Review of Economic Studies (2016) **83**, 87–117 doi:10.1093/restud/rdv039

Advance access publication 17 September 2015

Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity

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First version received August 2012*; final version accepted January* 2015 (*Eds.*)

We examine the impact of Chinese import competition on broad measures of technical change—patenting, IT, and TFP—using new panel data across twelve European countries from 1996 to 2007. In particular, we establish that the *absolute* volume of innovation increases within the firms most affected by Chinese imports in their output markets. We correct for endogeneity using the removal of product-specific quotas following China's entry into the World Trade Organization in 2001. Chinese import competition led to increased technical change *within firms* and reallocated employment *between firms* towards more technologically advanced firms. These within and between effects were about equal in magnitude, and account for 14% of European technology upgrading over 2000–7 (and even more when we allow for offshoring to China). Rising Chinese import competition also led to falls in employment and the share of unskilled workers. In contrast to low-wage nations like China, developed countries had no significant effect on innovation.

Key words: China, Technical change, Trade, Firm survival, Employment

JEL Codes: O33, F14, L25, L60

1. INTRODUCTION

A vigorous political debate is in progress over the impact of globalization on the economies of the developed world. China looms large in these discussions, as her exports grew by over 15% per year in the two decades up to the Great Recession of 2007–9. One major benefit of Chinese trade had been lower prices for manufactured goods. We argue in this article that increased Chinese trade has also induced faster technical change from both innovation and the adoption of new technologies, contributing to productivity growth. In particular, we find that the *absolute* volume of innovation (not just patents per worker or productivity) increases *within* the firms more affected by exogenous reductions in barriers to Chinese imports. We distinguish between the impact of import competition on technology through a within firm effect and a between firm (reallocation) effect, and find that both matter.

Several detailed case studies such as Bartel *et al.* (2007) on American valve-makers; Freeman and Kleiner (2005) on footwear; or Bugamelli *et al.* (2008) on Italian manufacturers show firms innovating in response to import competition from low-wage countries. A contribution of our article is to confirm the importance of low-wage country trade for technical change using a larger more representative sample of firms and plants.

A major empirical challenge in determining the causal effect of trade on technical change is the presence of unobservable technology shocks. To tackle this endogeneity issue we use China's entry into the World Trade Organization (WTO) in 2001 and the subsequent elimination of most quotas in the ensuing years under the Agreement on Clothing and Textiles (formerly the Multi-Fiber Agreement (MFA)). These sectors are relatively low tech, but were still responsible for over 31,000 European patents in our sample period. Importantly, our data allow us to trace the responses of firms to the relaxation of the quotas, allowing us to isolate the immediate, quota-related impacts of increased Chinese import competition from expectations that firms may have built up about the policy prior to 2001.

We present two core results. First, on the intensive margin, Chinese import competition increases innovation *within* surviving firms. Firms facing higher levels of Chinese import competition create more patents, raise their IT intensity, and increase their overall level of Productivity. They also increase R&D, management quality and skill levels, and reduce prices and profitability. Second, Chinese import competition reduces employment and survival probabilities in low-tech firms. Firms with lower levels of patents or TFP shrink and exit much more rapidly than high-tech firms in response to Chinese competition. Thus, our article jointly examines the effects of trade on survival/selection and innovation. The combined impact of these within and between firm effects causes technological upgrading in those industries most affected by Chinese imports. We focus on China both because it is the largest developing country exporter, and because China's accession to the WTO enables us to plausibly identify the causal effects of falling trade barriers. However, we also show results for imports from all other developing countries, and find a similar impact on technical change. In contrast, imports from developed countries appear to have little or no impact on technology.

We also offer some back of the envelope quantification of Chinese import effects on technical change. Over 2000–2007 China appeared to account for almost 15% of the increase in patenting, IT, and productivity. Furthermore, this effect is approximately doubled when we incorporate offshoring and allow for endogeneity. These results suggest that trade with emerging nations such as China may now be an important factor for technical change and growth in richer countries.

Our article relates to several literatures. First, there is a large literature on the relationship between trade and productivity. Although many papers have found that trade liberalization increases aggregate industry productivity,[1] the mechanism through which this occurs remains poorly understood. The literature focuses on reallocation effects, i.e., how trade induces a shift in output from less productive towards more efficient firms (e.g., Melitz, 2003; Melitz and Redding, 2013). However, the empirical evidence shows that *within* incumbent firm productivity growth typically accounts for at least as much as these *between*-firm reallocation effects. This evidence tends to be indirect since explicit measures of technical change are generally unavailable at the

1. See, for example, Pavcnik (2002), Trefler (2004), and Dunne *et al.* (2008).

micro-level.[2] A contribution of the article is to use direct measures of technological upgrading at the firm and plant level such as patents and IT. The within-firm effects could be due to innovation (firms make products or processes that are new to world and shift the global technology frontier) or "compositional" (a firm changes its product mix without innovating in this sense). We consider these alternative approaches in turn.

Innovation models have been a mainstay of the theoretical literature for many years.[3] Bloom *et al.* (2015) show how the Chinese accession to the WTO could in theory reduce the opportunity cost of innovating by releasing factors of production "trapped" in producing old goods. However, there are several alternative models of how reducing trade barriers against low-wage country goods could induce Northern innovation. First, lowering import barriers increases competitive intensity and such competition could benefit innovation through reducing agency costs (e.g., Schmidt, 1997), increasing the incentive to gain market share (Raith, 2003), or lowering cannibalization of existing profits.[4] However, there is a fundamental Schumpeterian force that competition lowers price-cost margins, thereby reducing the quasi-rents from innovation, so the effect of competition on innovation incentives is inherently ambiguous (Aghion *et al.*, 2005). A second class of innovation models stresses the importance of trade in increasing market size and fostering innovation through this market expansion effect.[5] Lower trade costs generate a larger market size over which to spread the fixed costs of investing in new technologies.[6] This works through export market expansion into China. Third, imports could enhance innovation by enabling domestic firms to access overseas' knowledge (e.g., Coe and Helpman, 1995 or Acharaya and Keller, 2008). This may occur through the imports of intermediate inputs and supply networks (e.g., Goldberg *et al.*, 2010a, 2010b).[7] These mechanisms do not seem appropriate in the Chinese context however, as European firms have (currently) a large technological lead over China.[8]

The other main strand of the trade and productivity literature is more focused on compositional effects. Consider a framework where we keep the menu of products fixed in the economy. When trade barriers fall between the EU/US and China, the high-tech industries will grow relatively faster than low-tech industries in the EU/US. The opposite will occur in China. On empirical grounds, this simple framework is unsatisfactory, as most of the aggregate changes we observe following trade liberalization have occurred *within* rather than *between* industries. This could be explained, however, by firms operating in more finely disaggregated industries and we will show that there are strong reallocation effects whereby low-tech firms tend to shrink and exit because

2. For low-wage countries, Bustos (2011) finds positive effects on innovation from lower export barriers for Argentinean firms and Teshima (2008) finds positive effects on process R&D from lower output tariffs for Mexican firms. The only study of Southern trade on Northern innovation is Lelarge and Nefussi (2008), who find that the R&D of French firms reacts positively to low-wage country imports.

