of the OP algorithm is:

$$y_{it} - \alpha_l l_{it} = \alpha_k k_{it} + \gamma X_{jt} + \omega_{it} + \eta_{it} \tag{C4}$$

Note that the expectation of productivity, conditional on the previous period's information set (denoted Ω_{t-1}) is:

$$\omega_{it} \mid (\Omega_{it-1}, S_{it} = 1) = E[\omega_{it} \mid \omega_{it-1}, S_{it} = 1] + \xi_{it} \tag{C5}$$

where $S_{it} = 1$ indicates that the firm has chosen not to shut down. We model the selection stage by assuming that the firm will continue to operate so long as its productivity is greater than a threshold productivity, ϖ_{it}. So the exit rule is $S_{it} = 1$ if $\omega_{it} \geq \varpi_{it}$, otherwise $S_{it} = 0$. Taking expectations:

$$E[\omega_{it} \mid (\Omega_{it-1}, S_{it} = 1)] = E[\omega_{it} \mid \omega_{it-1}, S_{it} = 1] = E[\omega_{it} \mid \omega_{it-1}, \omega_{it-1} \geq \varpi(k_{it}, X_{it})] = g(\omega_{it-1}, \varpi(k_{it}, X_{it}))$$

We do not know ϖ_{it} , but we can try to control for it using information on observed exit.

$$\Pr(S_{it} = 1 \mid \Omega_{it-1}) = \Pr(\omega_{it-1} \geq \varpi(k_{it}, X_{it}) \mid \Omega_{it-1}) = \Pr(\omega_{it-1}, \varpi(k_{it}, X_{it}))$$

We can write the last equality as a non-parametric function of lagged observables:

$$\Pr(S_{it} = 1 \mid \Omega_{it-1}) = P_{it} = s(i_{t-1}, k_{it-1}, X_{it-1})$$

So returning to the second stage coefficient of interest:

$$E(y_{it} - \alpha_l l_{it} \mid \Omega_{t-1}) = \alpha_k k_{it} + \gamma X_{jt} + g(\omega_{it-1}, \varpi_{it}) = \alpha_k k_{it} + \gamma X_{jt} + h(\omega_{it-1}, P_{it})$$

Including the shocks we have:

$$y_{it} - \alpha_l l_{it} = \alpha_k k_{it} + \gamma X_{jt} + g(\omega_{it-1}, \varpi_{it}) + \varsigma_{it} + \eta_{it} = \alpha_k k_{it} + \gamma X_{jt} + h(\varphi_{it-1} - \beta_k k_{it-1} - \gamma X_{jt-1}, P_{it}) + \varsigma_{it} + \eta_{it} \tag{C6}$$

Where $\varsigma_{it} + \eta_{it}$ are now uncorrelated with k_{it}. Since we already have estimates of the ϕ_{t-1} function and the P_{it} this amounts to estimating by Non-Linear Least Squares. We now have all the relevant parameters of the production function.

Our Implementation of Olley and Pakes

We used panel data from AMADEUS to estimate production functions between 1996 and 2006. Only four European countries had good coverage of all the factor inputs needed to estimate production function – France, Italy, Spain and Sweden. The main problem is that most countries do not insist on disclosure of both materials and capital for all unlisted private firms.

Following de Loecker (2011) we use a modified version of the Olley and Pakes (1996) approach. We allow endogeneity of the variable factor inputs (labor, capital and materials) using a control function approach and for selection through a non-parametric correction (in practice we use a second order series estimator). In addition we allow the trade variables to enter directly into the non-parametric controls for endogeneity and selectivity. As de Loecker (201) emphasizes, it is important to allow for this in order for the estimator to be consistent when the trade environment changes. We allow for imperfect competition by assuming that there is monopolistic competition which implies that the coefficients on the production function are a mix between the technological parameters and a mark-up term. The latter is identified from the coefficient on an additional control for industry output in the production function. Since some firms produce in multiple industries the relevant output term is firm-specific depending on the firm's distribution across industries. We exploit the fact that Amadeus reports the number of primary and secondary four-digit industries a firm operates in to construct this.

We do not have information on skill groups at the firm level so we also estimated TFP using the wage bill (rather than employment) as a measure of labor services, *L*. The idea is that wages reflect the different skill levels of workers in the firm, so multiplying the quantity of labor by its wage reflects the full value of labor services.

We use this method to obtain an estimate of the pure technological parameters and construct an estimate of TFP which is the variable used in the main part of the paper. We checked that the results were robust to many alternative assumptions such as estimating each parameter separately for each two-digit and country pair and by three-digit industry; allowing for higher order terms in the series approximation. Results were robust to these changes.

APPENDIX D: THE TEXTILE AND CLOTHING QUOTA RELAXATION AS A QUASI-EXPERIMENT

History of trade barriers in textiles and quotas and the WTO

In 2005 restrictions on the fourth (and final) set of products regulated by the Agreement on Tariffs and Clothing (ATC) were removed. The ATC was the successor to the Multi-Fiber Agreement (MFA). The removal of quotas under the ATC came in four stages (1995, 1998, 2002 and 2005) but because China only joined the WTO in December 2001, it did not benefit initially from the first two stages. China enjoyed a substantial fall in these quotas between the end of 2001 (when it joined the WTO) and 2005 (when the ATC quotas were essentially all removed). Brambilla et al (2010) describe how there was a huge jump in Chinese exports into textiles and clothing to the US during this period (e.g. 7 percentage points increase in China's share of all US imports in 2005-2006 alone). China's increase was substantially larger than other countries not just because it joined the WTO but also because the existing quotas seemed to bite more heavily on China as indicated by the higher "fill rates" of Chinese quotas. This seemed to be because under the ATC/MFA Chinese quotas were increased more slowly over time than those in other countries.

