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

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Abstract

We examine the impact of Chinese import competition on broad measures of technical change - patenting, IT and TFP – 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 in their output markets. We correct for endogeneity using the removal of product-specific quotas following China's entry into the World Trade Organization in 2011. 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 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 and the share of unskilled workers. In contrast to low-wage nations like China, developed countries imports had no significant effect on innovation.

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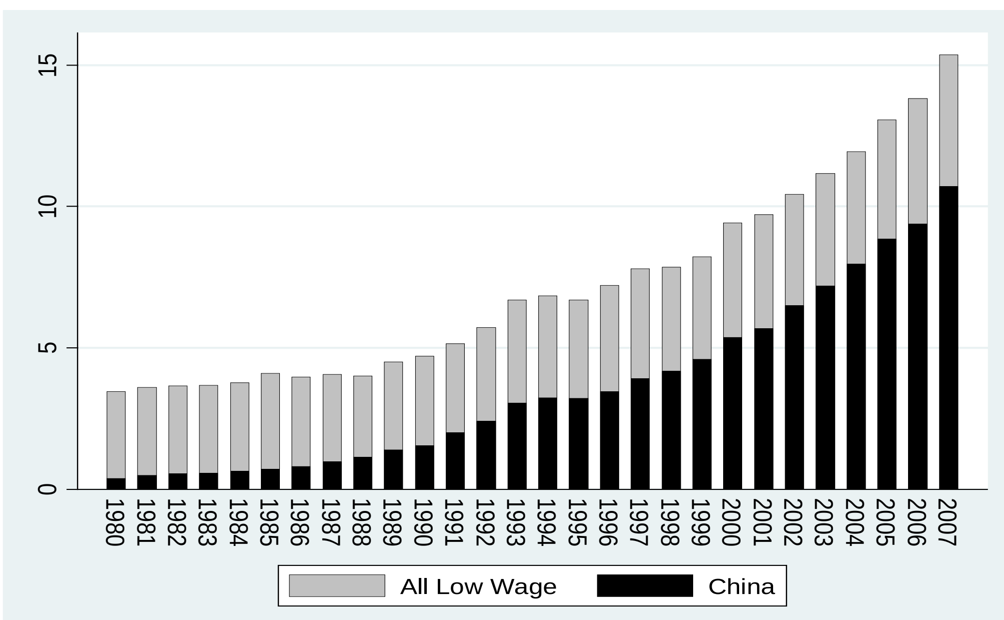
I. INTRODUCTION

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 grew by over 15% per year in the two decades up to the Great Recession of 2007-2009. 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. 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.

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.

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.

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 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. Importantly, our data allows us to trace the responses of firms as measured exposure to the quota relaxation policy increased. This allows us to isolate the immediate, quota-related impacts of increased Chinese import competition from expectations that firms may have built up about the policy prior to 2001.

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, raise their IT intensity and increase their overall level of TFP (they also increase R&D, management quality and skill levels and reduce prices and profitability). Second, Chinese import competition reduces employment and survival probabilities in low-tech firms. 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 and between firm effects is to cause technological upgrading in those industries most affected by Chinese imports. 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 be an important factor for technical change and growth in richer countries.

Our paper relates to several literatures. First, there is a large literature on the relationship between trade and productivity. Although many papers have found that trade liberalization increases aggregate industry productivity[1], the mechanism through which this occurs remains poorly understood. The literature focuses on reallocation effects, i.e. how trade induces a shift in output from less productive towards more efficient firms (e.g. Melitz, 2003; Melitz and Redding, 2013). However, the empirical evidence shows that *within* incumbent firm productivity growth typically accounts for at least as much as these *between*-firm reallocation effects. This evidence tends to be indirect since explicit measures of technical change are generally unavailable at the micro-level.[2] A contribution of paper is to use direct measures of technological upgrading at the firm and plant level such as patents and IT. The within firm effects could be due to innovation (firms make products or processes that are new to world and shift the global technology frontier) or "compositional" (a firm changes its product mix without innovating in this sense). We consider these alternative approaches in turn.

Innovation models have been a mainstay of the theoretical literature for many years.[3] In Bloom, Romer, Terry and Van Reenen (2013) we show how the Chinese accession to the WTO could in theory reduce the opportunity cost of innovating by releasing factors of production "trapped" in producing old goods. However, there are several alternative models of how reducing trade barriers against low wage country goods could induce Northern innovation. First, lowering import barriers increases competitive intensity and such competition could benefit innovation through reducing agency costs (e.g. Schmidt, 1997), increasing the incentive to gain market share (Raith, 2002) or lowering cannibalization of existing profits.[4] However, there is a fundamental Schumpeterian force that competition lowers price-cost margins, thereby reducing the quasi-rents from innovation, so the effect of competition on innovation incentives is inherently ambiguous (Aghion et al, 2005). A second class of innovation models stresses the importance of trade in increasing market size and fostering innovation through this market expansion effect.[5] Lower trade costs generate a larger market size over which to spread the fixed costs of investing in new

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

2 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.

3 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).

4 This is the Arrow (1962) "displacement effect". It shows up in different guises in Aghion et al's (2005) "escape competition" effect and the "switchover costs" of Holmes et al (2008).

5 Schmookler (1966); Krugman (1980); Grossman and Helpman (1991, 1992); and Acemoglu (2008)

technologies.[6] This works through export market expansion into China and we find that industry level variation in exports does not primarily drive our results.Third, 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).[7] These mechanisms do not seem appropriate in the Chinese context however, as European firms have (currently) a large technological lead over China.[8]

The other main strand of the trade and productivity literature is more focused on compositional effects. 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 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, 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 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

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

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

[8] 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.

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 – firms are adding products that are new to the world, not simply shifting around product portfolios that already exist in the world.

Our work is also related to the literature on skill biased technical change. We find a role for trade with low wage countries in increasing skill demand (at least since the mid-1990s) through inducing technical change.[9] 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[10], in part because this work used data up to the mid-1990s, which largely predates the rise of China (see Figure 1).[11] More recent work (Autor, Dorn and Hansen, 2013) finds a substantial impact of China in reducing US employment since 2000, particularly among low-skilled workers.

The structure of the paper is as follows: Section II describes the data, Section III details the empirical modeling strategy, Section IV describes our results and Section V discusses some extensions and robustness tests. Section VIII concludes.

II. 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

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9 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).

10 See, for example, Machin and Van Reenen (1998).

11 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. 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.

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 had zero patents. 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. We match these to the population of European firms in 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, with details given in Belenzon and Berkovitz (2010). Patents are dated by application year to measure the formal invention year of the patent.

B. Productivity and exit

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). 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 with multi-product firms. In the first stage, we estimate production functions separately by industry across approximately 1.4 million observations to recover the parameters on the factor inputs.[12] 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

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

finer level of industry aggregation which show similar results. Details of this procedure are contained in Bloom et al (2011, Appendix C).

Exit is measured using the Amadeus "status" variable, including extracting this from older Amadeus disks where necessary. We define exit as a firm being defined as "bankrupt", "liquidated" or "dormant". Firms that are taken-over or merged are not counted as exiting since the operations of the firm may still be continuing even though ownership has changed.

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 (reported in Table A13, Online Appendix).

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 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.[13]

D. UN Comtrade data

We use trade information 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

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[13] 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 essentially the full population of firms – between firms with less than and more than 100 employees. It is also worth noting that large firms account for most of European manufacturing employment (and an even larger share of value added), although the precise proportion will vary by country. For example, Firms with over 50 employees account for 82% of total manufacturing employment in Germany, 77% in the UK, 76% in Sweden, 72% in Ireland and 69% in France. In Greece this proportion falls to 59%, 56% in Italy and 50% in Portugal. See Eurostat *Structural Business Statistics*, http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/dataset?p_product_code=SBS_SC_2D_DADE95.

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[14] (see Appendix B for more information on these industry codes).

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 measures that use production in the denominator (see Table 1, Panel C), we prefer the normalization on world imports which does not have these data restrictions.

E. The Quota Instrument

To address the endogeneity of imports we exploit the accession of China to the WTO in 2001, which led to the abolition of import quotas on textiles and apparel. 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).

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

[14] The results are similar when we allocate firms to a single primary sector.

it led the European Union to re-introduce some limited quotas after 2005.[15] Since this re-introduction was endogenous, we use the initial level of quotas in 2000 ($QUOTA_j$) as our instrument to avoid using the potentially endogenous post-2005 quota levels.

The exclusion restriction is that shocks to technology are uncorrelated with changes in quotas. In our main IV regression we require that the shock to the change in technology 2000-2005 (the innovation in innovation) is uncorrelated with the height of quotas to non-WTO countries (like China) in 2000. Since, these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s was in preparation for the Uruguay Round this seems like an ex ante plausible assumption. For each four-digit industry we calculated the proportion of six digit product categories (HS6) that were covered by a quota, weighting each product by its share of import value. Consistent with our priors, the level of quotas varied quasi-randomly across four-digit industries. For example, they covered 77% of cotton fabric products (SIC 2211) but only 2% of wool fabric products (SIC 2231), and covered 100% of women's dresses (SIC 2334) but only 5% of men's trousers (SIC 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 likely to be uncorrelated to any technology trends in the industries as we show below.