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

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

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

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

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

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

of China. Bernard *et al.* (2006) show a similar result for US plants using proxies for technologies such as capital intensity.

We report that China induces faster technical change *within firms* and *plants*, a finding that goes beyond the existing results. In principle, firm TFP increases could be accounted for by two factors not strictly related to innovation: changes in a firm's product portfolio or offshoring. First, on product switching, Bernard *et al.* (2010) investigate the impact of trade liberalization in heterogeneous multi-product firms. In the face of falling trade costs with a low-wage country such as China, Northern firms shift their product mix towards more high-tech products (see Bernard *et al.*, 2007). We investigate this mechanism by examining how plants change their product classes, and find evidence for this. Second, a fall in trade costs with China will mean that producers of goods that can use Chinese intermediate inputs will benefit. For example, firms may slice up the production process and offshore the low tasks to China (see, e.g., Grossman and Rossi-Hansberg, 2008). This will have a compositional effect if the remaining activities in the home country are more technologically advanced. To investigate this mechanism we look explicitly at offshoring to China using a method introduced by Feenstra and Hanson (1999).

Although we will show evidence that both product switching and offshoring are important in our data, neither can fully explain our core findings. In particular, a large fraction of the China-induced increase in innovation comes from expanding the volume of patents within firms. This implies that changing composition can only be part of the story—firms are adding products that are new to the world, not simply shifting around product portfolios that already exist in the world.

Our work is also related to the literature on skill biased technical change. We find a role for trade with low-wage countries in increasing skill demand (at least since the mid-1990s) through inducing technical change.[9] The rise of China and other emerging economies such as India, Mexico, and Brazil has also coincided with an increase in wage inequality and basic trade theory predicts such South-North integration could cause this. Despite this, the consensus among most economists was that trade was less important than technology in explaining these inequality trends (e.g., Machin and Van Reenen, 1998), in part because this work used data up to the mid-1990s, which largely predates the rise of China (see Figure 1).[10] More recent work (Autor *et al.*, 2013) finds a substantial impact of China in reducing US employment since 2000, particularly among low-skilled workers.

The structure of the article is as follows: Section 2 describes the data, Section 3 details the empirical modelling strategy, Section 4 describes our results, and Section 5 discusses some extensions and robustness tests. Section 6 concludes.

2. DATA

We combine a number of rich datasets on technical change give an overview here (details in online Appendix A and a replication file available on http://www.stanford.edu/~nbloom/TITC.zip). Our base dataset is Bureau Van Dijk's (BVD) Amadeus that contains close to the population of public

9. Technological forces also have an effect on trade. For example, better communication technologies facilitate offshoring by aiding international coordination. This is another motivation for addressing the endogeneity issue. Additionally, there is the direct impact on local employment and welfare (e.g., Autor *et al.*, 2015).

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

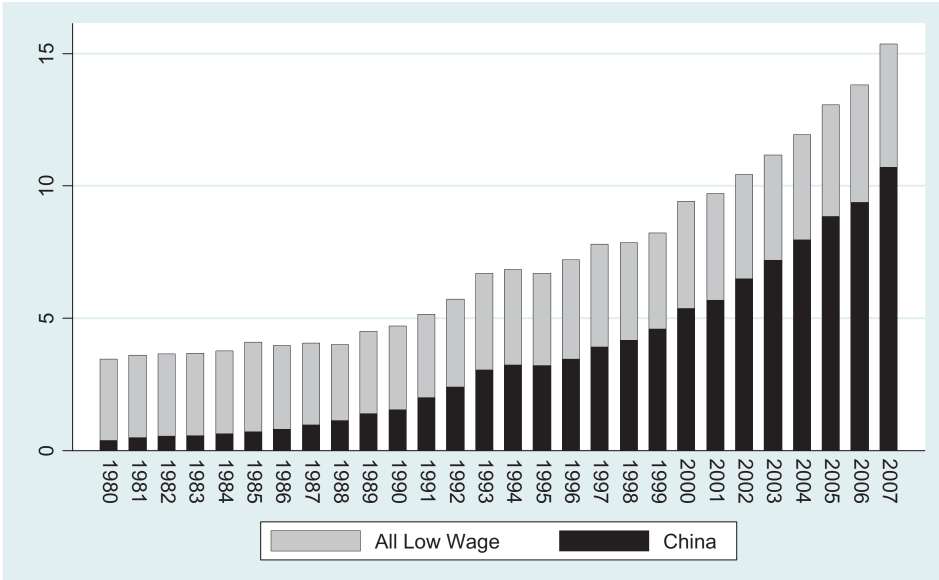

FIGURE 1

Share of all imports in the EU and US from China and all low-wage countries

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

and private firms in twelve European countries.[11] Firms in Amadeus have a list of primary and secondary four-digit industries which we use to match in the industry level trade data (the average firm had two primary codes, but some had as many as ten primary and eleven secondary codes). In our main results we use a weighted average of Chinese imports across all industries that the firm operates in, but we also present robust results where we allocate the entire firm's output to a single industry.

2.1. *Patents*

We combined Amadeus with the population of patent applications to the European Patent Office (EPO) through matching by name. Patent counts have heterogeneous values so we also use future citations to control for patent quality in some specifications. We consider both a baseline sample of "patenters"—Amadeus firms filing at least one EPO patent since 1978—and a wider sample where we assume that the firms unmatched to the EPO had zero patents. Patents data are obtained from the electronic files of the EPO that began in 1978. We take all the patents that were granted to firms and examine the assignee names. We match these to the population of firms in Amadeus (i.e., we do not insist that we have any accounting data in Amadeus when doing the matching to obtain the maximum match). The matching procedure was based on names and location, with details given in Belenzon and Berkovitz (2010). Patents are dated by application year to measure the formal invention year of the patent.

11. The twelve countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland, and the UK.

2.2. *Productivity and exit*

Amadeus contains accounting information on employment, capital, materials, wage bills, and sales. We calculate TFP using firms in France, Italy, Spain, and Sweden because of their near population firm coverage and inclusion of intermediate inputs (materials is not a mandatory accounting item in other countries) which is needed to estimate "three-factor" (labour, capital, and materials) TFP. We estimate TFP in a number of ways, but our core method is to use a version of the Olley and Pakes (1996) method applied by De Loecker (2011) to allow for trade and imperfect competition with multi-product firms. In the first stage, we estimate production functions separately by two digit industry across approximately 1.4 million observations to recover the parameters on the factor inputs.[12] We then estimate TFP and, in the second stage regression relate this to changes in the trade environment. As a robustness test we also allowed the production function coefficients to be different by country and industry as well as estimated at a finer level of industry aggregation which show similar results. Details of this procedure are contained in online Appendix B.