Although formally quotas fell to zero in 2005, for 22 product groups domestic industries successfully lobbied for some "safeguards" which were re-introduced after 2005. Nevertheless, these were much lower than the pre-existing quotas. As noted in the test we only use beginning of period quotas (in 2000) to avoid the problem that post 2005 quotas are endogenous to the growth of Chinese imports. The quota policy is EU wide. It is reported in the form of the SIGL (System for the Management of Licenses for Textile Imports) database that is available online at http://trade.ec.europa.eu/sigl/choice.html. This database is classified according to 172 grouped quota categories defined by the EU. However, these categories are closely based on HS6 products so we are able to map them into the US four-digit industry classification. In addition, we added in quotas on footwear and tableware products as described in the WTO's articles of accession articles of accession for China, available at http://www.wto.org/english/thewto_e/acc_e/completeacc_e.htm. These included a selection of footwear products in the 6401-6404 HS4 categories as well as tableware products in the HS 6911-6912 range.

Construction of the Instrument

For each four-digit industry we calculated the proportion of product categories that were covered by a quota in each year (data on the amount produced in each industry is not available so we use a simple mean proportion of products). For the five-year change in imports 2005 to 2000 in the technology equations we use the quota variable in 2000 immediately prior to China's WTO entry. Specifically, this proportion represents the share of all quota-affected HS6 products in the four-digit industry (we weight each HS6 in an industry by its 2000 import value). The idea is that the market expected at this point all the quotas to be lifted. Using the actual change renders similar results, but there is a concern that the quotas remaining in 2006 are endogenous as they were the result of lobbying by the effected sectors. The "fill rates" (the proportion of actual imports divided by the quota) for most quotas were close to 100% for China in the late 1990s implying that these constraints were binding[55]. This also limits anticipation effects, although to the extent that they exist this will make it harder for us to identify a first stage. The products upon which the quotas were set were determined in the 1950s to 1970s (Spinanger, 1999) which makes them likely to be exogenous to any post 2000 actual (or anticipated) shocks. To be specific, in the regression sample of Table 2 Panel A we use all four digit US sectors in SIC4 two-digit industries 22, 23, 28, 30 and three-digit industries 314 and 326. We show that the results are robust to dropping all four-digit industries within this group with zero quotas against China in 2000 and dropping the tableware and footwear quotas.

Anticipation of China's Accession to WTO? Problems and solutions

Even if there was an unanticipated component of the China shock, since firms knew China was going to join the WTO in 2001 does this invalidate the instrument? In a stylized way one can imagine two points at which firms will react. There is an "announcement" effect on the day China's accession is determined (Costantini and Melitz, 2008, emphasis this) and an "accession" effect when China joins. For the instrument to have power in the first stage (which it does empirically), all we need is that there was some uncertainty over the effects of the accession or that firms do not fully adjust between announcement date and accession. The instrument could still be invalid, however, because the increase in technological

[55] We attempted to use the fill rates in order to get a more refined measure of the instrument, but it had no additional power due to the uniformly high fill rates. Similarly, dropping all industries whose fill rates were less than 80% made no difference to the results for the same reason.

investments (or imports) prior to accession as a result of announcement may be correlated with post-accession investments (or imports).

Formally, say the true model has the dynamic form (say because of adjustment costs)

$$\Delta \ln TECH_{it} = \lambda \Delta \ln TECH_{it-5} + \beta_1 \Delta IMP_{it}^{CH} + \beta_2 \Delta IMP_{it-5}^{CH} + u_{it} \qquad \text{(D1)}$$

where *TECH* is one of our technological indicators (we use a lag of five years to be consistent with the five year differences). However, say we estimate our basic empirical model as:

$$\Delta \ln TECH_{it} = \alpha \Delta IMP_{it}^{CH} + \upsilon_{it} \qquad \text{(D2)}$$

Even under the assumption that our quota instrument, Z_{it-5}, satisfies the exclusion restriction $E(Z_{it-5}u_{it}) = 0$ an IV estimation of equation (D2) using the quota instrument will be inconsistent if quotas are correlated with $\Delta \ln TECH_{it-5}$ or ΔIMP_{it-5}^{CH} due to anticipation effects. Under this assumption $E(Z_{it-5}\upsilon_{it}) \neq 0$ because υ_{it} includes the omitted lagged technology and imports variables ($\Delta \ln TECH_{it-5}$ and ΔIMP_{it-5}^{CH}). Of course, since we are estimating in long differences, it may be that $\lambda = \beta_2 = 0$ in equation (D1) so IV estimation of equation (D2) will consistently estimate α even in the presence of partial anticipation effects.

There are several ways to tackle the potential problem of anticipation effects. A direct method is to explicitly estimate the dynamic model of equation (D1). This is demanding in data terms, because we need to use firms where we observe ten full years of technology data. There are too few firms to accomplish this task for IT and patents. However, it is possible to do this for TFP and we reported the results in Table A5. We found that our results were completely robust to using the alternative dynamic specification of equation (D2).

A second approach is to examine directly whether quotas are correlated with pre-WTO Accession trends in technology or Chinese imports. In our data there is a positive but small and statistically insignificant correlation between pre-WTO growth of technology (and Chinese imports) and quotas. Turning first to technical change if we regress the growth of TFP 1996-2000 (we do not have data pre-1996) on the quota instrument the coefficient (standard error) on quotas is 0.024(0.031). After China joined the WTO the five year difference 2000-2005 is 0.190(0.021) and the four year difference is 0.122(0.018). Similarly the standard reduced form for patent growth 2000-2005 has a coefficient on quotas of 0.264(0.088) whereas the regression of the pre-WTO growth of patents 1996-2000 on the quota IV has a coefficient (standard error) of 0.096(0.177).