Nevertheless, we examine several threats to the exclusion restriction. In particular, we show that our results are robust to including firm fixed effects in the differenced equations (i.e. trend-adjusted difference in differences). We also show that there is no evidence that the industries where quotas fell the fastest after China's WTO accession had any significant difference in their innovation behavior prior to the policy change.

Although the quota-covered industries are considered low-tech sectors, European firms in these industries still generated 21,638 patents in our sample. In Appendix B we give several examples of such patents taken out by European firms. We discuss more details of the quota instrument in Appendix D, including descriptive statistics on coverage in Appendix Table A2.

[15] The surge in Chinese imports led to strikes by dockworkers 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.

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 for our main regression samples 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. For plants with IT data, median employment is 140 and the average IT intensity is 0.58 computers per worker.

III. EMPIRICAL MODELING STRATEGY

Our empirical models analyze both the *within* firm intensive margin of technological upgrading and the *between* firm extensive 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:

$$\ln TECH_{ijkt} = \alpha IMP^{CH}_{jkt-l} + f_{kt} + \varepsilon_{ijkt} \tag{1}$$

TECH will be interpreted broadly and measured using a number of indicators such as patented innovations[16], IT and TFP. We measure IMP^{CH}_{jkt} mainly as the proportion of imports (M) in industry j and country k that originate from China $(M^{China}_{jk}/M^{World}_{jk})$ and the f_{kt} are a full set of country

[16] 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).

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 check the robustness of the results when using alternative lag lengths.[17]

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:

$$\Delta \ln TECH_{ijkt} = \alpha \Delta IMP^{CH}_{jkt} + f_{kt} + \upsilon_{ijkt} \tag{2}$$

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-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 Introduction, 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:

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

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. $\alpha^N < 0$) and *TECH* is the relevant technology

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[17] For patents, the largest effects appear after three years (see Table A14 in the Appendix) which is consistent with the idea that most firms take a few years to obtain innovations from their increased R&D spending.

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_{jkt}^{CH} 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:

$$SURVIVAL_{ijkt} = \alpha^S \Delta IMP_{jkt}^{CH} + \gamma^S (TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}) + \delta^S TECH_{ijkt-5} + f_{kt} + \upsilon_{ijkt}^S \tag{4}$$

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):

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

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.

IV. RESULTS

A. Within firm results: OLS estimates

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).[18]

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. In fact, the coefficient on Chinese imports is positive (although insignificant).[19]

In column (2) of Table 1, we examine IT intensity and again 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, we also investigate other measures of IT – the adoption of Enterprise Resource Planning, database software, and groupware tools – and find positive coefficients on Chinese imports.[20] Finally, in column (3) we use a wider measure of technical change as the dependent variable, TFP growth, and again establish a positive and significant association with Chinese imports.[21] Other

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18 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 also robust to controlling for employment growth.

19 The coefficient on cites per patent is 0.009 with a standard error of 0.029.

20 In online Appendix Table A13 we look at non-linearities through quintiles of the growth of Chinese imports as well as linear effects on these types of software.

21 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.

measures of productivity enhancing investment such as the growth of R&D expenditures and management quality are also positively associated with increased exposure to Chinese imports.[22]

B. Within Firm Results: Robustness of OLS estimates

We subjected the baseline results to a number of robustness checks. First, we were concerned that unobserved productivity shocks could be driving the positive correlation so in Panel B we include a full set of three-digit industry dummies in the growth specifications. 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.[23]

Second, we normalized Chinese imports by a measure of domestic activity such as production or apparent consumption instead of total imports in Panel C. Although the magnitude of the coefficients changes as the mean of the imports variable is different, the qualitative and quantitative results are remarkably similar.[24]

In addition to China's effect through competition in the final goods market, the opening up of China could have affected technical progress by allowing Western firms to buy cheaper intermediate inputs and offshore low value added parts of the production chain.[25] 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.[26] In Panel D, we find offshoring enters with a positive coefficient in all three equations (although insignificantly so in the patents equation). The share of Chinese imports in the final goods market (our baseline measure) remains positive and significant throughout with only slightly lower

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[22] The coefficient (standard error) on Chinese imports was 1.213(0.549) in the R&D equation and 0.814(0.314) in the management equation (defined as in Bloom and Van Reenen, 2007).

[23] 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(0.080) 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.

[24] For example, a one standard deviation increase in the import share in Table 1, Panel A 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 is associated with a 14% increase in patenting.

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

[26] 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.

coefficients.[27] This suggests 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.

C. Within Firm Results: Using China's WTO accession to generate Instrumental Variables

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. This could bias our results upward if, for example, Chinese imports were driven by domestic supply shocks, or downward if they are driven by demand shocks.

Table 2 presents the IV results using China's WTO accession.[28] 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.[29] The final three columns repeat the

[27] The coefficient estimates 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).

[28] In 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. Note that we include all firms who have any "primary" industry presence in textiles and clothing according to BVD. The main industry of some of these firms will be outside textiles, hence the large number of clusters. If we condition on only those firms whose main industry is textiles the results are robust (e.g. the coefficient on Chinese imports in column (3) is 2.010 with a standard error of 1.074).

[29] 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).

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.[30]

The major concern with the IV strategy is that there could be some unobserved trend in the sectors that had the highest quotas that meant they would have had faster technical change even in the absence of China joining the WTO. To examine this potential bias we subject the results to a tough test of including firm-specific trends.[31] If these firms were more likely to innovate in the high quota industries then we would expect to see our effects disappear when we condition on these firm-specific trends. We use the reduced forms for a longer time period covering pre and post WTO accession to capture the trend. Hence, we estimate:

$$\Delta \ln TECH_{ijkt} = \gamma \Delta z_{jt} + f_{kt} + \eta_{ijk} + e_{ijkt}$$

The treatment indicator, $\Delta z_{jt} = QUOTA_j * \mathrm{I}(YEAR \geq 2001)$, remains the "height" of the quotas in 2000, but is now interacted with a "policy on" dummy for the post WTO period ($\mathrm{I}(YEAR \geq 2001)$). Note that for IT we do not have any data pre-WTO accession so we can only present results for patents and TFP. The η_{ijk} are a full set of firm fixed effects that pick up trends as the equation is estimated in long-differences.

In column (1) of Table 3, we show that the firms more subject to quota removal had significantly higher rates of patenting after Chinese WTO accession. In column (2) we add the firm dummies to the growth specifications. The coefficient on Chinese imports actually increases, although the change is not statistically significant (p-value = 0.477). The fact that any bias is towards zero is intuitive, as the high quota industries tend to be low tech, low-skilled sectors with a slower rate of technical change prior to WTO accession. An alternative way to define exposure to the policy is to count the number of years since the 2001 accession instead of a simple binary dummy. Using this alternative measure in columns (3) and (4) produces qualitatively similar results to the first two columns. The final four columns (5) to (8) reproduce these four specifications but using TFP as the outcome. Again, the results with and without firm specific trends are similar. So overall, we find that controlling for prior firm-level trends in patenting and TFP appears to actually increase the estimated impact of Chinese imports on technical change.

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30 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).

31 Note that the quotas are firm-specific as many of our firms are multi-product so operate across several industries and face a firm-specific weighted average quota (see Appendices A and B).

A related issue is whether firms adjusted their innovation behavior in in *anticipation* of China joining the WTO. There was a large element of surprise in the impact of quota abolition because 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 would be temporary, as to some extent it was with the temporary reintroduction of some quotas in 2006. The fact that Table 3 finds a break in the trend of innovation in 2001 in those industries where the fall in quotas was greatest shows there was a change in behavior, over and above any pre-policy anticipation effects. A concern might be that firms *delayed* their normal innovations pre-accession in those sectors likely to be most affected by quota abolition causing us to infer a spurious positive effect of liberalization. We performed two tests of this idea. First, we examined whether innovation was significantly slower for firms more affected by quota abolition by regressing the five-year growth in innovation in the years *prior to* 2001 on the quota instrument: the coefficients were always insignificant.[32] Secondly, we ran the regressions in Table 3 columns (1), (3) and (4) conditioning on the lagged growth in innovation. So when examining the growth in patents 2005-2000 we control for the growth in patents 2000-1995, conditioning out any "anticipation effects". We still recovered a significant and positive effect of quota abolition on innovation. Details of all the experiments around identification are discussed in online Appendix C.

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. 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. Output quotas remained positive and significant in all three specifications.[33]

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[32] If we regress the growth of patents 2000-1995 on the quota instrument (in 2000) the coefficient (standard error) on quotas is -0.068(0.052). By contrast, the standard reduced form for patent growth 2005-2000 has a coefficient on quotas of 0.264(0.088). Similarly the regression of the pre-WTO growth of TFP 2000-1995 on the quota IV has a coefficient (standard error) of -0.010(0.040) whereas the standard reduced form for TFP 2005-2000 has a coefficient on quotas (standard error) of 0.190(0.021).

[33] In these reduced form models featuring both types of quota variables. 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. The coefficients (standard errors) for the output quotas were: 0.201 (0.080), 0.160 (0.046), and 0.101 (0.019). We estimate these equations on industries where at least 0.5% of imported inputs are from China.