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

2.3. *Information technology*

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

The fact that HH sells this data on to firms who use this for sales and marketing exerts a strong discipline on the data quality, as errors would be quickly picked up by clients in their sales calls. HH samples all firms with over 100 employees in each country. Thus, we do lose smaller firms, but since we focus on manufacturing the majority of employees are in these larger firms, and we find no evidence this sampling rule biases our results.[13]

12. The number of observations in the second stage is smaller than 1.4 million because we are estimating in five-year differences. Industry-specific coefficients on the production function are in online Table A15. When we used lagged TFP on the right-hand side of employment or survival regressions we always express it in deviations from the industry mean and average between adjacent years to smooth over transitory measurement error.

13. We find no systematic differences in results between firms with 100–250 employees and those above 250 employees, suggesting the selection on firms with over 100 employees is unlikely to cause a major bias. We also find no differences in our patenting results—where we have essentially the full population of firms—between firms with less than and more than 100 employees. It is also worth noting that large firms account for most of European manufacturing employment (and an even larger share of value added), although the precise proportion will vary by country. For example, firms with over fifty employees account for 82% of total manufacturing employment in Germany, 77% in the UK, 76% in Sweden, 72% in Ireland, and 69% in France. In Greece this proportion falls to 59%, 56% in Italy, and 50% in Portugal. See Eurostat *Structural Business Statistics*, http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/dataset?p_product_code=SBS_SC_2D_DADE95.

2.4. *UN Comtrade data*

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

We use the value of imports originating from China (M^{China}) as a share of total world imports (M^{World}) in a country by four-digit industry cell as our key measure of exposure to Chinese trade, following the "value share" approach outlined by Bernard *et al.* (2006); i.e., we use $\text{IMP}^{\text{CH}} = M^{\text{China}}/M^{\text{World}}$. As two alternative measures we also construct Chinese import penetration by normalizing Chinese imports either on domestic production (M^{China}/D) or on apparent consumption (domestic production less exports plus imports), M^{China}/C. For domestic production we use Eurostat's Prodcom database. Compared with Comtrade, Prodcom has no data prior to 1996, so this restricts the sample period. An additional problem is that some of the underlying six-digit product data are missing (for confidentiality reasons as the industry-country cells are too small), so some missing values for domestic production had to be imputed from export data. Although we obtain similar results with measures that use production in the denominator (see Table 1, Panel C), we prefer the normalization on world imports which avoids these data restrictions.

2.5. *The quota instrument*

Our main strategy to address the endogeneity of imports is to exploit the accession of China to the WTO in 2001, which led to the abolition of import quotas on textiles and apparel. European firms in these industries generated 31,052 patents in our sample.

The origin of these quotas dates back to the 1950s when UK and the US introduced quotas in response to import competition from India and Japan. Over time, this quota system was expanded to take in most developing countries, and was eventually formalized into the MFA in 1974. The MFA was itself integrated into GATT in the 1994 Uruguay round, and when China joined the WTO in December 2001 these quotas were eliminated in two waves in 2002 and 2005 (see Brambilla *et al.*, 2010).

When these quotas were abolished this generated a 240% increase in Chinese imports on average within the affected product groups. In fact, this increase in textile and apparel imports was so large it led the European Union to re-introduce some limited quotas after 2005.[14] Since this re-introduction was endogenous, we use the initial level of quotas in 2000 (QUOTA_j) as our instrument to avoid using the potentially endogenous post-2005 quota levels.

The exclusion restriction is that shocks to technology are uncorrelated with changes in quotas. In our main IV regression we require that the shock to the change in technology 2000–5 is uncorrelated with the strength of quotas to non-WTO countries (such as China) in 2000. Since, these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s was in preparation for the Uruguay Round this seems like a plausible assumption. For each four-digit industry we calculated the proportion of six-digit product categories (HS6) that were

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

covered by a quota, weighting each product by its share of import value. For example, quotas covered 77% of cotton fabric products (SIC 2211) but only 2% of wool fabric products (SIC 2231), and covered 100% of women's dresses (SIC 2334) but only 5% of men's trousers (SIC 2325). This variation presumably reflected the historic bargaining power of the various industries in the richer countries in the 1950s and 1960s when these quotas were introduced, but are now likely to be uncorrelated to any technology trends in the industries we study. We discuss more details of the quota instrument in sub-section 3.1 and in online Appendix B.

We examine several threats to the exclusion restriction underlying the quota IV. First, we confirmed that the industries with the toughest quotas in 2000 had no differential trends in observables prior to 2000. The growth of patents, TFP, labour productivity, the capital–labour ratio, the material–labour ratio, average wages, total employment, and total capital were not significantly correlated with the quota instrument.[15] As a second tough test we show that our results are robust to including firm fixed effects in the differenced equations (i.e., we estimate trend-adjusted difference in differences regressions). Thirdly, we present an alternative IV strategy exploiting the initial level of Chinese import penetration (an "initial conditions IV described in Section 5.2). This has the advantage that we can estimate on the entire sample without confining ourselves to the clothing and textile sector.

2.6. *Descriptive statistics*

The rise of China's share of all imports to the US and the twelve European countries in our sample is remarkable. In 2000 only 5.7% of imports originated in China, but by 2007 this had more than doubled to 12.4%. This increase also varies widely across sectors, rising most rapidly in industries such as toys, furniture, and footwear. Some basic descriptive statistics for our main regression samples are shown in online Tables A1 and A2. With the exception of the survival and worst-case bounds analyses, the regression samples condition on non-missing values of our key variables over a five-year period. The exact number of observations (and average firm size) differs between samples. In the sample of firms who have patented at least once since 1978 the mean number of patents per year is 1 and median employment is 100. When we condition the regressions on the TFP sample median employment in 30 (reflecting the fact that patenting firms are larger than average). For plants with IT data, median employment is 140 (reflecting the Harte–Hanks' sampling frame as discussed above) and the average IT intensity is 0.58 computers per worker.

3. EMPIRICAL MODELLING STRATEGY

Our empirical models analyse both the *within* firm intensive margin of technological upgrading and the *between* firm extensive margin of upgrading through selection effects.