We turn to pre-policy import trends in Table A11. We use the country by four-digit industry level information over the 1990-2007 period (we do not need technical change measures for this experiment so can use a longer period) and show regressions where the five year growth in Chinese imports is the dependent variable. Column (1) includes simply the quota (in 2000), and the positive coefficient on this variable indicates that industries where quotas were high had faster growth in Chinese imports throughout the period. Column (2) then interacts the quota variable with a policy dummy equal to one after China joined the WTO in 2001. The coefficient on this interaction is large and statistically significant, whereas the linear term on quota is small and statistically insignificant. The coefficients suggest that prior to China's joining the WTO in 2001 industries with high quotas (i.e. where all products where subject to some form of quota restriction) had 0.002 percentage point growth a year in Chinese imports (this is consistent with increases in the "fill rates" of quotas over this period as China grew). After China joined the WTO and quotas were relaxed this rose by 0.84 (= 4.2/5) percentage points per annum, a substantial amount. Column (3) includes an even more rigorous specification where we include industry dummies, allowing for industry trends over time. The coefficient on the policy-based instrumental variable remains significant with a similar magnitude of 0.04, implying that there was an increase in the Chinese growth trend post 2001.

Examples of patents taken out in the textiles and apparel industry

While the textiles and apparel sectors are relatively low tech, they were still responsible for 21,638 European patents in our sample period. These cover innovations such as new materials (for example the water resistant fabric described below), new designs (for example the more flexible ski-boat fastener described below) and new products (for example the design of an orthotic sock designed to aid ankle movement described below). Many more examples can be obtained simply by searching on the EPO web-site[56] for an appropriate textile or fabric term such as "shirt", "handbag" or "cotton".

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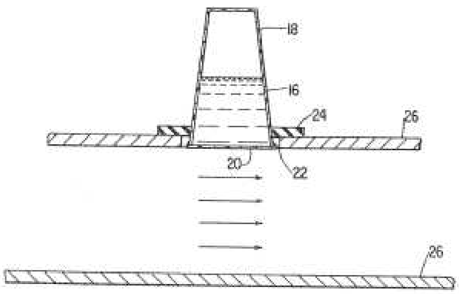
[56] http://worldwide.espacenet.com/quickSearch?locale=en_EP

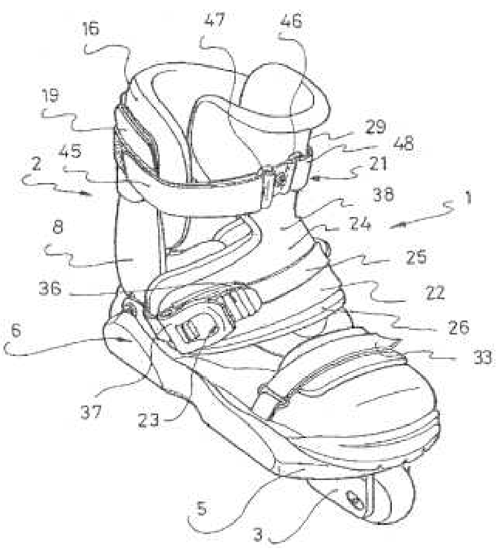
Patent EP1335063, taken out by a German firm for a "*Water vapor permeable, water-resistant composite material*"

This is for a waterproof fabric used in, for example, protective clothing. The fabric prevents liquid water from penetrating through while at the same time permitting moisture vapor such as perspiration to pass out through the article, similar to Gore-Tex. The article has two main layers: a microporous hydrophobic outer layer which permits the passage of moisture vapor but resists penetration by liquid water; and a hyrophilic inner layer permitting the transfer of moisture vapor but preventing surface tension lowering agents such as those contained in perspiration and/or body oils from reaching the hydrophobic layer.



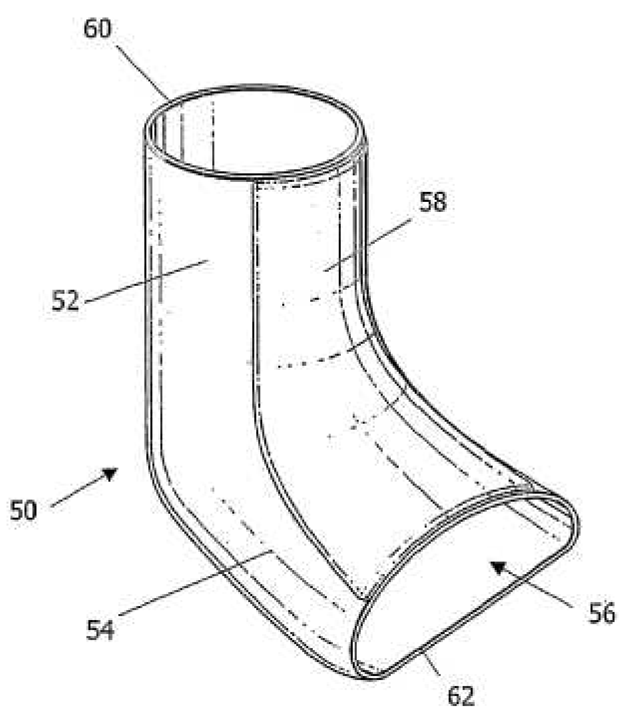
Patent: EP2082659, taken out by an Italian firm for a "*Fastening device for sports footwear*"

This patent is for a more flexible in-line skate or ski boot fastener. This allows adjustment of the angle of forward inclination of the skater's leg, the circular direction of the boots and also the overall tightness of the fastening. The fastener can also include a forward inclination pressure adjusting mechanism to adjust the pressure applied to the skater's leg by the boot when the skater moves forwardly. This boot fastener can be used for a variety of purposes, with the key one being in-line skating (roller-blading), ski and snowboarding boots, but also other semi-hard sports boots and work boots.



Patent: EP1626686, taken out by a UK firm for an "*Orthotic sock*"

This product provides an ankle-foot orthosis (a product to support the ankle) that comprises: an elastic structure formed of contiguous first and second tubular members, with the second tubular member set at an angle to the first tubular member to define, at least in use, a generally L-shaped cavity configured to accept and fit closely about the foot and ankle of a patient; and a rib which is permanently bonded to a region of the structure which overlies the dorsum of the patient's foot in use, with this being formed of a flexible material that has a resilience appropriate for resisting the particular degree of plantarflexion experienced by the patient.