Taking Tables 2 and 3 together, 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.[34]

D. Between Firm Results: jobs and survival

Table 4 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 3.6% fall in employment. Like Autor, Dorn and Hansen (2013) this suggests Chinese imports are associated with falling levels of manufacturing employment, at least within existing firms. 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 harmful effects of Chinese imports on jobs.[35] In columns (5) to (8) 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 technology. Chinese imports appear to have the largest impact on patents after three years whereas for jobs the largest impact for Chinese imports is contemporaneously (see Appendix A14). This is consistent with the idea that firms respond to Chinese imports by cutting employment and starting innovation projects, but it takes around three years for these projects to create patentable innovations.

For the survival equations in Panel B of Table 4 we consider a cohort of firms and plants alive in 2000 and model the 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

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[34] 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).

[35] 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.

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.[36] 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[37]. Columns (5) to (8) 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 significantly more likely to exit because of Chinese import competition.[38] 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.[39]

Table 5 looks at the between firm reallocation effects when we use Chinese WTO accession as an IV. Column (1) shows that the negative association between jobs and Chinese imports is lower for higher tech firms in the clothing and textiles sub-sample. Column (2) implements the IV approach. Although the standard error rises on the interaction and is no longer statistically significant the coefficient is largely unchanged (3.3 compared to 3.7 in column (1)). Columns (3) and (4) implement the same approach but use IT intensity as the technology measure instead of patents. In these specifications, the IV results look even stronger than OLS with the interaction remaining significant at the 5% level. The last two columns repeat the exercise for TFP and, like IT, we find a stronger and significantly positive interaction between Chinese imports growth and lagged technology.

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[36] Note the sample in columns (1) and (2) is the same as that in Table 1 column (1), namely those firms that patented at some point since 1978. We obtain similar results if we widened the same to include all firms, even those who had never patented. The coefficient (standard error) on the interaction term between initial technology and Chinese import growth was 1.546(0.134) for employment growth and 0.391(0.018) for survival.

[37] 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.

[38] For example, estimating column (5) but using a dummy for 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.

[39] We also experimented with including average firm wages (as a skill proxy) and capital-labor ratio (both interacted with Chinese import growth) in the employment regressions. These additional interaction terms were insignificant when the patents variables were also included. Further, the technology interactions remained positive and significant. For example, when these additional interactions with wages and capital (as well as the linear terms) were added to the specification in Table 4, Panel A column (2), the coefficient (standard error) on the interaction between Chinese import growth and lagged patents was 1.509(0.660).

The qualitative similarity between the IV and OLS results is reassuring because the specifications in Table 5 are quite demanding. The sample is smaller than Table 4 (just clothing and textile industries) and we are instrumenting both the linear effect (as in Table 3) *and* the interaction. The estimates were very unstable for the survival equation with no significant correlations, as the absolute number of exits was so low (only 37 clear incidences) in the textile and apparel industry for which we have our China joining the WTO instrument.

E. Magnitudes

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 through 3) and between firms by reallocating output to more technologically advanced firms (Tables 4 and 5). So a natural question is how large as these effects on an economy level? As Atkeson and Burstein (2010), Arkolakis, Costinot and Rodríguez-Clare (2010) and Ossa and Hsieh (2010) have stressed, when examining general equilibrium results we have to take into account a range of broader impacts. Nevertheless, we can use the regression coefficients to perform partial equilibrium calculations to get rough magnitudes for the potential importance of China in shaping technical change.

To run out magnitude calculations we use a standard productivity decomposition following papers like Foster, Haltiwanger and Krizan (2000), which decompose an aggregate increase in productivity into a within firm (or plant) term and between firm terms reflecting reallocation, entry and exit. In our magnitudes we take exactly the same approach – using the regression results to attribute the within and between terms to Chinese imports – except we have omitted the entry term since we do not observe entry (see Appendix D for details).

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.

Using this decomposition exercise (as shown in Table A5 (online appendix)), over the 2000-2007 period Chinese imports accounted for 14.7% of the increase in aggregate patenting per worker, 14.1% of the increase in IT intensity and 11.8% of TFP growth. We decompose these into the within firm component and a reallocation component between (incumbent firms) and from exit. For patents, the within firm component is 5.8%, almost equal to the between incumbents effect of

6.3% with the rest due to exit (2.5%). For IT and productivity, the *within c*omponent is larger (9.8% and 8.1% respectively).[40]

An alternative approach to gauging the magnitude of the within and between firm effect of China is to compare estimates at the industry level and at the firm level. 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.[41] For example, if Chinese competition discourages entry of innovative firms within an industry, then the magnitude calculations 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. We find results that are very consistent with the earlier calculations (See Table A6 (online appendix) for full results). The industry coefficients are all positive, significant and about twice as large as the firm level coefficients for patents and TFP (and about 10% larger for IT).[42]

V. EXTENSIONS AND ROBUSTNESS

A. 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 discussed in the previous sub-section are robust to this problem because they aggregate innovation. Dynamic selection bias would mean, however, that we attribute too much of this aggregate industry effect to the within firm component and too little to the reallocation component in the magnitude calculations.

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[40] We re-calculated the aggregate magnitudes of the effects of China on technical change including the offshoring terms (see Online Table A7). 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.

[41] 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).

[42] For patents, the coefficient at the industry level was 0.368 compared to 0.171 at the firm level. For TFP the coefficients were 0.326 vs. 0.164 and for IT they were 0.399 vs. 0.366. The firm level coefficients differ slightly from Table 1 because we allocate each firm to just one specific four-digit industry to be comparable to the industry results.

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.

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 giving 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.[43] 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) of Table 7 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-

[43] 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.

case lower bounds are again not much lower than the baseline, with the effect falling from 0.397 to 0.389.[44]

We conclude from Table 6 that the dynamic selection problem is not causing us to substantially overestimate the impact of Chinese competition on within firm increases in innovation.

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 Pakes (1996). Thus, our TFP estimates should be robust to this selection problem.

B. Low wage vs. high wage country trade

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 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

[44] We obtain similar results if we implement this approach on the textiles sub-sample in Table 2. The OLS coefficient (standard error) in column (1) of Table 2 fell to 1.131(0.369) and the IV estimate fell to 1.767(0.965).

(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. One explanation is 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 shrink profit margins, generating a negative Schumpeterian impact of innovation, offsetting any pro-innovation effects of competition.

C. Other Robustness Tests

<u>*Initial conditions as instrumental variables*</u> - 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 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 ($IMP^{CH}_{jt-6} * \Delta M^{China}_{t}$) 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.[46] Using this IV strategy

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[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. The second stage coefficient on imports was negative but very imprecisely determined: -2.310(4.392).

[46] 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. 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. This identification strategy is similar to the use of "ethnic enclaves" by

generated similar qualitative results to the quota instrument. The coefficient on Chinese imports was positive, significant and larger in the IV specifications compared to the OLS specifications in all three technology equations (see online Table A8).[47]

Heterogeneity of the China Effect on innovation - We examined the extent to which the China effect was heterogeneous across countries and industries. The coefficients were surprisingly stable across countries and we cannot statistically reject homogeneity of the coefficients across countries. For example, the F-statistics (p-values) for testing the joint significance of country interaction terms in our main technology regressions were: 0.84 [0.592], 1.53 [0.115] and 0.20 [0.659] (for patents, ICT and TFP respectively). More interestingly, there did appear to be some systematic differences across industries (online Table A3). Sectors which had higher industry-specific "wage rents" and/or higher lagged TFP responded more to the China shock than those that did not. We argue in online Appendix A that this is consistent with the trapped factor model of Bloom et al (2013), although there are alternative explanations, of course.

China's effect on skill demand - We estimated industry level skill demand equations (online Table A10) and found evidence to suggest Chinese imports are associated with a significant increase in the wage-bill share of college-educated workers, consistent with the idea of trade integration with low-wage countries reducing the relative demand for less skilled workers.[48] We suggest that trade is having an indirect effect on skill demand through inducing faster technical change which, in turn, increases the relative demand for human capital.

Product and industry switching - A leading compositional theory was that in the face of Chinese import competition European firms change their product mix. We do find evidence for substantial switching (see online Table A11), especially in sectors more exposed to the China shock consistent

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papers such as Card (2001) who use the proportion of current immigrants in an area as an instrument for future immigrants. The concern is that the initial conditions may not be excludable from the second stage, however. This may be because the initial level of Chinese imports is correlated with an unobservable industry characteristic that affects subsequent technology growth.

47 If we implement the initial conditions IV in the textiles sub-sample of Table 2 we obtain qualitatively similar results to using our baseline quota IV. The results for the textiles sub-sample are also robust to including three-digit industry trends as in Table 1 Panel B.

48 Decomposing the wage bill share, Chinese imports have a significant negative association with the total wage bill and the wage bill of non-college educated workers. There is a significant positive association with the total wage bill of college educated workers.

with Bernard et al (2010). However, this only accounts for a small fraction of the correlation of Chinese imports and technological upgrading.

Exports to China - We have focused on imports from China as driving changes in technology, but exports to China may also have an impact through market size effects. Our main results are all robust to including controls for exports to China in the regressions (online Table A12). Imports from China appear to be the dominant force on innovation, at least in the micro-data.

VI. 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 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 IV.D.

We should not jump too quickly to welfare conclusions from the results in the paper and many recent papers examine welfare more explicitly.[49] 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. We think that our results are also suggestive of a positive aggregate effect of Chinese trade on innovation and welfare.

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. Third, 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.

[49] 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. 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, but Melitz and Redding (2013) dispute this. 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).