3.1. *Technical change within surviving plants and firms*

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

$$\ln \mathrm{TECH}_{ijkt} = \alpha \mathrm{IMP}^{\mathrm{CH}}_{jkt-l} + \eta_i + f_{kt} + \varepsilon_{ijkt}. \tag{3.1}$$

15. These correlations are in online Table A3. High quota industry industries did have lower *levels* of these variables as they are typically low wage, low tech, labour-intensive sectors, but we control for the levels with industry-fixed effects.

TECH will be interpreted broadly and measured using a number of indicators such as patented innovations,[16] IT, and TFP. We measure $\mathrm{IMP}_{jkt}^{\mathrm{CH}}$ mainly as the proportion of imports (M) in industry j and country k that originate from China($M_{jk}^{\mathrm{China}}/M_{jk}^{\mathrm{World}}$), the f_{kt} are a full set of country dummies interacted with time dummies to absorb macro-economic shocks, and η_i is a firm fixed effect. The trade-induced technical change hypothesis is that $\alpha > 0$. Note that we allow for a dynamic response in Equation (3.1) depending on the lag length indicator l. Our baseline results will use $l=0$ to be consistent across all equations, but we check the robustness of the results when using alternative lag lengths.[17]

To sweep out firm fixed effects we estimate:

$$\Delta \ln \mathrm{TECH}_{ijkt} = \alpha \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} + \Delta f_{kt} + \Delta \varepsilon_{ijkt}, \tag{3.2}$$

where Δ denotes the long (usually five year) difference operator. Rapid growth in the Chinese import share is therefore used as a proxy for a rapid increase in trade competition from low-wage countries. We maximize the use of the data by using overlapping five-year differences (e.g., 2005–2000 and 2004–1999) but since we cluster at the country–industry pair level (or sometimes just industry level) this is innocuous. We report some results using non-overlapping five-year differences and specifications in levels (e.g., fixed effect Negative Binomial models).

The growth of Chinese imports may still be related to unobserved shocks, $\Delta\varepsilon_{ijkt}$ so we consider instrumental variables such as the removal of quotas when China joined the WTO to evaluate potential endogeneity biases. The first stage of the model can be written as:

$$\Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} = -\varphi \Delta \mathrm{QUOTA}_{jkt} + \Delta f_{kt}^{Q} + \Delta \varepsilon_{ijkt}^{Q},$$

where QUOTA_{jkt} is the toughness of the quota as measured by the (value-weighted) proportion of products in the industry that are covered by a quota against China. We expect that $\varphi>0$, i.e., the tougher the quotas the less imports that there will be from China. Consider the 2005–2000 long difference. Since quotas were abolished by 2005, $\Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} = \varphi \mathrm{QUOTA}_{jk,00} + \Delta f_{kt}^{Q} + \Delta \varepsilon_{ijkt}^{Q}$. In other words, the tougher the industry's quotas against China in 2000, the faster we would expect imports to grow in the subsequent five years. Note that we can write the reduced form for innovation as:

$$\Delta \ln \mathrm{TECH}_{ijkt} = \pi \mathrm{QUOTA}_{jk,00} + \Delta \varsigma_{kt} + \Delta e_{ijkt}.$$

To address the concern that there may be pre-trends in the growth of technology in those industries where quotas were toughest, we allow for firm-specific trends.

3.2. *Technological upgrading through reallocation between plants and firms*

In addition to examining whether Chinese import competition causes technological upgrading *within* firms we also examine whether trade affects innovation by reallocating economic activity *between* firms by examining employment and survival equations. As discussed in Section 1, compositional models would predict that China would cause low-tech plants to shrink and

16. Because of the zeros in patents when taking logarithms we use the transformation PATENTS = 1 + PAT, where PAT is the count of patents. The addition of unity is arbitrary, but equal to the sample mean of patents. We also compare the results with fixed effect Negative Binomial count data models below which generated similar results (see Table 7).

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

die, as they are competing most closely with Chinese imports. Consequently, we estimate firm employment growth equations of the form:

$$\Delta \ln N_{ijkt} = \alpha^N \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} + \gamma^N (\mathrm{TECH}_{ijkt-5} * \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}}) + \delta^N \mathrm{TECH}_{ijkt-5} + \Delta f_{kt}^N + \Delta \varepsilon_{ijkt}^N, \quad (3.3)$$

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

Equations (3.2) and (3.3) are estimated on surviving firms. However, one of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate:

$$\begin{aligned} \mathrm{SURVIVAL}_{ijkt} = S_{ijkt} &= \alpha^S \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} + \gamma^S (\mathrm{TECH}_{ijkt-5} * \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}}) + \delta^S \mathrm{TECH}_{ijkt-5} \\ &+ \Delta f_{kt}^S + \Delta \varepsilon_{ijkt}^S, \end{aligned} \quad (3.4)$$

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

When we implement the quota IV strategy in the employment and survival equations there are two endogenous variables: $\Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}}$ and $\mathrm{TECH}_{ijkt-5} * \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}}$. Hence, we use $\mathrm{QUOTA}_{jk,00}$ and $\mathrm{QUOTA}_{jk,00} * \mathrm{TECH}_{ijkt-5}$ as two instruments in each first stage.

To complete the analysis of between firm effects we would also need an entry equation. The fundamental problem is that there is no "initial" technology level for entering firms. We cannot use the current observed technology level (TECH_{ijkt}) as this is endogenous. We can address the issue of entry indirectly, however, by estimating an industry-level version of Equation (3.2):

$$\Delta \mathrm{TECH}_{jkt} = \alpha^{\mathrm{IND}} \Delta \mathrm{IMP}_{jkt}^{\mathrm{CH}} + \Delta f_{kt}^{\mathrm{IND}} + \Delta \varepsilon_{jkt}^{\mathrm{IND}}, \quad (3.5)$$

where the coefficient on Chinese imports, α^{IND}, in Equation (3.5) reflects the combination of within firm effects from Equations (3.1) and (3.2), the reallocation effects from Equations (3.3) and (3.4), and the unmodelled entry effects. In examining the magnitude of the Chinese trade effects, we will simulate the proportion of aggregate technical change that can be accounted for by Chinese imports using Equations (3.2)–(3.4) and break this down into within and between components. We will also compare the micro and industry estimates of Equation (3.5) which give an alternative estimate of the within and between effects, including entry.

3.3. *Sample size across regressions*

In the results that follow in the next section we generally use the largest possible sample of non-missing observations. Sample sizes differ between columns within a table primarily because of different samples for the three technology variables due to missing data (online Appendix A.3 gives full details, but broadly the sample is restricted because we drop firms who never patent when we run the patenting equation). Just about all firms have IT, but Harte–Hanks only surveys larger firms and only from 2000. We have, in principle, the largest sample for TFP, but accounting data (especially for materials) is only reliable in four of our twelve European countries. Samples also change when we move from pooling across all industries (e.g., Table 1) to focusing on just the clothing and textile sector (e.g., Table 2). We note other specific sample changes in the text and in table notes.