APPENDIX E: CALCULATING MAGNITUDES

The magnitudes in Table 4 attempt to quantify the potential contribution of Chinese imports to the overall increase in patents per worker, IT per worker and TFP among European manufacturing firms. Our basic approach to these calculations stems from the literature on productivity decompositions, for example, Bailey, Hulten and Campbell (1992). To explain this approach start by denoting P_t as a generic index of technology, for example aggregate patents, computers per person, or TFP. We can summarize the change in this aggregate technology index between time *t* and time *0* as:

$$\Delta P_t = \sum_{i=1}^{N} s_{it} p_{ijt} - \sum_{i=1}^{N} s_{i0} p_{ij0} \tag{E1}$$

where P_t, the aggregate level of the technology index, is given as a function of individual firms' technology levels (p_{ijt}) weighted by their employment shares (s_{it}), where s_{it} = firm employment divided by total employment in manufacturing. We will use patents per employee as our example, but the calculation is the same for IT per worker or TFP. This aggregate change can be decomposed into a variety of within and reallocation terms as follows:

$$\begin{aligned} \Delta P_t = & \sum_{i=1}^{N} s_{i0}(p_{ijt} - p_{ijo}) + \sum_{i=1}^{N} (s_{it} - s_{i0}) p_{ij0} + \sum_{i=1}^{N} (s_{it} - s_{i0})(p_{ijt} - p_{ij0}) \\ & - \sum_{i \in exit} s_{it}^{exit} (p_{ij0}^{exit} - \overline{p}_{jo}) + \sum_{i \in entrant} s_{it}^{entrant} (p_{ijt}^{entrant} - \overline{p}_{jt}) \end{aligned} \tag{E2}$$

where $\overline{p}_{jt}$ is the average technology level of all firms in industry *j* year *t*, p_{ij0}^{exit} is the technology level of an exiter, $p_{ijt}^{entrant}$ is the technology level of an entrant and the summations are over the *N* firms in the economy. In this breakdown in equation (E2) the first term is the *within* effect (the increase in technology holding firm size constant), the second term is the *between* component (the increase in technology from shifting employment from low-tech to high-tech firms), the third term is the *cross* effect (the correlation of the increase in technology within firms and their change in employment share)[57]. The fourth term is the *exit* component (the impact of the relative technology level of exiting firms versus incumbent firms) and the final term the *entry* component (the impact of technology level of entering firms versus incumbent firms). As noted in the text, we cannot directly model entrants because we do not observe their lagged technology levels. In the paper we can indirectly examine the effect of entry by comparing the industry level estimates to the four components we can identify.

We have explicitly modeled the main components of these terms in our econometric models of equations (1) - (4) in the main text. Given our estimates of these in Tables 1, 2 and 3 we can create predicted values for these observable components arising from the increase in Chinese imports (ΔP_t^{China}) as follows:

$$\begin{aligned} \Delta P_t^{China} = & \sum_{i=1}^{N} s_{i0} \alpha^{PAT} \Delta IMP_j + \sum_{i=1}^{N} (s_{it}^{between} - s_{i0}) p_{ij0} + \sum_{i=1}^{N} (s_{it}^{between} - s_{i0}) \alpha^{PAT} \Delta IMP_j \\ & - \sum_{i \in exit} s_{it}^{exit} (p_{ij0}^{exit} - \overline{p}_{jo}) \end{aligned} \tag{E3}$$

where α^{PAT} is the coefficient on Chinese imports in equation (1) in the main text. In Table 1 column (1) this is 0.321. $s_{it}^{between}$ is the predicted share of employment for incumbent firms and s_{it}^{entry} is the predicted share of employment in exiting firms (defined below),

$$s_{it}^{between} = \frac{N_{i0}(1 + \alpha^{N} \Delta IMP_j + \gamma^{NP} \Delta IMP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1 + \alpha^{N} \Delta IMP_j + \gamma^{NP} \Delta IMP_j p_{ij0})} \tag{E4}$$

57 Following the convention, we will aggregate the cross effect with the between effect when presenting results, but in practice this makes little difference as the cross-term is always small.

Where α^N is the coefficient on Chinese imports in the employment growth equation (equation (3) in the main text) and γ^{NP} the coefficient on Chinese imports interacted with the technology variable. The values of these are -0.352 and 1.546 respectively from column (2) in Table 3 Panel A. N_{i0} is employment in the firm[58].

$$s_{it}^{exit} = \frac{N_{i0}(1-\alpha^S \Delta IMP_j - \gamma^{SP}\Delta IMP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1-\alpha^S \Delta IMP_j - \gamma^{SP}\Delta IMP_j p_{ij0})} \tag{E5}$$

Where α^S is the coefficient on Chinese imports in the survival equation (equation (4) in the main text) and γ^{SP} is the coefficient on Chinese imports interacted with the technology variable. In column (2) of Table 3 Panel B these are -0.122 and 0.391. Note that in equation (E5) there is a negative sign before the coefficients because we estimate survival equations econometrically whereas the decomposition uses exit.

Given these equations we can then quantify the share of technical change predicted to arise from Chinese imports as the ratio $\Delta P_t^{China} / \Delta P_t$. Similarly, we can identify the contribution of each component. To calculate ΔP_t for IT intensity we calculate the total increase in technology in our sample firms, that is, the change in the weighted mean we observe in our sample. For patents we cannot use our sample because of: (i) delays in the provision of firms accounts (we match to firm accounts and some of these are not available yet for 2005/06 due to reporting delays) and (ii) processing delays at the European Patent Office since we only use granted patents (dated by their year of application). As a result we use instead the aggregate growth of the US Patent Office (which provides long-run total patent numbers) over the proceeding 10 years (1996-2005), which is 2.2%. This growth rate of total patents is stable over long-run periods, for example being 2.4% over the proceeding 20 years period of 1986 to 2005.[59] Similarly, for TFP we use 2% as our measure of the growth rate of TFP growth in manufacturing in recent years.[60]

APPENDIX F: DYNAMIC SELECTION BIAS

The dynamic selection problem

Consider the representation of our baseline equations (we ignore other variables for notational simplicity) as:

$$y_{it} = \alpha z_{it} + u_{it} + \eta_i + \varepsilon_{it} \tag{F1}$$

$$s_{it} = \pi w_{it} + u_{it} + \upsilon_{it} \tag{F2}$$

where y_{it} is the technology outcome (e.g. IT/N) of interest for firm *i* at time *t* (we suppress the industry-country *jk*-subscripts), z_{it} is Chinese imports and s_{it} = 1 if the firm is operating at time *t* and zero otherwise. We assume z_{it} is exogenous, but endogeneity can easily be allowed for by using the quota instrument, for example. Assume that the idiosyncratic error terms, ε_{it} and υ_{it} are i.i.d. and the vector w_{it} includes z_{it} .

