APPENDICES: FOR ON-LINE PUBLICATION

APPENDIX A: DATA

A1. 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) and disclosure is greater for publicly listed firms than for those with a private listing. For the accounting variables (employment, wages, capital) we winsorize at the 1^{st} and 99^{th} 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 the population. Hence, the patent 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.

Potentially more problematic are the regressions requiring employment information, as not all EU countries insist on reporting the jobs 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.[1] If we re-run the employment or TFP regressions focusing only on countries where we know we achieve a reasonably close correspondence between Amadeus and Eurostat, we obtain similar results to those in the main specifications.[2]

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 (assignee) 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

---

[1] 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.

[2] 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)).

filed financial reports in the last four consecutive years. 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 BVD 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 firms. 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.

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. 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). Specifically, we classify an establishment as having exited if it drops out of the panel and does not appear for four successive years. For the Amadeus firm-based measure we have a firm-based measure where exit is defined on the basis of whether a firm that was active in 2000 is recorded as either 'bankrupt', 'liquidated' or 'dormant' in the Company Status variable provided by BVD in 2005 and beyond. In other words, we do not include exits due to merger or takeover which may be indications of success rather than failure.

UN Comtrade - Our study uses data at the HS6 product level taken from the UN Comtrade online database. Comtrade details the value and volumes of bilateral imports and exports at the HS6 level for almost all countries. 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 Table 1 Panel C 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.

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.

A2. 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 Table A8.

We also compare the firm's multiple industry definition results to those where we allocate each firm to a single industry (see Table A5 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.

A3. Samples across regressions

The samples over which we run the regressions differs across tables and columns. Primarily this is because of the three different measures of technology that we use: patents, IT and TFP which are not available reliably for all firm-year observations. For example, firms who never patented are not included in the patent sample, and who never performed IT are not in the IT sample. TFP can, in principle be calculated for all firms, but as described above accounting data is only rich enough on all three key factors of production (labor, capital and materials) in four of these European nations (France, Italy, Spain and Sweden). Consider Table 1 to begin with. We have 30,277 observations on patents 2006-1996 because of the need to drop firms who never patent (we cannot be sure that all the missings are non-patenters rather than firms we have failed to match). We have 37,500 *plants* (not firms) in column (2) for IT 2007-2000. The plant data goes to a later year than the accounting data, but only starts in 2000. We have the largest sample for TFP in column (3) of 292,167 firms.

The sample also falls in size when we condition on the textile and apparel industries as we drop all other sectors (compare Table 2 to Table 1). It expands when we also use pre-1999 information (as in Table 3) to construct pre-WTO trends, but at the cost of losing IT which (as noted above) is only available for 2000 and the years thereafter.[3] In Table 4 and elsewhere we use employment so we have to drop observations where employment is missing. Hence, the sample size falls from 30,277 in column (1) of Table 1 to 19,844 in column (1) of Table 4A because of this restriction when we use the patents sample. Note that there are no missing values on employment for the samples used for IT and TFP so the number of observations is the same in Table 1 columns (2) and (3) as Table 4 column (3)-(6).

When we look at exit, we restrict ourselves to the cohort of firms alive in 2000. This is because the data on whether a firm truly exits (or was acquired by another firm) is not reliable for all years. Hence, the sample is smaller in Figures B of Tables 4 and 5 compared to Figure A.

We note in the text and tables when there are other departures from these rules.

[3] In principle we could use a larger number of years before 1996 in Table 1 for patents as we do in Table 3, but since we cannot do that for IT or TFP due to data constraints this would make the sample periods less comparable. Our results for patents in Table 1 are robust to doing this.