4. RESULTS

4.1. *Within firm results: OLS estimates*

Table 1 presents our core results: within firm measures of technical change. All columns control for fixed effects by estimating in long differences and country-specific macro shocks by including a full set of country dummies interacted with a full set of time dummies. Our key measure of innovation, patents, is the dependent variable in Column (1). The coefficient suggests that a increase in Chinese import penetration is associated with a 3.2% increase in patenting. Since jobs fell in those industries affected by Chinese imports we underestimate the growth in patent intensity (patents per worker) by not controlling for (endogenous) employment. If we also include the growth of employment in Column (1), the coefficient (standard error) on imports is slightly larger at 0.387 (0.134).[18]

A concern with patenting as an innovation indicator is that firms may simply be taking out more patents to protect their existing knowledge in the face of greater Chinese competition. To test this "lawyer effect" we also look at citations per patent—if firms are now patenting more incremental knowledge for fear of being copied by the Chinese, the average quality of their patents should fall, so citations per patent should drop. In fact, the coefficient on Chinese imports is positive (although insignificant).[19]

In Column (2) of Table 1, we examine IT intensity and again find a positive and significant coefficient on Chinese imports. We use computers per employee as our main measure of IT diffusion as this is a good indicator of a general-purpose technology used widely across industries. However, we also investigate other measures of IT—the adoption of Enterprise Resource Planning, database software, and groupware tools—and also find positive effects of Chinese imports.[20] Finally, in Column (3) we use a wider measure of technical change as the dependent variable, TFP growth, and again establish a positive and significant association with Chinese imports.[21] Other measures of productivity enhancing investment such as the growth of R&D expenditures and management quality are also positively associated with increased exposure to Chinese imports.[22]

18. The coefficient (standard error) on employment in the patents equation was 0.015 (0.008) implying that larger firms have a higher volume of patents. If we include the ln(capital/sales) ratio as well as ln(employment) in the regression this barely shifts the results (the coefficient on Chinese imports is 0.370 with a standard error of 0.125). Thus, the correlation with Chinese trade is not simply an increase in all types of capital, but seems related specifically to technical change. The other results in Table 1 are also robust to controlling for employment growth.

19. For example, when we estimate a specification like Column (1) of Table 1 except using cites per patent as the dependent variable, the coefficient on Chinese imports is 0.009 with a standard error of 0.029.

20. Online Appendix E also investigates non-linearities through examining quintiles of the growth of Chinese imports as well as linear effects on these types of software.

21. Note that our pooling across multiple overlapping years to construct five-year differences is largely innocuous as we are clustering the standard errors by country-industry pair. For example, if we use only the last five-year difference the qualitative results are similar. In this experiment the coefficient (standard error) is 0.591 (0.201) for patents; 0.314 (0.077) for IT; and 0.400 (0.079) for TFP.

22. The coefficient (standard error) on Chinese imports was 1.213 (0.549) in the R&D equation. See Bloom *et al.* (2015) for analysis of management (defined as in Bloom and Van Reenen (2007)).

TABLE 1
Technical change within incumbent firms and plants

Panel A: Baseline results			
	(1)	(2)	(3)
Dependent variable	Δln(PATENTS)	Δln(IT/N)	ΔTFP
Estimation method	Five-year differences	Five-year differences	Five-year differences
Change in Chinese imports	0.321***	0.361**	0.257***
ΔIMP_{jk}^{CH}	(0.102)	(0.076)	(0.072)
Sample period	2005–1996	2007–2000	2005–1995
Number of units	8,480	22,957	89,369
Number of country by industry clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167
Panel B: Include industry trends			
Dependent variable	Δln(PATENTS)	Δln(IT/N)	ΔTFP
Change in Chinese imports	0.191*	0.170**	0.128**
ΔIMP_{jk}^{CH}	(0.102)	(0.082)	(0.053)
Number of units	8,480	22,957	89,369
Number of country by industry clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167
Panel C: Normalize imports by domestic production			
Dependent variable	Δln(PATENTS)	Δln(IT/N)	ΔTFP
Change in Chinese imports	0.142**	0.129***	0.065***
ΔIMP_{jk}^{CH}	(0.048)	(0.028)	(0.020)
Number of units	8,474	20,106	89,369
Number of country by industry clusters	1,575	2,480	1,210
Observations	30,221	31,820	292,167
Panel D: Offshoring			
Dependent variable	Δln(PATENTS)	Δln(IT/N)	ΔTFP
Change in Chinese imports	0.313***	0.279***	0.188***
ΔIMP_{jk}^{CH}	(0.100)	(0.080)	(0.082)
Change Chinese imports	0.174	1.685***	1.396***
in source industries ΔOFFSHORE	(0.822)	(0.517)	(0.504)
Number of units	8,480	22,957	89,369
Number of country by industry clusters	1,578	2,816	1,210
Observations	30,277	37,500	292,167

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. Sample period is the same in all panels, i.e., 2005–1996 for Column (1); 2007–2000 for Column (2), and 2005–1995 for Column (3). Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses. All changes are in five-year differences, e.g., ΔIMP_{jk}^{CH} represents the five-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. All columns include a full set of country by year dummies. Δln(PATENTS) is the change in ln(1+PAT), PAT = count of patents. IT/N is the number of computers per worker. TFP is estimated using the De Loecker (2011) version of the Olley–Pakes (1996) method separately for each industry (see online Appendix C). Panel B includes three-digit industry trends. Panel C normalizes Chinese imports on domestic production (instead of total imports as in other columns). Panel D includes a measure of offshoring defined as in Feenstra and Hanson (1999) except it is for Chinese imports only, not all low-wage country imports (see online Appendix A). The twelve countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland, and the UK for all columns except (3) which only includes France, Italy, Spain, and Sweden (the countries where we have good data on intermediate inputs). Dummies for establishment type (Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch) are included in Column (2). Units are firms in Columns (1) and (3) and plants in Column (2).