The selection problem arises from the fact that u_{it} can affect survival as well as being correlated with z_{it} .To see this consider the differenced form of equation (F1) and take expectations conditional on surviving:

$$E(\Delta y_{it} \mid \Delta z_{it}, s_{it} = 1) = \alpha + E(\Delta u_{it} \mid \Delta z_{it}, s_{it} = 1) \tag{F3}$$

[58] Note that we re-weight employment throughout the calculations so that the regression sample is representative of the entire population of Amadeus firms. This avoids any differences in data sampling or matching rates affecting the aggregate calculations.

[59] The data goes back to 1986 on aggregate USPTO patents and comes from http://www.uspto.gov/go/taf/cbcby.htm. The EPO does not have this long-run of time series aggregate patents data since it was only founded in 1977 and was not widely accepted (over European national patent offices) until the late 1980s making the time series unreliable prior to the 1990s.

[60] The growth rate of European multifactor productivity growth 1995-2008 was 1.9% per annum according to Conference Board (http://www.conference-board.org/economics/downloads/Summary_Statistics_2010.pdf, taken from Table 12 for the EU-12).

The potential bias arises from the $E(\Delta u_{it} \mid \Delta z_{it}, s_{it} = 1)$ term. Under the assumption that we have instruments for Chinese imports (or they are exogenous) this simplifies to $E(\Delta u_{it} \mid s_{it} = 1)$. If the selection was solely in terms of the fixed effect, η_i or captured by the observables w_{it}, then this expectation would be zero and our estimate of the effect of trade would be unbiased, so "static selection" is not a problem. The concern is that there is "dynamic selection" on technology shocks, Δu_{it}, so $E(\Delta u_{it} \mid s_{it} = 1) \neq 0$.

To see the dynamic selection problem in our context consider two industries A and B, one (industry A) has an increase in Chinese imports (e.g. from a relaxation of quotas) and the other (B) has not. Now consider the reaction to this shock of two identical firms who both have had the same negative productivity shock unrelated to China. If the firm in industry A is more likely to exit (as life will get harder in the future) then it will appear that within firm productivity growth improves in industry A, even if nothing else changes. Although there is a genuine increase in productivity in industry A as more of the low productivity firms are "cleansed" by Chinese competition, we attribute too much of this to the within firm component.

One strategy for dealing with this problem is to consider "instruments" for survival i.e. variables that effect the probability of survival that do not affect the technology shock. This is the standard Heckman (1979) selection equation where we would include selection correction terms generated from equation (F2) augmented to equation (F3). It is difficult to think of such exclusion restrictions in our context, however, that could enter w_{it} but be excluded from z_{it} [61]. Instead we take two alternative approaches: (i) placing a lower bound on the selection bias and (ii) adopting a non-parametric control function approach to control for the bias.

Bounding the Selection Bias

A recent literature in econometrics emphasises that even when point identification is not feasible, it may be possible to achieve set identification. In our context, this means that we may be able to place a lower bound on the effect of Chinese imports on technology. Following Manski (1994), Manski and Pepper (2000) and Blundell et al (2007) we consider the "worst case bounds", i.e. what could be the lowest effect of imports if selection effects were severe. What helps out in our application is that there is a finite lower support at zero for the distribution of patents and IT. If the firm had survived it could never have less than zero patents or zero computers. In this case we can impute that all the exiting firms would have performed zero patents and lost all their computers had they survived. Any positive effect remaining from α will be the "worst case" bounds.

Control function approach for selection

The worst-case bounds approach is infeasible for TFP as it is a continuous variable without finite support. One approach would be to use less conservative bounds (e.g. assume that the exiters were all from the lowest decile of the TFP distribution). These approaches need some rather arbitrary cut-off rule so instead we the same control function approach suggested by Olley and Pakes (1996) to add a non-parametric term in the propensity score based on observed exiters when estimating the production function. This is described above in Appendix C (e.g. see equation C6)

[61] Some possibilities based on alternative (usually strong) dynamic assumptions include Kyriazidou (1997), Honore and Kyriazidou (2000) or Wooldridge (1995).

TABLE A1: CHINA'S SHARE OF GLOBAL IMPORTS – TOP TEN INDUSTRIES, 1999-2007

Top Ten Industries in 1999 (by China's import share)		China's Share of all Imports IMP^{CH}		
Industry Description	Industry Code	1999	2007	Change 2007-1999
Dolls and Stuffed Toys	3942	0.817	0.859	+0.042
Drapery, Hardware and Window Blinds	2591	0.527	0.574	0.047
Rubber and Plastics Footwear	3021	0.532	0.618	0.086
Leather Gloves and Mittens	3151	0.517	0.574	0.057
Women's Handbags and Purses	3171	0.470	0.517	0.047
Manufacturing NEC	3999	0.458	0.521	0.064
Games, Toys and Children's Vehicles	3944	0.434	0.765	0.331
Luggage	3161	0.432	0.680	0.248
Personal Leather Goods	3172	0.416	0.432	0.016
Apparel and other Finished Fabric Products	2386	0.415	0.418	0.003
All Industries		0.057	0.124	0.068
(standard-deviation)		(0.102)	(0.152)	(0.089)

Notes: Calculated using product-level UN Comtrade data aggregated to four-digit US SIC codes. There are 430 four-digit industries in our dataset. China's share of all imports IMP^{CH}_{1999} total world imports. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland, the UK and the US. the Manufacturing industries (not elsewhere classified) includes many miscellaneous goods such as hairdressing equipment, tobacco pipes, cigarette holders, artificial flower arrangements, and amusement or arcade machines.