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TABLE 1: TECHNICAL CHANGE WITHIN INCUMBENT FIRMS AND PLANTS

PANEL A: BASELINE RESULTS

	(1)	(2)	(3)
Dependent variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**ΔTFP**
Estimation method	**5 year diffs**	**5 year diffs**	**5 year diffs**
Change in Chinese Imports	0.321***	0.361**	0.257***
ΔIMP_{jk}^{CH}	(0.102)	(0.076)	(0.072)
Sample period	2005-1996	2007-2000	2005-1995
Number of Units	8,480	22,957	89,369
Number of country by industry clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167

PANEL B: INCLUDE INDUSTRY TRENDS

Dependent variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**ΔTFP**
Change in Chinese Imports	0.191*	0.170**	0.128**
ΔIMP_{jk}^{CH}	(0.102)	(0.082)	(0.053)
Number of Units	8,480	22,957	89,369
Number of country by industry clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167

PANEL C: NORMALIZE IMPORTS BY DOMESTIC PRODUCTION

Dependent variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**ΔTFP**
Change in Chinese Imports	0.182**	0.129***	0.065***
ΔIMP_{jk}^{CH}	(0.074)	(0.028)	(0.020)
Number of Units	8,364	20,106	89,369
Number of country by industry clusters	1,527	2,480	1,210
Observations	29,062	31,820	292,167

PANEL D: OFFSHORING

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

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is the same in all panels, i.e. 2005-1996 for column (1); 2007-2000 for column (2) and 2005-1995 for column (3). Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses. 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. 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. 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). Panel B includes three digit industry trends. Panel C normalizes Chinese imports on domestic production (instead of total imports as in other columns). Panel D includes a measure of offshoring defined as in Feenstra and Hansen (1999) except it is for Chinese imports only, not all low wage country imports (see Appendix B). 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). Dummies for establishment type (Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch) are included in column (2). Units are firms in columns (1) and (3) and plants in column (2).

TABLE 2: WITHIN FIRM EFFECTS - USING CHANGES IN QUOTAS AS AN IV FOR CHINESE IMPORTS (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***	0.902***		1.629**
	(0.377)		(1.001)	(0.172)		(0.400)	(0.087)		(0.326)
Quotas removal		0.108***			0.088***			0.107***	
		(0.022)			(0.019)			(0.032)	
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	12,247	12,247	12,247
Number industry clusters	149	149	149	83	83	83	177	177	177
Observations	3,443	3,443	3,443	2,891	2,891	2,891	20,625	20,625	20,625

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 C for details). 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. Sample is firms in the textile and apparel industry. Standard errors for all regressions are clustered by four-digit industry in parentheses.

TABLE 3: WITHIN FIRM EFFECTS – INCLUDING FIRM-SPECIFIC TRENDS WHEN USING QUOTAS AS AN IV (REDUCED FORM SPECIFICATION)

	PATENTING				TOTAL FACTOR PRODUCTIVITY			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent Variable:	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**ΔTFP**	**ΔTFP**	**ΔTFP**	**ΔTFP**
Quotas removal	0.129**	0.216**			0.143***	0.178***		
*I(year>2000)	(0.063)	(0.105)			(0.018)	(0.037)		
Quotas removal			0.047**	0.075**			0.043***	0.033*
* # years after 2000			(0.020)	(0.033)			(0.005)	(0.017)
Firm-specific trends?	No	Yes	No	Yes	No	Yes	No	Yes
Sample period	2005-1992	2005-1992	2005-1992	2005-1995	2005-1995	2005-1995	2005-1995	2005-1995
Number of units	2,435	2,435	2,435	2,435	16,495	16,495	16,495	16,495
Number industry clusters	159	159	159	159	187	187	187	187
Observations	14,768	14,768	14,768	14,768	55,791	55,791	55,791	55,791

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. These are the equivalent of the reduced form specifications in Table 2. We use a longer sample period in order to include trends. “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 C for details). I(year>2000) is an indicator variable = 1 if observation is after 200 (i.e. after China’s WTO accession). “# years after 2000” is the number of years after 2000 and zero in 2000 and before (i.e. “# years after 2000”=1 in 2001, =2 in 2002, etc.). All estimates are in five year differences as usual, so we control for firm specific trends by including a firm dummy in columns (2), (4), (6) and (8). 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. Sample is firms in the textile and apparel industry. Standard errors for all regressions are clustered by four-digit industry in parentheses.

TABLE 4: BETWEEN FIRM EFFECTS - EMPLOYMENT AND SURVIVAL

PANEL A: EMPLOYMENT

Dependent Variable: Employment Growth, $\Delta \ln N$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable (TECH)	Patents	Patents	IT	IT	TFP	TFP
Sample						
Change in Chinese Imports	-0.361***	-0.434***	-0.203**	-0.379***	-0.369***	-0.382***
ΔIMP^{CH}_{jk}	(0.134)	(0.136)	(0.086)	(0.105)	(0.091)	(0.093)
Change in Chinese imports*technology at t-5		1.434**		0.385**		0.956**
ΔIMP^{CH}_{jk} *$TECH_{t-5}$		(0.649)		(0.157)		(0.424)
Technology at t-5	0.389***	0.348***	0.241***	0.230***	0.278***	0.256***
$TECH_{t-5}$	(0.043)	(0.049)	(0.010)	(0.010)	(0.016)	(0.016)
Number of Units	6,335	6,335	22,957	22,957	89,369	89,369
Number of country by industry clusters	1,375	1,375	2,816	2,816	1,210	1,210
Observations	19,844	19,844	37,500	37,500	292,167	292,167

PANEL B: SURVIVAL

Dependent Variable: ***SURVIVAL***	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sample	Patents	Patents	IT	IT	TFP	TFP
Change in Chinese Imports	-0.065	-0.089	-0.118**	-0.182**	-0.191***	-0.191***
ΔIMP^{CH}_{jk}	(0.047)	(0.050)	(0.047)	(0.072)	(0.057)	(0.057)
Change in Chinese imports*technology at t-5		0.261**		0.137		0.075
ΔIMP^{CH}_{jk} *$TECH_{t-5}$		(0.114)		(0.112)		(0.077)
Technology at t-5	-0.006	-0.014	0.001	-0.002	0.007	-0.002
$TECH_{t-5}$	(0.007)	(0.009)	(0.005)	(0.006)	(0.003)	(0.004)
Survival Rate for Sample (mean)	0.977	0.977	0.886	0.886	0.930	0.930
Number of country by industry clusters	1,647	1,647	2,863	2,863	1,294	1,294
Observations (and number of units)	7,985	7,985	28,624	28,624	103,993	103,993

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) - (2) *TECH* is ln[(1+ the firm's patent stock)/employment]. In columns (3) and (4) *TECH* is computers per employee *(IT/N)* and in columns (5) and (6) *TECH* is *TFP*. 12 Countries in all columns except column (5)-(6) which is for four countries. Sample period is 2005-1996 for patents, 2007-2000 for IT, and 2005-1995 for TFP. Number of units is the number of firms in all columns except IT 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 each sample. Specifically, we classify an establishment as having exited if it drops out of the panel and does not appear for four successive years. In the other columns it is based on Amadeus company status (Appendix B) survival/exit is defined on the basis of whether a firm is recorded as either 'bankrupt', 'liquidated' or 'dormant' in the Company Status variable provided by Bureau Van Dijk..

TABLE 5: BETWEEN FIRM EFFECTS - USING CHANGES IN QUOTAS AS AN IV FOR CHINESE IMPORTS

Dependent Variable: Employment Growth, $\Delta \ln N$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Technology variable (TECH)	Patent stock	Patent stock	IT	IT	TFP	TFP
Estimation Technique	OLS	IV	OLS	IV	OLS	IV
Change in Chinese Imports	-1.068**	-3.266***	-1.119***	-2.746***	-0.433**	-4.252**
ΔIMP_{jk}^{CH}	(0.453)	(1.148)	(0.227)	(0.735)	(0.183)	(1.997)
Change in Chinese imports*technology at t-5	3.670*	3.256	1.341**	3.481**	0.157	3.317**
ΔIMP_{jk}^{CH} $*TECH_{t-5}$	(2.162)	(4.609)	(0.509)	(1.584)	(0.508)	(1.388)
Technology at t-5	0.445***	0.453***	0.239***	0.189***	0.272***	0.173***
$TECH_{t-5}$	(0.120)	(0.152)	(0.027)	(0.031)	(0.022)	(0.038)
First Stage F-Stat (ΔIMP_{jk}^{CH})		11.65 [0.000]		11.64 [0.000]		5.22 [0.006]
First Stage F-Stat (ΔIMP_{jk}^{CH} $*TECH_{t-5}$)		2.77 [0.066]		11.74 [0.000]		9.45 [0.000]
Number of Units	1,388	1,388	2,891	2,891	16,495	16,495
Number of country by industry clusters	140	140	83	83	187	187
Observations	2,377	2,377	2,891	2,891	55,791	55,791

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) and (2) *TECH* is ln[(1+ the firm's patent stock)/employment]. 12 Countries in all columns except columns (5) and (6) which is for four countries. In columns (1) and (2) only "patenting firms" (defined as a firm that had at least one European patent between 1978 and 2007) included. Sample period is 2005-1999 for patenting, 2000-2005 for IT, and 1995-2005 for TFP. Number of units is the number of firms in all columns except (3) and (4) where it is the number of plants. Sample is firms in the textile and apparel industry. All columns include country by year effects.