4.2. *Within firm results: Robustness of OLS estimates*

We subjected the baseline results to a number of robustness checks. First, we were concerned that unobserved productivity shocks could be driving the positive correlation so in Panel B we include a full set of three-digit industry dummies in the growth specifications. Although the magnitude of the coefficient on Chinese imports is smaller in all cases, it remains significant at the 10% level or greater across all three specifications. Note that the industry trends are jointly insignificant in all three cases. It is unsurprising that the coefficient falls as we are effectively switching off much of the useful variation and exacerbating any attenuation bias.[23]

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

In addition to China's effect through competition in the final goods market, the opening up of China could have affected technical progress by allowing Western firms to buy cheaper intermediate inputs and offshore low value-added parts of the production chain.[25] We investigate this by adapting the offshoring measure of Feenstra and Hanson (1999) for China, which uses the input–output tables to measure for each industry the share of Chinese inputs in total imported inputs.[26] In Panel D, we find offshoring enters with a positive coefficient in all three equations (although insignificantly so in the patents equation). The share of Chinese imports in the final goods market (our baseline measure) remains positive and significant throughout with lower coefficients.[27] This suggests that while offshoring does not increase overall innovation (as measured by patents) it does increase IT intensity and productivity, presumably since offshoring moves the less IT intensive and lower productivity parts of the production process overseas to China.

4.3. *Within firm results: Using China's WTO accession to generate instrumental variables*

An obvious problem with estimating these equations is the potential endogeneity of Chinese imports due to unobserved technology shocks correlated with the growth of Chinese imports. For example, when a domestic industry is subject to a positive technology shock it is harder for foreign exporters to compete in the same market, especially low-skill, low-tech exporters such as China. This is most likely to cause a downward bias on the OLS estimates of the effects of China on technology, as more exogenous innovation will lead to fewer Chinese imports (China is

23. If we include four-digit industry trends the coefficient (standard errors) in the patent, IT, and TFP regressions are 0.185 (0.125), 0.170 (0.082), and 0.232 (0.064). If we include three-digit dummies interacted with country dummies the results are 0.274 (0.101), 0.176 (0.080), and 0.167 (0.052). Hence, the primary source of identification is (i) multi-product firms who face differential industry effects in addition to their primary sector and (ii) the acceleration of import growth and technology. The continued importance of the trade variable even after this tough test is remarkable.

24. For example, a one standard deviation increase in the import share in Table 1, Panel A Column (1) is associated with a 10% increase in patenting. By contrast, a one standard deviation increase in the import share in Column (1) of Panel B in is associated with a 14% increase in patenting.

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

26. See online Appendix A for details. We also considered the share of total imported inputs in all inputs (or all costs) like Feenstra–Hanson, but as with our analysis of total imports in the final goods market, it is the Chinese share (reflecting low wage country inputs) that is the dominant explanatory factor.

27. The coefficient estimates imply a one standard deviation increase in offshoring has a similar marginal effect on IT and TFP (0.014 and 0.008, respectively) to a one standard deviation increase in Chinese imports (0.015 and 0.006, respectively).

still a relatively low-tech, low skilled country compared with Europe). Nevertheless, there could be demand side shocks working in the opposite direction, so ultimately the direction of the OLS bias is an empirical question.

Table 2 presents the IV results using China's WTO accession.[28] Since this is only relevant for textiles and clothing, we first present the OLS results for these sectors for all the technology indicators in Columns (1), (4), and (7). In Column (1), there is a large positive and significant coefficient on the Chinese trade variable, reflecting the greater importance of low-wage country trade in this sector. Column (2) presents the first stage using the (value-weighted) proportion of products covered by quotas in 2000. Quota removal appears to be positively and significantly related to the future growth of Chinese imports. Column (3) presents the IV results that show a significant effect of Chinese imports on patents with a higher coefficient than OLS (1.86 compared with 1.16).

Columns (4)–(6) of Table 2 repeat the specification but uses IT intensity instead of patents as the dependent variable. Column (4) shows that the OLS results for IT are also strong in this sector and Column (5) reports that the instrument has power in the first stage. The IV results in Column (6) also indicate that the OLS coefficient appears downward biased.[29] The final three columns repeat the specification for TFP showing similar results to patents and IT. So overall, there is a large OLS coefficient for patents, IT, and TFP, but an even larger IV coefficient and certainly no evidence of upwards bias for OLS.[30]

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

$$\Delta \ln \mathrm{TECH}_{ijkt} = \pi \Delta z_{jkt} + \eta_{ijk} + \Delta \varsigma_{kt} + \Delta e_{ijkt},$$

where $\Delta z_{jkt} = \mathrm{QUOTA}_{jk,00} * I(YEAR \geqslant 2001)$ 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 ($I(YEAR \geqslant 2001)$). Note that for IT we do not have any data pre-WTO accession so we can only present results for patents and TFP. The η_{ijk} are a full set of firm fixed effects that pick up trends as the equation is estimated in long differences.

28. In Table 2, we cluster by four-digit industry as the instruments have no country-specific variation. We also drop years after 2005 so the latest long difference (2005–2000) covers the years before and after China joined the WTO. Note that we include all firms who have any "primary" industry presence in textiles and clothing according to BVD. The main industry of some of these firms will be outside textiles, hence the large number of clusters. If we condition on only those firms whose main industry is textiles the results are robust (e.g., the coefficient on Chinese imports in Column (3) is 2.010 with a standard error of 1.074).

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

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

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

TABLE 2

Within firm results—using changes in quotas as an IV for chinese imports (clothing and textile industries only)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Patenting activity			Information technology			Total factor productivity	
Dependent variable	Δln(PATENTS)	ΔIMP^{CH}	Δln(PATENTS)	Δln(IT/N)	ΔIMP^{CH}	Δln(IT/N)	ΔTFP	ΔIMP^{CH}	ΔTFP
Method	OLS	First stage	IV	OLS	First stage	IV	OLS	First stage	IV
Change Chinese imports	1.160***		1.864*	1.284***		1.851***	0.902***		1.629**
	(0.377)		(1.001)	(0.172)		(0.397)	(0.118)		(0.326)
Quotas removal		0.108***			0.088***			0.107***	
QUOTA		(0.022)			(0.019)			(0.032)	
F-statistic		24.1			21.4			11.5	
Sample period	2005–1999	2005–1999	2005–1999	2005–2000	2005–2000	2005–2000	2005–1999	2005–1999	2005–1999
Number of units	1,866	1,866	1,866	2,891	2,891	2,891	12,247	12,247	12,247
Number industry clusters	149	149	149	83	83	83	177	177	177
Observations	3,443	3,443	3,443	2,891	2,891	2,891	20,625	20,625	20,625

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. In all panels we use the same specifications as Table 1 Columns (1), (2), and (3) but estimate by instrumental variables (IV). In Panel A the IV is "Quota removal" is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the four-digit industry that were covered by a quota restriction on China in 2000 (prior to China's WTO accession) that were planned to be removed by 2005 (see online Appendix C for details). The number of units is the number of firms in all columns except the IT specification where it is the number of plants. All columns include country by year effects. Sample is firms in the clothing and textile. Standard errors for all regressions are clustered by four-digit industry in parentheses (the quota IV is defined at the SIC4 industry level and does not vary across countries like the Chinese import share, which is why we take the more conservative approach to clustering compared with Table 1).