TABLE A2: DESCRIPTIVE STATISTICS

Variable	Mean	Stan. Dev.	Median	Minimum	Maximum
Patenters sample - Firms with at least one EPO patent since 1978					
Number of Patents (per firm-year)	1.022	10.40	0	0	882
Employment	739.5	6,526.7	100	1	463,561
Number of Observations	30,277				
IT sample (Harte-Hanks)					
Number of Employees	248.3	566.1	140	1	50,000
IT Intensity (computers per worker)	0.580	0.385	0.398	0.05	2.00
Industry switchers (% plants switching four-digit sector in five year period)	0.112	0.316			
Number of Observations	37,500				
R&D sample (Osiris)					
R&D/Sales ratio	0.152	0.888	0.034	0.001	17.3
Employment	17,230	46,422	2054	4	464,841
Number of Observations	1,626				
TFP sample (Amadeus)					
Employment	79.4	333.9	30	10	84,252
Number of Firms (in TFP sample)	89,369				
Number of Observations	292,167				
Management sample					
Management score	3.11	0.58	3.14	1.11	4.89
Employment	716	902	350	100	5,000
Number of firms	1576				
Number of observations	3,607				
Employment sample (Amadeus)					
Number of Patents (per firm-year)	0.019	5.741	0	0	882
Employment	99.95	1,504.9	17	1	372,056
Number of Observations	581,474				
Survival sample (Amadeus)					
Number of Patents	0.049	2.80	0	0	830
Employment	97.8	2,751.7	14	2	1,469,840
Number of Observations	490,095				

Notes: Standard deviations in parentheses. Samples are based on those used to run regressions, so we condition on having non-missing values over a five-year period for the relevant variable. "Patenters sample" are those firms who have at least one patent in the European Patent Office (EPO) since 1978. Employment sample is based on Amadeus (again firms have to have reported employment over a five-year period as this is the dependent variable in the regressions. IT sample is HH. IT intensity is computers per worker. R&D sample is from Osiris (publicly listed firms). TFP sample is Amadeus firms in France, Italy, Spain and Sweden. Management sample covers all firms in France, Germany, Italy, Ireland, Sweden and the UK with multiple management interviews.

TABLE A3: NO FALLS IN CITATIONS PER PATENTS BECAUSE OF CHINESE IMPORTS

Dependent Variable:	**Δln(CITES)**	**Δ ln(CITES/PATENTS)**
Change in Chinese Imports	0.118	0.009
ΔIMP_{jk}^{CH}	(0.081)	(0.029)
Number of industry-country clusters	1,578	1,578
Number of Firms	8,480	8,480
Observations	30,277	30,277

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses. Estimation by five-year differences. ΔIMP^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. All specifications include country-year fixed effects. 12 Countries. Sample period is 1996 to 2006. *Δ(CITES)* is defined as the change in *ln(1+CITES)* where *CITES* = count of citations and *Δ(CITES/PATENT)* is defined as the change in *ln[(1+CITES)/(1+PAT)* where *PAT* = count of patents.

TABLE A4: ALTERNATIVE IT ADOPTION MEASURES

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
		ΔERP (ENTERPRISE RESOURCE PLANNING)			**ΔDATABASE**			**ΔGROUPWARE**	
Change in Chinese Imports	0.040			0.002			0.249***		
ΔIMP_{jk}^{CH}	(0.034)			(0.070)			(0.083)		
Highest Quintile for ΔIMP_{jk}^{CH}		0.013***			0.020**			0.034**	
		(0.005)			(0.010)			(0.014)	
2nd Highest Quintile of ΔIMP_{jk}^{CH}		0.006			0.030***			0.021	
		(0.005)			(0.010)			(0.013)	
3rd Highest Quintile for ΔIMP_{jk}^{CH}		0.014***			0.043***			-0.008	
		(0.005)			(0.010)			(0.013)	
4th Highest Quintile for ΔIMP_{jk}^{CH}		0.010**			0.024***			-0.018	
		(0.005)			(0.011)			(0.013)	
Lowest Quintile for ΔIMP_{jk}^{CH}			-0.011***			-0.028**			-0.000
			(0.004)			(0.009)			(0.001)
Number of Observations	24,741	24,741	24,741	24,741	24,741	24,741	24,741	24,741	24,741

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four-digit industry pair) in parentheses. There are 2,728 distinct country by industry pairs. . Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their change in Chinese Imports, that is, quintiles of ΔIMP^{CH} . 12 Countries. All regressions have site-type controls, employment growth and country by year dummies

TABLE A5: CHECKING PRE-POLICY TFP TRENDS

	(1)	(2)	(3)	(4)
Dependent Variable:	**ΔTFP**	**ΔTFP**	**ΔTFP**	**ΔTFP**
Estimating Method:	**IV**	**IV**	**IV**	**IV**
Δ Chinese Imports$_t$	1.897**	1.491***	1.608***	1.635***
	(0.806)	(0.264)	(0.410)	(0.313)
ΔTFP$_{t-5}$			-0.211***	0.378***
			(0.024)	(0.063)
ΔChinese Imports$_{t-5}$			-0.531	-0.450
			(0.602)	(0.423)
Endogenous right-hand side variables	Chinese Imports	Chinese Imports	Chinese Imports	Chinese Imports, ΔTFP(t-5)
Number of units	55,791	3,107	3,107	3,107
Number of clusters	187	126	126	126
Observations	55,791	3,107	3,107	3,107

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by four-digit industry in parentheses. These are estimates from the textile and apparel industries following Table 2 Panel A. Five-year differences covering the period 1999-2005. Estimation by five-year differences. Quota removal is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the four-digit industry that were covered by a quota restriction on China in 1999 (prior to China's WTO accession) that were planned to be removed by 2005 (see the Appendix D for details). In columns (1)-(3) we use quota removal to instrument Chinese imports. In column (4) we also use TFP_{t-10} as an instrument for ΔTFP_{t-5}. 4 Countries.