APPENDIX B: PRODUCTION FUNCTION ESTIMATION

To calculate use TFP we must first estimate production functions.[4]

The Basic Olley-Pakes Approach

Consider the basic ln(value-added), y_{it} function for firm *i* at time *t* as:

$$y_{it} = \alpha_l l_{it} + \alpha_k k_{it} + \gamma X_{jt} + \omega_{it} + u_{it} \qquad \text{(C1)}$$

Where l is ln(labor) k is ln(capital), ω_{it}, is the unobserved productivity state that will be correlated with both output and the variable input decision, and u_{it} is an independent and identically distributed (i.i.d) error term. We use the convention of lower case letters when taking the natural logarithms of a variables. X_{jt} are the other exogenous variables in the model which are common to all firms in the industry, such as the level of Chinese imports. Assume that the capital stock is predetermined and current investment, I_{it-1}, (which will react to productivity shocks) takes one period before it becomes productive, that is:

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

Where δ^K is the depreciation rate. It can be shown that the investment policy functions are monotonic in capital and the unobserved productivity state:

$$i_{it} = i_t\ (k_{it}, \omega_{it}, X_{jt}) \qquad \text{(C2)}$$

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

$$\begin{aligned} y_{it} &= \alpha_l l_{it} + \alpha_k k_{it} + \gamma X_{it} + \omega_t\ (i_{it}, k_{it}, X_{jt}) + u_{it} \\ &= \alpha_l l_{it} + \varphi(i_{it}, k_{it}, X_{jt}) + u_{it} \end{aligned} \qquad \text{(C3)}$$

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

$$y_{it} - \alpha_l l_{it} = \alpha_k k_{it} + \gamma X_{jt} + \omega_{it} + u_{it} \qquad \text{(C4)}$$

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

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

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

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

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

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

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

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

So returning to the second stage coefficient of interest:

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

Including the shocks we have:

---

[4] For expositional simplicity we just have labor as the single variable input, but in the empirical estimates we also include materials which we treat symmetrically with the labor input and use output as the dependent variable.

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

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

Our Implementation of Olley and Pakes

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

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

We estimate the regression coefficients in the production function separately for each two digit industry with the results presented in Table A15. When using lagged TFP on the right hand side of the employment growth and survival regressions we always express this relative to the industry average and smooth by averaging over t-5 an t-6 to reduce measurement error.

We do not have information on skill groups at the firm level so our baseline estimates just use employment as the labor input. However, we also experimented with using wage bill (rather than employment) as a measure of labor services, *L*. The idea is that wages reflect the different skill levels of workers in the firm, so multiplying the quantity of labor by its wage reflects the full value of labor services. Results are robust to this alternative specification.

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

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 main paper 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 gives 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.[5] 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. As noted in the main text and shown in Table A3 there is no correlation between the toughness of the quotas in 2000 and the changes in industry technology, size, capital intensity or wages in the pre-2000 period (the years leading up to Chinese accession).

In specifications where we use just the textiles and apparel sub-sample (e.g. Tables 2,3 and 5) we use all four digit sectors in the 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 (ignoring for simplicity the industry-country (*jk*) sub-scripts and abstracting away from country by time dummies, f_{kt}):

$$\ln TECH_{it} = -\pi QUOTA_{it} + \eta_{it} + e_{it} \qquad \text{(C1)}$$

[5] 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 $QUOTA_{it}$ is the toughness 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:

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

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:

$$\Delta \ln TECH_{it} = \pi QUOTA_{i00} + \Delta e_{it} \,.$$

Trend-adjusted difference in difference estimator

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

n EMBED Equation.DSMT4 $$\ln TECH_{it} = -\pi QUOTA_{it} + (t * \eta_i) + e_{it}$$

For example, if the sectors with tougher 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:

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

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:

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

Where the treatment indicator, $\Delta z_{jt} = QUOTA_{i00} * \mathrm{I}(YEAR \geq 2001)$, remains the toughness 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).