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 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.321*** (0.102)	0.271*** (0.098)		
Level of Chinese Imports $\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.397*** (0.168)	0.389*** (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. Dependent variable is log patents in columns (1) and (2), and patents in the Negative Binomial specification in columns 3 and 4. 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: DEP. VAR. ΔLN(PATENTS)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Change in Chinese Imports $\Delta\left(M_{jk}^{China}/D_{jk}\right)$	0.182** (0.074)	0.063 (0.125)			0.182** (0.073)		0.178** (0.077)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$		0.152 (0.128)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$			0.106*** (0.040)				
Change in High Wage Imports $\Delta\left(M_{jk}^{High}/D_{jk}\right)$				0.004 (0.019)	0.003 (0.019)		
Change in World Imports $\Delta\left(M_{jk}/D_{jk}\right)$						0.017 (0.018)	0.004 (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: DEP. VAR. Δ(IT/N)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Change in Chinese Imports $\Delta\left(M_{jk}^{China}/D_{jk}\right)$	0.129*** (0.028)	0.126*** (0.029)			0.128*** (0.028)		0.120*** (0.029)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$		0.018 (0.051)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$			0.127*** (0.025)				
Change in High Wage Imports $\Delta\left(M_{jk}^{High}/D_{jk}\right)$				0.014 (0.009)	0.002 (0.009)		
Change in World Imports $\Delta\left(M_{jk}/D_{jk}\right)$						0.024*** (0.009)	0.007 (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: DEP. VAR. ΔTFP	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Change in Chinese Imports $\Delta\left(M_{jk}^{China}/D_{jk}\right)$	0.065*** (0.020)	0.092** (0.048)			0.071*** (0.021)		0.062** (0.022)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$		-0.026 (0.041)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$			0.050*** (0.014)				
Change in High Wage Imports $\Delta\left(M_{jk}^{High}/D_{jk}\right)$				0.007 (0.006)	-0.006 (0.007)		
Change in World Imports $\Delta\left(M_{jk}/D_{jk}\right)$						0.014** (0.006)	0.002 (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%, ** denotes 5% and * denotes 10% significance. Estimation is by OLS with standard errors clustered by four-digit industry. In the first row $\Delta\left(M_{jk}^{China}/D_{jk}\right)$ is the 5-year difference in Chinese imports normalized by domestic production. In the second, fourth and fifth rows are the 5-year differences in All Low Wage Country, All High Wage Country and World Imports respectively normalized by domestic production. All specifications include country-year dummies. Panel B includes site-type dummies and employment growth. Sample is 2000-2007 for Panel B and 1996-2005 for Panels A and C.

APPENDICES: FOR ON-LINE PUBLICATION (INCLUDED HERE FOR REFEREES)

APPENDIX A: TRAPPED FACTOR MODELS: THEORY AND MEASUREMENT

A1. A Theory of Trapped Factors and Innovation

We sketch a simple model to examine the impact in the North of a removal of trade barriers against the South. Bloom, Terry, Romer and Van Reenen (2013) embed this idea within a general equilibrium model with endogenous growth. 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": 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 significant 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. [1] 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.

A2. 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-

[1] 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.

industry wage premia which, in our context will be a measure of the product-specific human capital. To do this we use 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[2] – 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. 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).

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,…,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. The estimates of the coefficients on the industries are our proxies for trapped factors.

In column (1) of Table A3 we repeat our basic patents equation from Table 1A column (1). 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. 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 A3, column (3) were 2.807(0.960) for the interaction term and 0.394 (0.068) for the linear industry wage premia term.

A3. 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 $U_i + \bar{\theta}_i S_i$. 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:

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

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:

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

If there are no trapped factors then $\bar{\theta}_i = 1$ and measured and true TFP are the same. Firms which have more trapped factors, $\bar{\theta}_i > 1$, 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.

[2] 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.

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.

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. 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 A3 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 "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.[3]

We could not find any evidence that larger firms responded more to Chinese imports. However, 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, this evidence of heterogeneity of the effect of trade on innovation is broadly consistent with the trapped factor model of Bloom et al (2013).

APPENDIX B: DATA

B1. 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 CDs 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) do and disclosure is greater for public firms than private firms. For the accounting variables (employment, wages, capital) we winsorize at the 1st and 99th percentiles.

How comprehensive is the Amadeus dataset? Since registration of some form of company accounts is a legal requirement of all incorporated firms under EU law, the list of names should be comprehensive at least from the population. Hence, the patent analysis and survival analysis (that does not require any accounting information) is unaffected by reporting of accounting items – we only require an industry code which is always available.

[3] 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.

Potentially more problematic are the employment regressions, as not all EU countries insist on reporting the number, especially for smaller firms. We investigated this issue by comparing the aggregate number of workers in Amadeus to the population numbers published by national statistical agencies and reported by Eurostat. Bloom, Sadun and Van Reenen (2013) report on this in more detail, but essentially we take six of our twelve European countries (mainly focusing on the largest: France, Germany, Ireland, Italy, Sweden and the UK) for an in-depth investigation of comparing the aggregate employment in Amadeus with Eurostat data (which uses data derived from the National Statistical Agencies). After making corrections to allow for comparability (dealing with issues of parents and subsidiaries and splitting total employment into the domestic and foreign components) we found a reasonably good match. For all countries except Ireland the aggregate numbers from Amadeus are within 10% of the aggregate from Eurostat.[4] If we re-run the employment or TFP regressions focusing only on countries where we know we achieve a close correspondence between Amadeus and Eurostat, we obtain similar results to those in the main specifications.[5]

EPO Patents Counts and matching- 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. The methodology is the same as described in Belenzon and Berkovitz (2010) except we use a more recent version of PATSTAT covering the population of patents filed from 1978 through 2007. We match the name of each EPO applicant to the population of European firm names 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). Because we are interested only in matching patent applicants to firms, we exclude applicant names that fall into the following categories: government agencies, universities, and individuals. We identify government agencies and universities by searching for a set of identifying strings in their name. We identify individuals as patents where the assignee and the inventor name are identical.

The matching procedure follows two main steps. (i) Standardizing names of patent applicants. This involves replacing commonly used strings that symbolize the same thing, for example “Ltd.” and “Limited” in the UK. We remove spaces between characters and transform all letters to capital letters. (ii) Name matching: Match the standard names of the patent applicants with Amadeus firms. If there is no match, then try to match to the old firm name available in Amadeus. We need to confront a number of issues. First, in any given year the Amadeus database excludes the names of firms that have not filed financial reports for four consecutive years (e.g., M&A, default). We deal with this issue in several ways. First, we use information from historical versions of the Amadeus database (1995–2003) on names and name changes. Second, even though Amadeus contains a unique firm identifier (BvD ID number), there are cases in which firms with identical names have different BvDEP numbers. In these cases, we use other variables for identification, e.g., address (ZIP code), date of incorporation (whether consistent with the patent application date), and more. Finally, we manually match most of the remaining corporate patents to. 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 patenter sample (the dependent variable has no variation in the non-patenters sample by definition). In order to maintain comparability we use the same sample when we show the between firm results in Table 4. Bloom et al (2011) show that we obtain similar results if we were to expand the sample and treat those firms who we did not match as zero patenters.

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.

[4] As a proportion of the Eurostat employment total, Amadeus is 90% of the total for France, 108% for Germany, 73% for Ireland, 104% for Italy and 96% for Sweden.

[5] For example, we ran the employment regressions on just France, Italy, Sweden and the UK. The coefficient(standard error) on the interaction between Chinese imports and lagged patents was 1.313(0.667) rather than 1.435(0.649) in the full sample (Table 4, Panel A, column (2)).

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).

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 most 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 A13. 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).

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 divided by the value of total world imports flowing into the same cell.

Eurostat Prodcom Production database - In Tables 1C and some columns of Table 7 we use measures of four-digit industry-level production (D_{jk}) 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.

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, the Chinese share (reflecting low wage country imported inputs) is the dominant explanatory factor.

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.

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).

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. To merge the management data into the yearly trade data we linearly interpolated scores between survey waves for the same firm. 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.

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.

B2. 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 A11 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 Amadeus data (used for the patents, TFP and employment equations) 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. 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.

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). We follow the same procedure for calculating import penetration for the alternative normalizations presented in Tables 7 and A7.

We also compare the firm's multiple industry definition results to those where we allocate each firm to a single industry (see Table A6 Panel A) and show that the results are similar. 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.

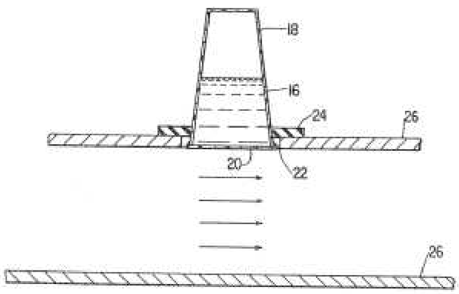
B3. Examples of patents taken out in the textiles and apparel industry

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[6] for an appropriate textile or fabric term such as "shirt", "handbag" or "cotton".