TABLE A6: DYNAMICS OF THE EFFECT OF CHINA ON PATENTS AND EMPLOYMENT

PANEL A: PATENTS, Δln(PATENTS)	(1)	(2)	(3)	(4)	(5)	(6)
5-year lag of Change in Chinese Imports	0.328***					
ΔIMP_{t-5}^{CH}	(0.110)					
4-year lag of Change in Chinese Imports		0.394***				
ΔIMP_{t-4}^{CH}		(0.110)				
3-year lag of Change in Chinese Imports			0.402***			
ΔIMP_{t-3}^{CH}			(0.120)			
2-year lag of Change in Chinese Imports				0.333***		
ΔIMP_{t-2}^{CH}				(0.113)		
1-year lag of Change in Chinese Imports					0.314***	
ΔIMP_{t-1}^{CH}					(0.102)	
Contemporaneous change in Chinese Imports						0.321***
ΔIMP_{t}^{CH}						(0.102)
Number of country-industry pairs	1,578	1,578	1,578	1,578	1,578	1,578
Number of Firms	8,480	8,480	8,480	8,480	8,480	8,480
Observations	30,277	30,277	30,277	30,277	30,277	30,277

PANEL B: EMPLOYMENT, Δln(N)	(1)	(2)	(3)	(4)	(5)	(6)
5-year lag of Change in Chinese Imports	-0.188					
ΔIMP_{t-5}^{CH}	(0.140)					
4-year lag of Change in Chinese Imports		-0.241*				
ΔIMP_{t-4}^{CH}		(0.139)				
3-year lag of Change in Chinese Imports			-0.306**			
ΔIMP_{t-3}^{CH}			(0.155)			
2-year lag of Change in Chinese Imports				-0.275*		
ΔIMP_{t-2}^{CH}				(0.160)		
1-year lag of Change in Chinese Imports					-0.285**	
ΔIMP_{t-1}^{CH}					(0.143)	
Contemporaneous change in Chinese Imports						-0.309**
ΔIMP_{t}^{CH}						(0.138)
Number of country-industry pairs	1,464	1,464	1,464	1,464	1,464	1,464
Number of Firms	7,030	7,030	7,030	7,030	7,030	7,030
Observations	22,938	22,938	22,938	22,938	22,938	22,938

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses. All columns estimated as 5-year differences ΔIMP_{t-l}^{CH} represents the 5-year change in Chinese imports (where l = lag length). 12 Countries. Sample period is 1996 to 2005.

TABLE A7: ALTERNATIVE MEASURES OF THE CHANGE IN CHINESE IMPORTS

PANEL A: CHINESE IMPORTS NORMALIZED BY DOMESTIC PRODUCTION

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(IT/N)	(3) Δln(TFP)	(4) Δln(N)	(5) SURVIVAL
Change in Chinese Imports (over production)	0.142***	0.053**	0.065***	-0.232***	-0.103***
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$	(0.048)	(0.024)	(0.020)	(0.033)	(0.017)
Change in Chinese imports*ln(Patent stock per worker at t-5)				0.507	0.456***
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$ *(PATSTOCK/N)$_{t-5}$				(0.431)	(0.111)
ln(Patent stock per worker at t-5)				0.503***	0.041***
(PATSTOCK/N)$_{t-5}$				(0.054)	(0.009)
Number of Units	8,474	20,106	89,369	189,309	488,270
Number of industry-country clusters	1,575	2,480	1,210	3,115	3,335
Observations	30,221	31,820	293,167	579,818	488,270

PANEL B: CHINESE IMPORTS NORMALIZED BY APPARENT CONSUMPTION

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(IT/N)	(3) Δln(TFP)	(4) Δln(N)	(5) SURVIVAL
Change Chinese Imports (over apparent consumption)	0.349***	0.169*	0.045**	-0.477***	-0.203***
$\Delta\left(M_{jk}^{China} / C_{jk}\right)$	(0.122)	(0.089)	(0.019)	(0.078)	(0.034)
Change in Chinese imports*ln(Patent stock per worker at t-5)				1.385	0.476***
$\Delta\left(M_{jk}^{China} / C_{jk}\right)$ **(PATSTOCK/N)$_{t-5}$*				(1.238)	(0.187)
ln(Patent stock per worker at t-5)				0.490***	0.041***
(PATSTOCK/N)$_{t-5}$				(0.078)	(0.009)
Number of Units	8,474	19,793	89,369	189,309	488,270
Number of industry-country clusters	1,575	2,406	1,210	3,115	3,335
Observations	30,221	31,225	293,167	579,818	488,270

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses. $\Delta\left(M_{jk}^{China} / D_{jk}\right)$ represents the 5-year difference Chinese Imports normalized by domestic production (D). $\Delta\left(M_{jk}^{China} / C_{jk}\right)$ is the 5-year difference in Chinese imports normalized by apparent consumption (C). Apparent consumption defined as Production - Exports + Imports (C=D-X+M). Variables D and C is from Eurostat's Prodcom database with full details given in the Data Appendix. Quintile 1 is a dummy variable for firms in the lowest quintile of IT intensity in the baseline year. Note that Switzerland is not included because it does not report production data to Eurostat's Prodcom database. Sample period is 2000 to 2007 for the IT equation and 1996-2005 for patents equations. Column (2) controls for the growth in employment.