An alternative dynamic model

An alternative dynamic representation of the technology equation is:

$$\Delta \ln TECH_{it} = \chi_1 \Delta \ln TECH_{it-5} + \chi_2 \Delta QUOTA_{it} + \chi_3 \Delta QUOTA_{it-5} + \Delta \xi_{it} \tag{C4}$$

Such a specification allows for the fact that there may be some true state dependence in the technology process (χ_1 >0) arising from, say adjustment costs. Note if the true model was as equation (C3) then the trend adjusted difference-in-difference estimator in equation (C3) imposes $\chi_1 = 1; \chi_2 = -\chi_3$, i.e. a double difference. In the context of equation (C4) this simplifies to:

$$\Delta \ln TECH_{it} = \chi_1 \Delta \ln TECH_{it-5} + \chi_2 QUOTA_{i00} + \Delta \xi_{it} \tag{C5}$$

Estimating equation (C5) is very demanding on the data. First, we need to have at least ten years data of on a firm, so this reduces the sample size. Second, the lagged dependent variable will be correlated with the error term even if ξ_{it} is serially uncorrelated (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 $\Delta \ln TECH_{it-5}$. However, if the true underlying model does have a firm-specific trend as in equation (C3) then equation (C4) has $\Delta\xi_{it} = \Delta\Delta e_{it}$. In this case $TECH_{it-10}$ is invalid even if e_{it} is serially uncorrelated. In principle even longer dated lags of $TECH$ could be used as instruments, but we do not have empirical data of this length. Hence equation (C5) should be regarded as an alternative dynamic specification rather than nesting (C3).

Estimating the more general dynamic models of equations (C3) and (C5) potentially helps to 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 (C5). 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 (C5). 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 this table.

A second approach is to examine directly whether quotas are correlated with pre-WTO accession trends in technology or Chinese imports. As discussed in the text and Table A3 there is no evidence for this.

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.

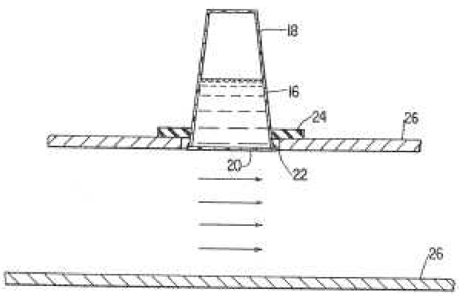
Intensity of treatment
Consider a single 5-year difference post China accession. In the 2005-2000 long difference, a firm/industry has been treated for 4 years (2001, the first year of accession, through 2005) and not treated for one year (2000). By contrast, for the 2004-1999 long difference a firm 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). This is shown in Table 3 columns (3), (4), (7) and (8).

C4. 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".

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

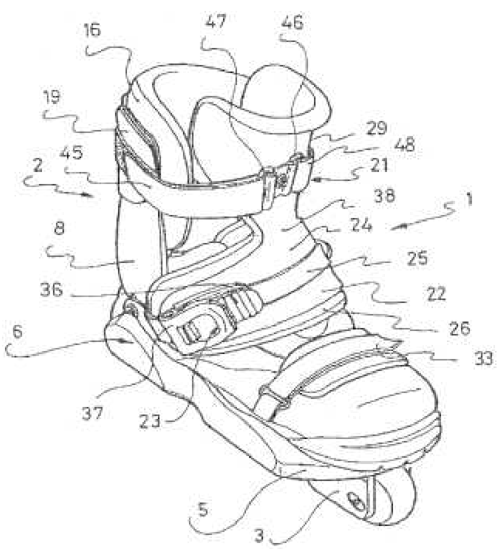
[6] http://worldwide.espacenet.com/quickSearch?locale=en_EP

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.