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

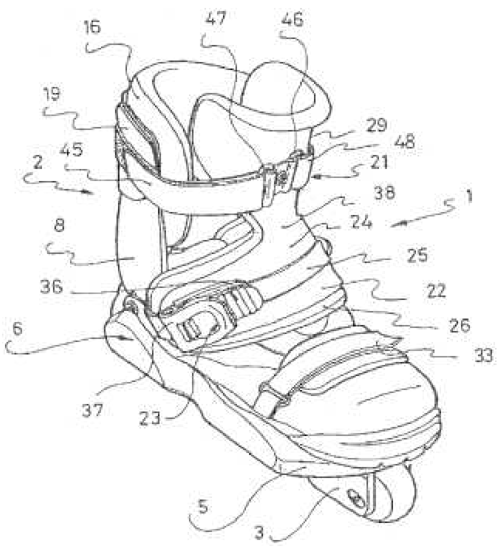
Patent EP1335063, taken out by a German firm for a "*Water vapor permeable, water-resistant composite material*"

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 that 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.



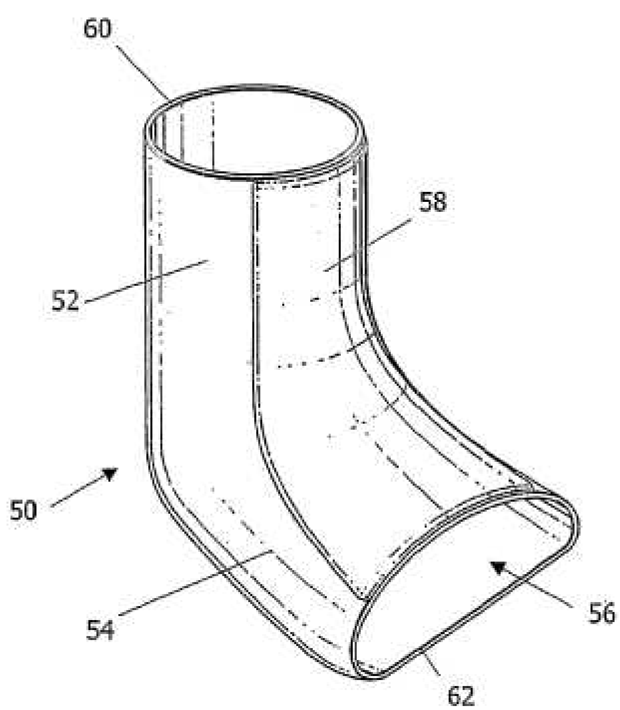
Patent: EP2082659, taken out by an Italian firm for a "*Fastening device for sports footwear*"

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

C1. 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.

C2. Construction of the Quotas 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.[7] 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. 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.

C3. Identification when using China's WTO Accession

Baseline Method

Consider the reduced form of the technology equation (abstracting away from other conditioning variables like country by time dummies, f_{kt}):

$$\ln TECH_{it} = \pi QUOTA_{it} + \eta_{it} + e_{it} \tag{C1}$$

---

[7] 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.

Where quota is the level of quotas facing firm *i* at time *t* and we hypothesize that π <0, i.e. high quotas discourage innovation because they reduce Chinese import competition. We have decomposed the error term into a truly idiosyncratic error e_{it} and an error component η_{it} that could be correlated with the variable of interest $QUOTA_{it}$ and hence bias our estimate of π. Our baseline method is to assume that $\eta_{it} = \eta_i$, i.e. we allow for firm fixed effects in levels and estimate in long differences:

$$\Delta \ln TECH_{it} = \theta \Delta QUOTA_{it} + e_{it} \tag{C2}$$

Where Δ is a five year difference. For simplicity, consider one long difference 2005 to 2000. In 2000 the level of quotas against China were $QUOTA_{i00}$ prior to China jointing the WTO in 2001. By 2005, the quota levels had effectively fallen to zero so $\Delta QUOTA_{it} = QUOTA_{i05} - QUOTA_{i00} = -QUOTA_{i00}$ and the regression becomes:

$$\Delta \ln TECH_{it} = \lambda QUOTA_{i00} + e_{it}$$

where λ = - θ > 0.

Trend-adjusted difference in difference estimator

A concern is that there remains a correlation between *QUOTA* and e_{it}, even conditional on the fixed effects. Consider a more general model with different technology trends in different industries:

$$\ln TECH_{it} = \theta QUOTA_{it} + (t * \eta_i) + e_{it}$$

For example, if the sectors with high quotas had a slower trend rate of technical change we would under-estimate the positive effect of China on innovation (and vice versa if they had faster rates of technical change). In this case estimating in differences would still not remove the bias as the true model is:

$$\Delta \ln TECH_{it} = \lambda QUOTA_{i00} + \eta_i + e_{it}$$

We can estimate such a model if we have (at least) one more long-difference in the pre-policy period. For example, consider adding an additional long difference to equation (C1), say 2000-1995. In this case $\Delta QUOTA_{i00} = QUOTA_{i00} - QUOTA_{i95} = 0$, as European quotas against China imports were basically stable over this period. Hence $\Delta QUOTA_{it} = QUOTA_{i00}$ in the later period (2005-2000) and $\Delta QUOTA_{it}$ = 0 in the earlier period (2000-1995). Thus in Table 3 columns (2) and (6) we estimate:

$$\Delta \ln TECH_{it} = \gamma \Delta z_{jt} + \eta_i + e_{it} \tag{C3}$$

Where the treatment indicator, $\Delta z_{jt} = QUOTA_{i00} * \mathrm{I}(YEAR \geq 2001)$, remains the "height" of the quotas in 2000, but we make explicit that we are interacting this with a "policy on" dummy for the post WTO period ($\mathrm{I}(YEAR \geq 2001)$). In our context, this is simply the trend-adjusted difference in difference estimator recommended by inter alia Angrist and Pischke (2008).

Generalizing the trend-adjusted difference in difference equations

We can write a generalization of the trend-adjusted difference in difference regression as:

$$\Delta \ln TECH_{it} = \chi_1 \Delta \ln TECH_{it-5} + \chi_2 \Delta QUOTA_{it} + \chi_3 \Delta QUOTA_{it-5} + \Delta e_{it}$$

Such a specification allows for the fact that there may be some true state dependence in the technology process arising from, say adjustment costs. The trend adjusted difference-in-difference estimator in equation (C3) imposes $\chi_1 = -1; \chi_2 = -\chi_3$, i.e. a double difference. In our set-up this simplifies to:

$$\Delta \ln TECH_{it} = \chi_1 \Delta \ln TECH_{it-5} + \chi_2 QUOTA_{i00} + \Delta e_{it} \tag{C4}$$

Estimating equation (C4) is very demanding on the data. First, we need to have ten years of on a firm, so this reduces the sample size. Second, the lagged dependent variable will be correlated with the error term even if e_{it} is i.i.d. (e.g. Anderson and Hsaio, 1982). The standard solution to this problem is to use lags as instruments, so in our context this means using $TECH_{it-10}$ as an instrument for $\Delta \ln TECH_{it-5}$.

Estimating the more general dynamic models of equations (C3) and (C4) helps deal with the issue of anticipation effects. Even if there was some shock element to the full effects of China's WTO accession, some firms might anticipate that China was going to join the WTO many years prior to 2001. 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, emphasise this) and an "accession" effect when China formally joins. If firms start innovating more quickly in advance of the China shock this will show up as an increase in innovation and tend to cause us to underestimate the China effect. In this case the trend adjustment protects us against spurious correlation, but could cause an underestimation of the China effect. On the other hand, if firms chose to innovate less prior to WTO accession and then did more when China joined (i.e. they strategically delayed their innovation) we would exaggerate the positive effect of China on innovation. Looking over a longer period (five year differences) mitigates the risk of this, but we can also deal with the problem directly and condition on the lagged dependent variable as in equation (C4). We control for the possibly lower innovation in the pre-accession period and identify only off larger than expected innovation in the more quota sensitive sectors in the post China period.

We show these results in Table A4. Column (1) presents the equivalent of Table 3 column (1) for the sub-sample where we are able to include the lagged dependent variable and confirms a significant effect of quota reduction on patenting. Column (2) adds the lagged dependent variable and instruments the lag with $patents_{t-10}$ as in equation (C4). The quota effect remains positive and significant with a larger magnitude. Column (3) presents the reduced form for TFP on the sample where we have data on the lagged dependent variable and column (4) includes the lagged change. We find similar results in both columns. There is no evidence of any upwards bias on the quota instrument in Table 3 from these more dynamic extensions.

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 statistically insignificant correlation between pre-WTO growth of technology and quotas. Turning first to technical change if we regress the growth of patents 2000-1995 on the quota instrument (in 2000) the coefficient (standard error) on quotas is -0.068(0.052). The standard reduced form for patent growth 2005-2000 has a coefficient on quotas of 0.264(0.088). Similarly the regression of the pre-WTO growth of TFP 2000-1995 on the quota IV has a coefficient (standard error) of -0.010(0.040) whereas the standard reduced form for TFP 2005-2000 has a coefficient (standard error) of 0.190(0.021).

Overlapping long differences

We estimate in long differences to smooth out over measurement error, reduce attenuation bias and allow for short-run dynamics. To increase efficiency we allow the five-year differences to overlap, but cluster the standard errors at the industry by country level to allow for serial correlation (and cross firm correlation within the industry-country pair). When using the quota IV we cluster at the industry level as there is no cross country within industry variation in the quotas by construction.