TABLE A8: OFFSHORING TO CHINA – FULL RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**	**Δln(N)**	**Δln(N)**	**Δln(N)**	**SURVIVAL**	**SURVIVAL**	**SURVIVAL**
Measure of Lagged TECH:				**Patent stock**	**IT**	**TFP**	**Patent stock**	**IT**	**TFP**
ΔIMP_{jk}^{CH}	0.313***	0.279***	0.189***	-0.392***	-0.269***	-0.374***	-0.090	-0.110	-0.172**
	(0.100)	(0.080)	(0.082)	(0.145)	(0.105)	(0.103)	(0.060)	(0.079)	(0.074)
$\Delta IMP_{jk}^{CH} * TECH_{t-5}$				0.142*	-0.362**	0.679	0.339**	0.071	0.053
				(0.086)	(0.168)	(0.477)	(0.167)	(0.138)	(0.075)
$\Delta OFFSHORE_{jk}^{CH}$	0.173	1.685***	1.396***	-1.643	-2.802***	-0.227	-0.500	-1.546***	-0.533**
	(0.822)	(0.517)	(0.504)	(1.202)	(0.682)	(0.544)	(0.316)	(0.550)	(0.223)
$\Delta OFFSHORE_{jk}^{CH} * TECH_{t-5}$				1.064	1.406	4.874**	1.950	1.315**	0.568
				(0.70)	(1.111)	(2.181)	(2.030)	(0.710)	(0.411)
$TECH_{t-5}$				-0.012	0.219***	0.231***	0.016	-0.125	-0.007
				(0.008)	(0.013)	(0.019)	(0.018)	(0.008)	(0.005)
Number of units	8,480	22,957	89,369	6,335	22,957	89,369	1,647	2,863	1,294
Number of industry-country clusters	1,578	2,816	1,210	1,375	2,816	1,210	7,985	28,624	268,335
Observations	30,277	37,500	292,167	19,844	37,500	292,167	7,985	28,624	268,335

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four-digit industry pair) in parentheses. ΔIMP^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The variable $\Delta OFFSHORE$ is the 5-yerar change in Chinese imports in source industries, defined following Feenstra and Hansen (1999) – see Appendix B. Countries in all columns except for TFP models which is for four countries. Columns(1)-(3) repeat the results reported in Table 10. Columns (4)-(6) repeat the analysis of employment changes in Table 3 Panel A but also include the control for offshoring (and its interaction with lagged technology). Columns (7)-(9) repeat the analysis of survival (conducted in Table 3, Panel B) with a control for offshoring (and its interaction with lagged technology). All columns include country by year effects. 12 countries (except in column (3), (6) and (9) which are four countries).

TABLE A9: MAGNITUDES ALLOWING FOR OFFSHORING

All Figures are as a % of the total increase over the period 2000-2007

PANEL A: Increase in Patents per employee attributable to Chinese imports

Period	Within	Between	Exit	Total
Product Market	4.6	7.6	2.0	14.2
Product market + Offshoring	5.1	8.0	1.4	14.5

PANEL B: Increase in IT per employee attributable to Chinese imports

Period	Within	Between	Exit	Total
Product Market	9.8	3.1	1.2	14.1
Product market + Offshoring	20.9	5.3	3.3	29.5

PANEL C: Increase in Total Factor Productivity attributable to Chinese imports

Period	Within	Between	Exit	Total
Product Market	10.1	4.4	0.3	14.7
Product market + Offshoring	24.6	7.6	0.8	33.0

Notes: Panel A reports the share of aggregate patents per worker accounted for by China, Panel B the increase in IT per worker and Panel C the increase in total factor productivity. In each panel the first row ("Product Market") simply reports the same results following methodology in Appendix E implemented in Table 4 (the results differ slightly from Table 4 because we only use the single industry version of Chinese imports as in Table 5 Panel B as the multiple industry version is not available for offshoring). We then extend the methodology to allow for offshoring to China. All underlying regression specifications are extended to allow for offshoring to China. The full specifications of the within firm (same as Table 10), between and exit specifications are those in Table A8. We multiply the relevant coefficients by the observed Chinese import share growth to generate a predicted change in IT/Employee, Patents/Employee and TFP between 2000 to 2007 inclusive. The lower row in each panel ("Product Market + Offshoring") decomposes the total change (final column) into within, between and exit effects for the combined product market and "offshoring elements.

TABLE A10: EXPORTS TO CHINA

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(IT/N)	(3) ΔTFP
Change in Chinese Imports	0.322***	0.361***	0.254***
ΔIMP_{jk}^{CH}	(0.102)	(0.076)	(0.072)
Change in Exports to China	-0.243	0.028	-0.125
$\Delta\left(X_{jk}^{China} / X_{jk}^{World}\right)$	(0.200)	(0.118)	(0.126)
Number of Units	8,480	22,957	89,369
Number of Industry-country clusters	1,578	2,816	1,210
Number of Observations	30,277	37,500	292,167

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry in parentheses.12 Countries except column (3) where there are four countries. "Number of units" represents the number of firms in all columns except (2) where it is plants. 12 countries except in column (3) where it is four countries.

TABLE A11: THE QUOTA INSTRUMENT IS UNCORRELATED WITH THE GROWTH IN CHINESE IMPORTS PRIOR TO THE ACCESSION TO THE WTO

Dependent Variable	(1) ΔIMP^{CH}	(2) ΔIMP^{CH}	(3) ΔIMP^{CH}
Quota Removal*Post WTO		0.042***	0.039***
		(0.010)	(0.010)
Quota Removal	0.036***	0.009	
	(0.008)	(0.008)	
Country by Year Effects	Yes	Yes	Yes
Country by industry trends	No	No	Yes
Number of clusters	84	84	84
Observations	11,138	11,138	11,138

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by four-digit industry pair in parentheses. This data is a four-digit industry by country panel between 1990 and 2007. Sample is the textiles and clothing industries only. The dependent variable is the five-year difference in Chinese import share. Quota removal is the height of the quota in the four-digit industry in 2000 prior to China joining the WTO. "Post WTO" is a dummy equal to unity after 2001 (and zero before). 12 countries.