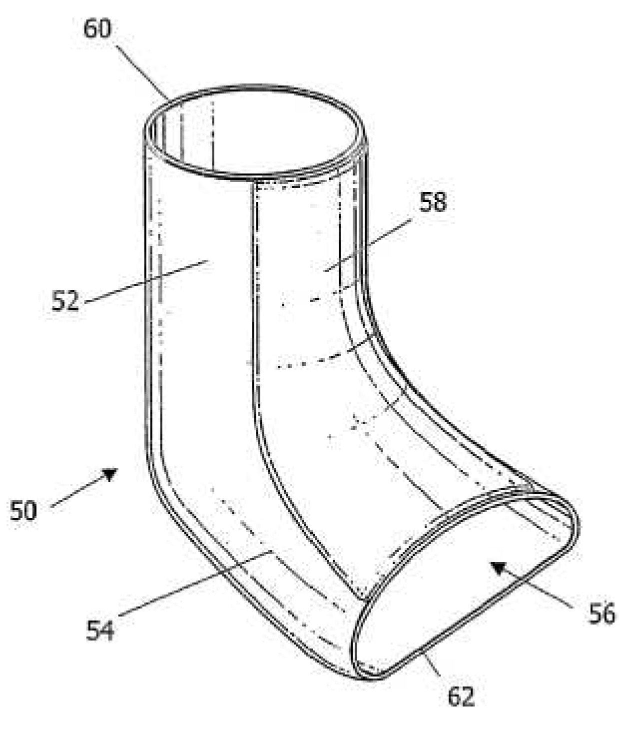
Patent: EP2082659, taken out by an Italian firm for a "*Fastening device for sports footwear*"

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 D: CALCULATING MAGNITUDES

In Table 6 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:

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

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:

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

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)[7]. The fourth term is the *exit* component (the impact of the relative technology level of exiting firms versus incumbent firms) and the final term the *entry* component (the impact of technology level of entering firms versus incumbent firms). As noted in the text, we cannot directly model entrants because we do not observe their lagged technology levels. In the paper, we can indirectly examine the effect of entry by comparing the industry level estimates to the four components we can identify.

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

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

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 (see below) and s_{it}^{exit} is the predicted share of employment in exiting firms,

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

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

where α^N is the coefficient on Chinese imports in the employment growth equation (equation (3) in the main text) and γ^{NP} the coefficient on Chinese imports interacted with the technology variable. The values of these are -0.434 and 1.434 respectively from column (2) in Table 4, Panel A. N_{i0} is employment in the firm.[8]

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

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 and 0.261. Note that in equation (D5) 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.[9] Similarly, for TFP we use 2% as our measure of the growth rate of TFP growth in manufacturing in recent years.[10]

The basic magnitude calculations are in Table 6. 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 13.9% for patents, 14.1% for IT and 12.5% for TFP. For patents, about one third of this (5.1%) is within firm and two-thirds reallocation (6.7% between and 2.1% exit). For TFP and IT, the split is two-thirds within and one third between.

Table A5 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 6.

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

[9] 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.

[10] 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, Table 12 for the EU-12).

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 6) 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 A8.

E3. Low Wage and High Wage Countries

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 A9 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 A9 includes the growth of imports from high wage countries. The coefficient is positive in all panels, but insignificant. High wage imports are also easily dominated by Chinese imports when both are included in column (5). Column (6) uses total import penetration that is positive but again dominated by China in column (7). One concern is that the endogeneity bias may be greater for high wage country imports than Chinese imports. We followed Bertrand (2004) and used trade-weighted exchange rates as an instrument that, although generally significant in the first stages, did not qualitatively change any of our results.[11]

Taken as whole Table A9 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.

E4. 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 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

[11] 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).

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. The results are in Table 8 in the main text.

E5. 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, 2014, 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.[13] 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.

E6. 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 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.[14]

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

[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] 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.

[14] 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.

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.

E7. 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.

E8. Alternative measures of Information and Communication Technologies

Table A13 examines alternative measures of ICT software available from the HH dataset: ERP (Enterprise Resource Planning), 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. Quintiles are included as separate dummy variables. 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).

E9. 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.

E10. R&D and Management

We consider two other technological change measures in Table A16: Research and Development (R&D) expenditures and management practices. Increases in Chinese imports are also significantly and positively associated with changes both of these measures

R&D is 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).

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, Sadun and Van Reenen, 2014). 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.

APPENDIX F: DYNAMIC SELECTION BIAS AND WORST CASE LOWE BOUNDS

F1. The dynamic selection problem

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

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

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

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

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

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

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 the abolition of quotas) and the other (industry 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}.[15] Instead, we place a lower bound on the selection 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. This analysis is contained in Table 7.