Intensity of treatment

Consider a single 5-year difference post China accession. In the 2005-2000 long difference, a firm/industry has been treated for 4 years (2001, the first year of accession, through 2005) and not treated for one year (2000). By contrast, for the 2004-1999 long difference a firm has been treated for three years (2001-2004) and not treated for two years. Therefore, an alternative intensity of treatment indicator is the number of years since WTO accession that will be equal to four in the 5-year difference ending in 2005, 3 in the 5-year difference ending in 2004 and so on (zero in years ending in 2000 and earlier).

APPENDIX D: CALCULATING MAGNITUDES

In Table A5 we make some crude calculations of the magnitudes of 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:

$$\Delta P_t = \sum_{i=1}^{N} s_{it} p_{ijt} - \sum_{i=1}^{N} s_{i0} p_{ij0} \qquad \text{(D1)}$$

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:

$$\Delta P_t = \sum_{i=1}^{N} s_{i0}(p_{ijt} - p_{ijo}) + \sum_{i=1}^{N}(s_{it} - s_{i0})p_{ij0} + \sum_{i=1}^{N}(s_{it} - s_{i0})(p_{ijt} - p_{ij0}) \\ - \sum_{i \in exit} s_{it}^{exit}(p_{ij0}^{exit} - \overline{p}_{jo}) + \sum_{i \in entrant} s_{it}^{entrant}(p_{ijt}^{entrant} - \overline{p}_{jt}) \tag{D2}$$

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 (D2) 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)[8]. 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:

$$\Delta P_t^{China} = \sum_{i=1}^{N} s_{i0}\alpha^{PAT}\Delta IMP_j + \sum_{i=1}^{N}(s_{it}^{between} - s_{i0})p_{ij0} + \sum_{i=1}^{N}(s_{it}^{between} - s_{i0})\alpha^{PAT}\Delta IMP_j \\ - \sum_{i \in exit} s_{it}^{exit}(p_{ij0}^{exit} - \overline{p}_{jo}) \tag{D3}$$

where α^{PAT} is the coefficient on Chinese imports in equation (1) in the main text. In Table 1 Panel A 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),

$$s_{it}^{between} = \frac{N_{i0}(1 + \alpha^N \Delta IMP_j + \gamma^{NP}\Delta IMP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1 + \alpha^N \Delta IMP_j + \gamma^{NP}\Delta IMP_j p_{ij0})} \tag{D4}$$

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 -0.434 and 1.434 respectively from column (2) in Table 4, Panel A. N_{i0} is employment in the firm.[9]

$$s_{it}^{exit} = \frac{N_{i0}(1 - \alpha^S \Delta IMP_j - \gamma^{SP}\Delta IMP_j p_{ij0})}{\sum_{i=1}^{N} N_{i0}(1 - \alpha^S \Delta IMP_j - \gamma^{SP}\Delta IMP_j p_{ij0})} \tag{D5}$$

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 4 Panel B these are -0.089

[8] 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.

[9] 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.

and 0.261. 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 the 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.[10] Similarly, for TFP we use 2% as our measure of the growth rate of TFP growth in manufacturing in recent years.[11]

The basic magnitude calculations are in Table A5. The first row considers econometric specifications from the baseline specifications and the next two rows repeat this but also consider the specifications extended to allow for offshoring. The overall contribution of China to upgrading is 14.2% for patents, 14.1% for IT and 14.7% for TFP. For patents, about one third of this (4.6%) is within firm and two-thirds reallocation (7.6% between and 2% exit). For TFP and IT, the split is two-thirds within and one third between.

Table A6 presents a further cross check on the magnitudes where we estimate all equations at the industry level and compare these with the firm level results. Panel A repeats the firm and plant level regressions of Table 1 Panel A but allocates all firms to a single industry using the main sector code (instead of multiple industries as in our baseline results). The results are very similar to Table 1. Panel B runs the regressions at the four-digit industry level. Reassuringly, we find significant effects at the industry level (which allows for within firm and between firm - entry, exit, market share shifts – effects that are similar to the simulation results in Table A5.

APPENDIX E: OTHER RESULTS

We conducted a large number of other robustness results, some of which are mentioned in the main paper and working paper (Bloom et al, 2011).

E1. Offshoring

The full results for offshoring (summarized in Table 1 Panel D and used in the magnitudes calculations in Table A5) are contained in Table A7.

E2. Alternative normalizations of Chinese Imports

The full results for the alternative normalizations of Chinese imports on domestic production and apparent consumption are in Table A9.

E3. 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 in our sample period is fundamentally 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 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

[10] 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.

[11] 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 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.[12] 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. Of course, a concern with the exclusion restriction is that the level of lagged Chinese imports may be correlated with an industry-specific unobservable that could be correlated with future changes in technology independently of China.

Column (1) of Table A8 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.[13] 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.[14] Taking Table A8 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.[15]

E4. Skills

Does China trade competition reduce the relative demand for less skilled workers? We examine this by examining changes in the college share of college-educated workers. This is only available at the industry level at the three-digit level for a small number of countries. Table A10 examines the case of the UK where we can generate a long run of data from the Labor Force Survey (see Michaels, Natraj and Van Reenen, 2013, for an analysis of more countries at the two-digit level that shows consistent results with these). Column (1) regresses the growth of the college wage bill share on the growth of Chinese imports. As expected there is a positive and significant coefficient. 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.[16] 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.

E5. Product and industry switching

A leading 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

[12] 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.

[13] 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.

[14] 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).

[15] 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).

[16] 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.

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.[17]

Table A11 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 the Table 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 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. Another disadvantage is that we do not distinguish between switches to technologically more advanced products from switches to less technologically advanced products.

E6. 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 A12 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.

E7. Alternative measures of Information and Communication Technologies

Table A13 examines alternative measures of ICT software available from the HH dataset: ERP, Database and Groupware. Greater Chinese imports are associated with more use of all of these major technologies. We separate the growth of Chinese imports into quintiles to examine evidence of non-linearities. For ERP and Databases it is the bottom quintile that appears to have significantly slower upgrading in columns (2) and (5). Groupware shows some non-linearity, although the mean is positive and significant in column (7) there is some evidence of an "inverted U" in column (8).

E8. Dynamic of adjustment

Table A14 examines alternative dynamic specifications of the effect of China on technology (we focus on our key patent results) and employment. The China effect on patents is weaker in the first two years than in years three and four. By contrast, the effect of China on imports is stronger in the first few years than in the last two years. This is as we expect: the effect of Chinese competition should affect innovation with a lag whereas it will have an immediate effect on employment. The final column puts in all the lags simultaneously. Due to the high correlation of the lag structure, the results are more imprecise, but the same basic message is clear with the largest negative effect of China on contemporaneous employment and the largest effect on innovation four years lagged.

E9. Industry specific coefficients in the production function

The industry-specific coefficients on the factor inputs that are used in the calculation of TFP are presented in Table A15.

[17] 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.

APPENDIX F: DYNAMIC SELECTION BIAS

F1. The dynamic selection problem

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

$$y_{it} = \alpha z_{it} + u_{it} + \eta_i + \varepsilon_{it} \quad \text{(F1)}$$

$$s_{it} = \pi w_{it} + u_{it} + \upsilon_{it} \quad \text{(F2)}$$

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:

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

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} [18]. 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.

F2. Bounding the Selection Bias

A recent literature in econometrics emphasizes 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 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.

F3. Control function approach for selection

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

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 in Appendix C of Bloom et al (2011).

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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				
TFP sample (Amadeus)					
Employment	79.4	333.9	30	10	84,252
Number of Observations	292,167				
Textile and Clothing Sample (Patents sample)					
Employment (long-run sample, Table 3)	1,144	8,906.3	143	1	287,000
Quota Height (% of industry output covered in 2000) - All	0.037	0.167	0	0	1.0
Quota Height (% of industry output covered in 2000) - Sectors with Quota>0	0.569	0.356	0.661	0.015	1.0
Number of Observations (long-run sample, Table 3)	14,768				

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. IT sample is HH. IT intensity is computers per worker. TFP sample is Amadeus firms in France, Italy, Spain and Sweden. Quota heights are defined as the proportion of each SIC4 industry’s HS6 (6-digit) products subject to quota restrictions prior to 2001 (products are weighted according to the value of imports in 2000).

TABLE A3: HETEROGENEITY - THE CHINA EFFECT ON INNOVATION IS GREATER FOR FIRMS WITH MORE "TRAPPED FACTORS"

Dependent Variable: Δln(PATENTS)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
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)
$\Delta IMP_{jk}^{CH} *TFP_{t-5}$						
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.

TABLE A4: CONTROLLING FOR LAGGED TECHNOLOGY

Dep. variable:	(1) **Δln(PATENTS)**	(2) **Δln(PATENTS)**	(3) **ΔTFP**	(4) **ΔTFP**
Quotas removal	0.207**	0.490***	0.201***	0.204***
*I(year>2000)	(0.098)	(0.157)	(0.038)	(0.047)
Include lagged dependent variable(t-5)?	No	Yes	No	Yes
IV lagged dependent variable?		Yes		Yes
Years				
Number of units	675	675	675	675
Number industry clusters	104	104	104	104
Observations	6,075	6,075	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 3. 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 2000 (prior to China's WTO accession) that were planned to be removed by 2005. In columns (2) we instrument $\Delta\ln(\text{PATENTS}_{t-5})$ with $\ln(\text{PATENTS}_{t-10})$. In column (4) we use TFP_{t-10} as an instrument for $\Delta\ln(\text{TFP}_{t-5})$.