In Column (1) of Table 3, we show that the firms more subject to quota removal had significantly higher rates of patenting after Chinese WTO accession. In Column (2) we add the firm dummies to the growth specifications. The coefficient on Chinese imports actually increases, although the change is not statistically significant (p-value $= 0.477$). An alternative way to define exposure to the policy is to count the number of years since the 2001 accession instead of a simple binary dummy. Using this alternative measure in Columns (3) and (4) produces qualitatively similar results to the first two columns. The final four Columns (5)–(8) reproduce these four specifications but using TFP as the outcome. Again, the results with and without firm-specific trends are similar. So overall, we find that the results are robust to controlling for longer-run trends in technical change.[32]

Do firms adjust their innovation behaviour in in *anticipation* of China joining the WTO? There was a large element of surprise in the impact of quota abolition because at the time there was considerable uncertainty over whether the liberalization would actually take place. A common view was that even if there was an abolition of quotas this would be temporary, as to some extent it was with the temporary reintroduction of some quotas in 2006. The fact that Table 3 finds a break in the trend of innovation in 2001 in those industries where the fall in quotas was greatest shows there was a change in behaviour, over and above any pre-policy anticipation effects. A concern might be that firms *delayed* their normal innovations pre-accession in those sectors likely to be most affected by quota abolition causing us to infer a spurious positive effect of liberalization. We performed two tests of this idea. First, we examined whether innovation was significantly slower for firms more affected by quota abolition by regressing the five-year growth in innovation in the years *prior to* 2001 on the quota instrument: the coefficients were always insignificant.[33] Secondly, we ran the regressions in Table 3 Columns (1), (3), and (4) conditioning on the lagged growth in innovation. So when examining the growth in patents 2005–2000 we control for the growth in patents 2000–1995, conditioning out any "anticipation effects". We still recovered a significant and positive effect of quota abolition on innovation (details are discussed in online Appendix F).

We also investigated using the WTO quasi-experiment of Table 2 to construct "input quotas" using the input–output tables to calculate predicted falls in the barriers to using Chinese inputs. Looking at the reduced forms for the technology equations (i.e., simply regressing the five-year growth of each technology measure on input quotas and country dummies interacted with time dummies), removal of input quotas had no significant impact on patents, but significantly increased IT intensity and TFP. When output quotas were also included in this specification, input quotas remained significant at the 5% level for the TFP equation, but were only significant at the 10% level for the IT equation. Output quotas remained positive and significant in all three specifications.[34]

32. We focus on the reduced form for reasons of transparency. We also estimated IV versions of these trend-adjusted difference in difference regressions and also found that the coefficients on Chinese imports tended to be higher than in the simpler IV counterparts. However, the instruments in the first stages were weak with F-statistics generally below 10.

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

34. These are from reduced form models including input and output quotas simultaneously. The coefficients (standard errors) on input quotas were 0.727 (0.523), 0.696 (0.365), and 0.290 (0.136) in the patents, IT, and TFP equations. The coefficients (standard errors) for the output quotas were: 0.201 (0.080), 0.160 (0.046), and 0.101 (0.019). We estimate these equations on industries where at least 0.5% of imported inputs are from China.

TABLE 3
Within firm effects—including firm-specific trends with quotas; textile and clothing industry

	Patenting				Total factor productivity			
Dependent variable	(1) Δln(PATENTS)	(2) Δln(PATENTS)	(3) Δln(PATENTS)	(4) Δln(PATENTS)	(5) ΔTFP	(6) ΔTFP	(7) ΔTFP	(8) ΔTFP
Quotas removal	0.197**	0.216**			0.152***	0.178***		
*I(year >2000)	(0.095)	(0.105)			(0.037)	(0.037)		
Quotas removal			0.066**	0.075**			0.028**	0.033*
* # years after 2000			(0.029)	(0.033)			(0.014)	(0.017)
Firm-specific trends?	No	Yes	No	Yes	No	Yes	No	Yes
Sample period	2005–1992	2005–1992	2005–1992	2005–1995	2005–1995	2005–1995	2005–1995	2005–1995
Number of firms	2,435	2,435	2,435	2,435	16,495	16,495	16,495	16,495
Number industry clusters	159	159	159	159	187	187	187	187
Observations	14,768	14,768	14,768	14,768	55,791	55,791	55,791	55,791

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. These are the equivalent of the reduced forms underlying Table 2. We use a longer sample period than Table 2 in order to include trends. "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 online Appendix C for details). I(year >2000) is an indicator variable = 1 if observation is after 200 (i.e., after China's WTO accession). "# years after 2000" is the number of years after 2000 and zero in 2000 and before (i.e., "# years after 2000" = 1 in 2001, = 2 in 2002, etc.). All estimates are in five-year differences as usual, so we control for firm-specific trends by including a firm dummy in Columns (2), (4), (6), and (8). All columns include country by year effects. Sample is firms in the clothing and textile industry. Standard errors for all regressions are clustered by four-digit industry in parentheses (the quota IV does not vary across within industry across countries like the Chinese import share, which is why we take the more conservative approach compared with Table 1).

Taking Tables 2 and 3 together, there is no evidence that we are over-estimating the effects of China on technical change in the OLS estimates in Table 1. If anything, we may be too conservative.[35]

4.4. *Between firm results: jobs and survival*

Table 4 examines reallocation effects by analysing employment growth in Panel A and survival in Panel B. The sample size is smaller for the survival analysis because we focus on the cohort alive in 2000 where we have reliable data for exit to bankruptcy by 2005. Sample sizes are identical for Columns (3)–(6) as Table 1, but are smaller in Columns (1) and (2) because there are some missing values on employment in our patents sample. We first examine the basic associations in Column (1) of Panel A, which suggests a strong negative effect of Chinese imports—a 10 percentage point increase in imports is associated with a 3.6% fall in employment. Like Autor *et al.* (2013) this suggests Chinese imports are associated with falling levels of manufacturing employment. In addition, high-tech firms (as indicated by a high level of lagged patents per worker) were more likely to grow. Most importantly, the interaction of Chinese trade and lagged patent stock enters with a positive and significant coefficient in Column (2). This suggests that more high-tech firms are somewhat "shielded" from the harmful effects of Chinese imports on jobs.[36] In Columns (3)–(6) we run similar employment estimations using the initial level of IT and TFP and again find similar positive and significant interaction terms, suggesting high-tech firms are somewhat protected from the effects of Chinese import competition.[37]

We also examined the dynamic effects of Chinese imports on employment and technology. Chinese imports appear to have the largest impact on patents after three years whereas for jobs the largest impact for Chinese imports is contemporaneously. This is consistent with the idea that firms respond to Chinese imports by cutting employment and starting innovation projects, but it takes around three years for these projects to create patentable innovations.