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

APPENDIX BIBLIOGRAPHY

Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith and Peter Howitt (2005) "Competition and Innovation: An Inverted U Relationship", *Quarterly Journal of Economics*, 120(2): 701-728.

Amiti, Mary, and Caroline Freund (2010) "An Anatomy of China's Export Growth", in Robert Feenstra and Shang-Jin Wei (eds) *China's Growing Role in World Trade*, Chicago Press.

Anderson, Theodore W and Cheng Hsiao (1982) "Formulation and Estimation of Dynamic Models Using Panel Data", *Journal of Econometrics*, 18(1): 47-82.

Angrist, Joshua and Steve Pischke (2008) *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton: Princeton University Press.

Auer, Raphael and Andreas Fischer (2010) "The Effect of Low Wage Import Competition on US Inflationary Pressure", *Journal of Monetary Economics*, 57(4),491-503.

Bailey, Martin, Charles Hulten and David Campbell (1992) "Productivity Dynamics in Manufacturing Firms", *Brookings Papers on Economic Activity: Microeconomics*, 4: 187-267.

Belenzon, Sharon and Tomer Berkovitz (2010) "Innovation in Business Groups", *Management Science* 56(3): 519-535.

Bernard, Andrew, Bradford Jensen and Peter Schott (2006) "Survival of the Best Fit: Exposure to Low-wage Countries and the (uneven) Growth of US Manufacturing Establishments", *The Journal of International Economics*, 68(1): 219-237.

Bernard, Andrew, Stephen Redding and Peter Schott (2010) "Multi-product Firms and Product Switching", *American Economic Review,* 100(1): 70-97.

Bertrand, Marianne (2004) "From Invisible Handshake to the Invisible Hand? How Import Competition Changes the Employment Relationship", *Journal of Labor Economics*, 22(4):723-765.

Bloom, Nicholas, Paul Romer, Stephen Terry and John Van Reenen (2013) "A Trapped Factor Model of Innovation", LSE/Stanford mimeo http://www.stanford.edu/~nbloom/TF.pdf

Bloom, Nicholas and John Van Reenen (2007) "Measuring and Explaining Management Practices across Firms and Countries", *Quarterly Journal of Economics*, 122(4), 1341-1408.

Bloom, Nicholas, Raffaella Sadun and John Van Reenen (2014) "Management as a Technology" *LSE mimeo* http://cep.lse.ac.uk/textonly/_new/staff/vanreenen/pdf/mat_2013dec1.pdf

Blundell, Richard, Rachel Griffith and John Van Reenen (1999) "Market Share, Market Value and Innovation", *Review of Economic Studies* 66(3): 529-554.

Brambilla, Irene, Amit Khandewal and Peter Schott (2010) "China's Experience under the Multi-Fiber Agreement (MFA) and the Agreement on Textile and Clothing (ATC)", in Robert Feenstra and Shang-Jin Wei (eds) *China's Growing Role in World Trade*, Chicago: Chicago University Press.

Card, David (2001) "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration", *Journal of Labor Economics*, 19(1): 22-64.

Constantini, James and Melitz, Marc (2008) "The Dynamics of Firm-Level Adjustment to Trade Liberalization", in Elhanan Helpman; David Marin and Thierry Verdier (eds) *The Organization of Firms in a Global Economy*, Cambridge: Harvard University Press.

Feenstra, Robert and Gordon Hansen (1999) "The Impact of Outsourcing and High-technology Capital on Wages: Estimates for the US, 1979-1990", *Quarterly Journal of Economics,* 114(3): 907-940.

Goldberg, Pinelopi, Amit Khandewal, Nina Pavcnik and Petia Topalova (2010a) "Multi-product Firms and Product Turnover in the Developing World: Evidence from India." *Review of Economics and Statistics*, 92(4), 1042-1049.

Goldberg, Pinelopi, Amit Khandewal, Nina Pavcnik and Petia Topalova (2010b) "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India", *Quarterly Journal of Economics*, 125(4), 1727-1767.