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TABLE A5: MAGNITUDES

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 A6: COMPARING INDUSTRY LEVEL REGRESSIONS TO FIRM LEVEL REGRESSIONS

PANEL A. INDUSTRY-COUNTRY LEVEL

	(1)	(2)	(3)
Dependent Variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**
Change in Chinese Imports	0.368 *	0.399***	0.326***
ΔIMP_{jk}^{CH}	(0.200)	(0.120)	(0.072)
Change in employment			
Sample period	2005-1996	2007-2000	2005-1996
Country by industry clusters	1,646	2,902	1,140
Observations	6,888	7,409	5,660

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

Dependent Variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**
Change in Chinese Imports	0.171**	0.361**	0.164***
ΔIMP_{jk}^{CH}	(0.082)	(0.076)	(0.051)
Years	2005-1996	2007-2000	2005-1996
Country by industry clusters	1,578	2,816	1,018
Observations	30,277	37,500	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 column (3) which is 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 (3) which only includes France, Italy, Spain and Sweden (where we have good data on intermediate inputs). All columns include country-year effects. In column (3) 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 A7: 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 A8: USING "INITIAL CONDITIONS" AS AN INSTRUMENTAL VARIABLE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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)
Initial Condition IV		0.167***			0.124***			0.078***	
		(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

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). The Initial Conditions IV is the share of Chinese imports (in all imports) in the four-digit industry across the whole of the Europe and the US (6 years earlier) interacted with the aggregate growth in Chinese imports in Europe. 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.

TABLE A9: ALTERNATIVE NORMALIZATIONS 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 A10: 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 A11: 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 ΔIMP_{jk}^{CH}	0.138***	0.132***	0.131***		0.469***	0.466***
	(0.050)	(0.050)	(0.050)		(0.083)	(0.083)
IT intensity (t-5) $(IT/N)_{t-5}$		-0.018**	-0.018**			
		(0.007)	(0.008)			
Industry Switching				0.025***		0.023*
				(0.012)		(0.012)
Employment growth $\Delta \ln(Employment)$			-0.002			
			(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.

TABLE A12: 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 A13: ALTERNATIVE IT ADOPTION MEASURES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		ΔERP (ENTERPRISE RESOURCE PLANNING)			**ΔDATABASE**			**ΔGROUPWARE**	
Change in Chinese Imports ΔIMP_{jk}^{CH}	0.040 (0.034)			0.002 (0.070)			0.249*** (0.083)		
Highest Quintile for ΔIMP_{jk}^{CH}		0.013*** (0.005)			0.020** (0.010)			0.034** (0.014)	
2nd Highest Quintile of ΔIMP_{jk}^{CH}		0.006 (0.005)			0.030*** (0.010)			0.021 (0.013)	
3rd Highest Quintile for ΔIMP_{jk}^{CH}		0.014*** (0.005)			0.043*** (0.010)			-0.008 (0.013)	
4th Highest Quintile for ΔIMP_{jk}^{CH}		0.010** (0.005)			0.024*** (0.011)			-0.018 (0.013)	
Lowest Quintile for ΔIMP_{jk}^{CH}			-0.011*** (0.004)			-0.028** (0.009)			-0.000 (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 A14: DYNAMICS OF THE EFFECT OF CHINA ON PATENTS AND EMPLOYMENT

PANEL A: PATENTS, $\Delta\ln(PATENTS)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
5-year lag of Chinese Imports Change	0.328***						0.013
ΔIMP_{t-5}^{CH}	(0.110)						(0.163)
4-year lag of Chinese Imports Change		0.394***					0.280*
ΔIMP_{t-4}^{CH}		(0.110)					(0.149)
3-year lag of Chinese Imports Change			0.402***				-0.005
ΔIMP_{t-3}^{CH}			(0.120)				(0.178)
2-year lag of Chinese Imports Change				0.333***			0.074
ΔIMP_{t-2}^{CH}				(0.113)			(0.136)
1-year lag of Chinese Imports Change					0.314***		-0.069
ΔIMP_{t-1}^{CH}					(0.102)		(0.145)
Contemporaneous Chinese Imports Change						0.321***	0.203
ΔIMP_{t}^{CH}						(0.102)	(0.163)
Number of country-industry pairs	1,578	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	8,480
Observations	30,277	30,277	30,277	30,277	30,277	30,277	30,277
PANEL B: EMPLOYMENT, $\Delta\ln(N)$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
5-year lag of Chinese Imports Change	-0.188						-0.020
ΔIMP_{t-5}^{CH}	(0.140)						(0.197)
4-year lag of Chinese Imports Change		-0.241*					-0.028
ΔIMP_{t-4}^{CH}		(0.139)					(0.180)
3-year lag of Chinese Imports Change			-0.306**				-0.050
ΔIMP_{t-3}^{CH}			(0.155)				(0.184)
2-year lag of Chinese Imports Change				-0.275*			0.023
ΔIMP_{t-2}^{CH}				(0.160)			(0.174)
1-year lag of Chinese Imports Change					-0.285**		-0.084
ΔIMP_{t-1}^{CH}					(0.143)		(0.145)
Contemporaneous Chinese Imports Change						-0.309**	-0.210
ΔIMP_{t}^{CH}						(0.138)	(0.171)
Number of country-industry pairs	1,464	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	7,030
Observations	22,938	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 A15:
EXAMINING CROSS-INDUSTRY HETEROGENIETY IN PRODUCTION FUNCTION COEFFICIENTS.

Industry Code (US SIC 1987)	Coefficient on Labor	Coefficient on Capital	Coefficient on Materials
20 Food & Kindred Products	0.272	0.074	0.629
21 Tobacco Products	0.104	0.300	0.624
22 Textile Mill Products	0.363	0.060	0.493
23 Apparel & Other Finished	0.400	0.068	0.489
24 Lumber & Wood Products	0.353	0.060	0.552
25 Furniture & Fixtures	0.341	0.038	0.582
26 Paper & Allied Products	0.344	0.059	0.548
27 Printing, Publishing & Allied	0.489	0.043	0.435
28 Chemicals and Allied Products	0.359	0.067	0.558
29 Petroleum Refining & Related	0.325	0.121	0.449
30 Rubber & Miscellaneous Plastics	0.314	0.071	0.541
31 Leather and Leather Products	0.290	0.065	0.583
32 Stone, Clay, Glass and Concrete Products	0.323	0.080	0.543
33 Primary Metal Industries	0.324	0.075	0.520
34 Fabricated Metal Products	0.440	0.067	0.437
35 Industrial & Commercial Machinery	0.405	0.048	0.489
36 Electronic and Other Electrical	0.380	0.051	0.505
37 Transportation Equipment	0.439	0.066	0.475
38 Measurement & Control Instruments	0.420	0.075	0.455
39 Miscellaneous Manufacturing	0.366	0.066	0.534

Notes: These are the underlying industry specific coefficients used to calculate TFP in the regressions in column (3) of Table 1 and elsewhere. We use the de Loecker (2011) version of Olley-Pakes (1996) for multi-product firms.

TABLE A16: BETWEEN FIRM EFFECTS – OLS AND IV ESTIMATES FOR FIRM SURVIVAL.

Dependent Variable: *SURVIVAL*	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Method	OLS	IV	OLS	IV	OLS	IV
Sample:	PATENTS	PATENTS	IT	IT	TFP	TFP
Change in Chinese Imports	-0.183	-0.272	-0.458**	-1.090***	-0.373	-1.665*
ΔIMP_{jk}^{CH}	(0.176)	(0.268)	(0.179)	(0.383)	(0.074)	(0.949)
Change in Chinese imports*	0.482	0.641	0.007	-0.142	0.080	0.978
$TECH_{t-5}$	(0.296)	(0.407)	(0.331)	(0.654)	(0.109)	(1.107)
ΔIMP_{jk}^{CH} *$TECH_{t-5}$						
Technology at t-5	-0.029	-0.033	-0.015	-0.028*	-0.003	-0.046
$TECH_{t-5}$	(0.036)	(0.039)	(0.011)	(0.015)	(0.012)	(0.065)
First Stage F-Stat (ΔIMP_{jk}^{CH})		44.3 [0.00]		14.2 [0.00]		4.36[0.02]
First Stage F-Stat (ΔIMP_{jk}^{CH} *$TECH_{t-5}$)		25.1 [0.00]		11.1 [0.00]		47.7[0.00]
Survival Rate for Sample (mean)	0.977	0.977	0.874	0.874	0.904	0.904
No of Industry Clusters	113	113	84	84	87	87
Observations (and number of units)	1,624	1,624	5,980	5,980	52,401	52,401

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) - (2) *TECH* is ln[(1+ the firm's patent stock)/employment]. In columns (3) and (4) *TECH* is computers per employee *(IT/N)* and in columns (5) and (6) *TECH* is *TFP*. 12 Countries in all columns except column (5)-(6) which is for four countries. Sample period is 2005-1996 for patents, 2007-2000 for IT, and 2005-1995 for TFP. Number of units is the number of firms in all columns except IT where it is the number of plants. All columns include country by year effects. The dependent variable (*SURVIVAL*) refers to whether an establishment that was alive in 2000 was still alive in 2005 for the IT sample. Specifically, we classify an establishment as having exited if it drops out of the panel and does not appear for four