Holmes, Thomas and John Stevens (2010) "An Alternative Theory of the Plant Size Distribution with an Application to Trade", mimeo University of Minnesota.

Honoré Bo and Kyriazidou, Ekaterini (2000) "Panel Data Discrete Choice Models with Lagged Dependent Variables" *Econometrica*, 68, 839-874

Krueger, Alan and Summers, Lawrence (1988) "Efficiency Wages and the Inter-industry Wage Structure". *Econometrica,* 56(2), 259-93.

Manski, Charles (1994): "The Selection Problem," in *Advances in Econometrics, Sixth World Congress*
Michaels, Guy, Ashwini Natraj and John Van Reenen (2014) "Has ICT Polarized Skill Demand? Evidence from 11 Countries Over 25 Years". *Review of Economics and Statistics*. 96(1) 60–77
Pierce, Justin and Peter Schott (2010) "Concording US Harmonized System Codes Over Time", Mimeo, Yale University
Spinanger, Dean (1999) "Textiles beyond the MFA Phase out" *World Economy*, 22(4) 455-476
Wooldridge, Jeff (1995) "Selection Corrections for Panel Data Models under Conditional Mean Independence Assumptions*," Journal of Econometrics* 68, 115-132

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 included here are the 12 used in the regressions (Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK) as well as 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	Standard Deviation	Median
Patenters sample - Firms with at least one EPO patent since 1978			
Number of Patents (per firm-year)	1.022	10.40	0
Employment	739.5	6,526.7	100
Number of Observations	30,277		
IT sample (Harte-Hanks)			
Number of Employees	248.3	566.1	140
IT Intensity (computers per worker)	0.580	0.385	0.398
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
Number of Observations	292,167		
Textile and Clothing Sample (Patents sample)			
QUOTA (% of industry output covered by quotas in 2000) - All	0.037	0.167	0
QUOTA (% of industry output covered by quotas in 2000) - Sectors with Quota>0	0.569	0.356	0.661
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: NO SIGNIFICANT CORRELATION BETWEEN QUOTAS IN 2000 AND PRE-2000 TRENDS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δln(PATENTS)	**Δln(TFP)**	**Δln(Output/ Labor)**	**Δln(Capital/ Labor)**	**Δln(Materials/ Labor)**	**Δln(Labor)**	**Δln(Capital)**	**Δln(Wages)**
QUOTA	-0.263	0.010	0.006	0.059	0.068	-0.053	0.001	0.032
	(0.195)	(0.023)	(0.041)	(0.071)	(0.054)	(0.035)	(0.073)	(0.023)
Observations	203	115	115	114	116	113	117	116

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by SIC4 industry) in parentheses. The dependent variable is the toughness of quotas in 2000. “Quota removal” (QUOTA) 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 right hand variable denoted at the head of the column is in five year long difference 1995 to 2000. Country dummies included. An observation is a county by industry pair in the textiles and apparel industry for our 12 European countries.

TABLE A4: CONTROLLING FOR LAGGED TECHNOLOGY

	(1)	(2)	(3)	(4)
Dep. variable:	**Δln(PATENTS)**	**Δln(PATENTS)**	**ΔTFP**	**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?	No	Yes	No	Yes
Years	2005-1995	2005-1995	2005-1995	2005-1995
Number of units	675	675	675	675
Number of 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 (QUOTA) 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 Δln(PATENTS $_{t-5}$) with ln(PATENTS $_{t-10}$). In column (4) we use TFP_{t-10} as an instrument for Δln(TFP $_{t-5}$).

.

TABLE A5: COMPARING INDUSTRY LEVEL REGRESSIONS TO FIRM LEVEL REGRESSIONS

PANEL A. INDUSTRY-COUNTRY LEVEL

	(I) Full Sample OLS Estimates			(II) Quota Industries Sample, IV Estimates.		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**
Change in Chinese Imports	0.368 *	0.399***	0.326***	6.970***	7.038**	1.712**
ΔIMP_{jk}^{CH}	(0.200)	(0.120)	(0.072)	(2.220)	(2.950)	(0.772)
Sample period	2005-1996	2007-2000	2005-1996	2005-1999	2005-2000	2005-1999
Industry clusters	1,646	2,902	1,140	83	83	73
F-statistic				20.1	20.5	11.98
Observations	6,888	7,409	5,660	624	513	625

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

Dependent Variable:	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(TFP)**
Change in Chinese Imports	0.171**	0.361**	0.164***	1.570***	1.851***	1.630***
ΔIMP_{jk}^{CH}	(0.082)	(0.076)	(0.051)	(0.753)	(0.400)	(0.326)
Years	2005-1996	2007-2000	2005-1996	2005-1999	2005-2000	2005-1999
Country by industry clusters	1,578	2,816	1,018	83	83	73
Observations	30,277	37,500	241,810	3,149	2,891	19,669

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. The industry clusters are *country-SIC4 industry* for Panel I and SIC4 industry for Panel II Panel A uses data aggregated to the industry by country level and panel B is the firm level equivalent specification with firms allocated to a single industry (except columns (2) and (5) which are plant level). Coefficients estimated by OLS in five-year differences with standard errors (clustered by industry-country pair) in parentheses below coefficients. Chinese imports are measured by the value share of Chinese imports in total imports. There are 12 countries in all columns except (3) which only includes France, Italy, Spain and Sweden (where we have good data on intermediate inputs). All columns include country-year effects. In columns (3) and (6) 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 A6: MAGNITUDES USING INSTRUMENTAL VARIABLE COEFFICIENTS

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
2000-2007	28.6	27.9	0.5	57.1

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

Period	Within	Between	Exit	Total
2000-2007	27.5	26.5	0.6	54.5

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

Period	Within	Between	Exit	Total
2000-2007	22.2	15.6	0.5	38.3

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 we report the same results following methodology in Appendix D but using the IV coefficients from Tables 2 and 5 to impute the within, between and total impacts of Chinese import competition on European technology as discussed in sub-section IV.E. We use the baseline "product market" version of the regressions. Note that the magnitudes are larger because (i) the OLS estimates are bigger in the textiles and clothing sub-sample than the overall industry and (ii) the IV estimates are larger than the OLS estimates.

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 A. 12 countries in all columns except for TFP models which is for four countries. Columns(1)-(3) repeat the results reported in Table 1 Panel D. Columns (4)-(6) repeat the analysis of employment changes in Table 4 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 4, Panel B) with a control for offshoring (and its interaction with lagged technology). All columns include country by year effects.

TABLE A8: 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 A9: LOW WAGE COUNTRY AND HIGH WAGE COUNTRY IMPORTS

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

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

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

Notes: *** denotes 1%, ** 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.

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, Δln(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, Δln(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: RESEARCH AND DEVELOPMENT (R&D) AND MANAGEMENT AS TWO OTHER PROXIES OF TECHNOLOGICAL UPGRADING

	(1)	(2)
Dependent variable:	**Δln(R&D)**	**ΔMANAGEMENT**
Estimation method	**5 year diffs**	**3 year diffs**
Change in Chinese Imports	1.213**	0.814***
ΔIMP_{jk}^{CH}	(0.549)	(0.314)
Sample period	2007-1996	2010-2002
Number of Firms	459	1,576
Number of country by industry clusters	196	579
Observations	1,626	3,607

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses (except columns (3) and (5) which are three-digit industry by country). All changes are in five-year differences, e.g. ΔIMP_{jk}^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair (except column (2) which is in three-year long differences). *Management* is the average score on the 18 Bloom and Van Reenen (2007) management questions around monitoring, targets and incentives. In column (2) 12 countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Column (1) only includes France, Germany, Italy, Ireland, Sweden and the UK. Standard survey noise controls such as interviewer dummies and interview/interviewee controls (e.g. tenure in firm) are included in column (2) as in Bloom and Van Reenen (2007).