For the survival equations in Panel B of Table 4 we consider a cohort of firms and plants alive in 2000 and model the probability that they survived until 2005 as a function of the growth of industry-wide Chinese imports and the initial technology levels. Column (1) shows firms facing higher rates of Chinese import growth are less likely to survive: a ten percentage point increase in Chinese imports is associated with a decrease in the survival probability of 0.57 percentage points. Since the mean exit rate is 2.3% (a relatively rare event in our patenters sample which may help explain the insignificance of the linear imports coefficient), this represents about a 25% increase in exit rates. Column (2) analyses the interaction term between Chinese import growth and lagged patents and finds again a positive "shielding" effect: firms with a low initial patent stock have a significantly higher change of exiting when faced by an influx of Chinese

35. The downward bias on OLS of trade variables is also found in Auer and Fisher (2010) who examine the impact of trade with less developed countries on prices. They use a variant of an initial conditions estimator based on the industry's labour intensity. Like them, we also find important import effects on prices (see sub-section 6.2).

36. This result is not driven by the inclusion of employment in our patent stock measure on the right-hand side. To test this we estimated both a model where employment was removed from the denominator (i.e., a simple patent stock measure) and a model that also included lagged employment and its interaction with Chinese imports. The estimate of our imports growth and lagged technology interaction terms for these models were 0.192 (0.086) and 0.160 (0.083), respectively.

37. We also examined including firm-specific trends in these regressions. The interaction between Chinese import growth and lagged technology remained positive although the standard errors rise a lot. The coefficient (standard error) in the equivalent of Column (2) for patents was 0.182 (1.110), in Column (4) for IT was 0.377 (0.324) and in Column (6) for TFP was 0.556 (0.268).

TABLE 4
Between firm effects—employment and survival

Panel A: Employment $\Delta \ln N$

Dependent variable: Employment growth, $\Delta \ln N$	(1)	(2)	(3)	(4)	(5)	(6)
Technology variable (TECH)	PATENTS	PATENTS	IT	IT	TFP	TFP
Change in Chinese imports	−0.361***	−0.434***	−0.203**	−0.379***	−0.377***	−0.377***
$\Delta \mathrm{IMP}^{CH}_{jk}$	(0.134)	(0.136)	(0.086)	(0.105)	(0.094)	(0.096)
Change in Chinese imports * technology at $t-5$		1.435**		0.385**		0.795**
$\Delta \mathrm{IMP}^{CH}_{jk} * TECH_{t-5}$		(0.649)		(0.157)		(0.307)
Technology at $t-5$	0.389***	0.348***	0.241***	0.230***	0.152***	0.136***
TECH_{t-5}	(0.043)	(0.049)	(0.010)	(0.010)	(0.012)	(0.012)
Number of units	6,335	6,335	22,957	22,957	89,369	89,369
Countries by industry clusters	1,376	1,376	2,816	2,816	1,210	1,210
Observations	19,844	19,844	37,500	37,500	292,167	292,167

Panel B: Survival

Dependent Variable: SURVIVAL	(1)	(2)	(3)	(4)	(5)	(6)
Technology variable (TECH)	PATENTS	PATENTS	IT	IT	TFP	TFP
Change in Chinese imports	−0.057	−0.078	−0.118**	−0.182**	−0.207***	−0.208***
$\Delta \mathrm{IMP}^{CH}_{jk}$	(0.046)	(0.049)	(0.047)	(0.072)	(0.051)	(0.050)
Change in Chinese imports * technology at $t-5$		0.260**		0.137		0.110*
$\Delta \mathrm{IMP}^{CH}_{jk} * \mathrm{TECH}_{t-5}$		(0.122)		(0.112)		(0.059)
Technology at $t-5$	0.003	−0.005	0.001	−0.002	−0.001	−0.004
TECH_{t-5}	(0.007)	(0.009)	(0.005)	(0.006)	(0.003)	(0.003)
Survival rate for sample (mean)	0.977	0.977	0.886	0.886	0.927	0.927
Number of country by industry clusters	1,647	1,647	2,863	2,863	1,242	1,242
Observations (and number of units)	7,928	7,928	28,624	28,624	60,883	60,883

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four-digit industry pair) in parentheses. $\Delta \mathrm{IMP}^{CH}$ is the five-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. In Columns (1) and (2) TECH is ln[(1+ the firm's patent stock)/employment]; in Columns (3) and (4) TECH is computers per employee, and in Columns (5) and (6) it is TFP. Twelve countries in all columns except Columns (5) and (6) which is four countries. Number of units is the number of firms in all columns except IT where it is the number of plants. All columns include country by year effects. In Panel A, the dependent variable is the five-year difference of ln(employment). The sample period is 2005–1996 for patents, 2007–2000 for IT, and 2005–1995 for TFP. In Panel B, the sample period is the 2000–2005 cross-section. The dependent variable is SURVIVAL which refers to whether an establishment in Columns (3) or (4) or firm (in all other columns) that was alive in 2000 was still alive in 2005. Specifically, we classify an establishment as having exited if it drops out of the panel and does not appear for four successive years in Columns (3) and (4). In the other columns SURVIVAL it is based on Amadeus company status (see online Appendix B) 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.

imports.[38] Columns (3)–(6) show that there are also positive interaction effects when we use IT or TFP as alternative measures of technology.[39] These findings on the impact of low-wage country imports on reallocation is consistent with those found in US manufacturing establishments in

38. Note the sample in Columns (1) and (2) is the same as in other patent samples, i.e., those firms that patented at some point since 1978. We obtain similar results if we widened the same to include all firms, even those who had never patented. The coefficient (standard error) on the interaction term between initial technology and Chinese import growth was 1.546 (0.134) for employment growth and 0.391 (0.180) for survival.

39. Further investigation reveals that the main interaction effect is coming from firms in the bottom quintile of the technology distribution who were significantly more likely to exit because of Chinese import competition. For example, estimating Column (3) but using a dummy for the lowest quintile of the IT intensity distribution rather than the linear IT intensity gave a coefficient (standard error) of 0.214 (0.102) on the interaction.

Bernard *et al.* (2006) using indirect measures of technology (capital intensity and skills) for the pre-1997 period in the US.[40]

Table 5 looks at the between firm reallocation effects when we use Chinese WTO accession as an IV. Column (1) of Panel A shows that the higher tech firms appear to be somewhat protected from Chinese imports, just as we found in the larger sample. In the IV results in Column (2) the standard error rises on the interaction, but the coefficient is largely unchanged (3.3 compared with 3.7 in Column (1)). Columns (3) and (4) implement the same approach but use lagged IT intensity as the technology measure instead of lagged patents. In these specifications, the IV results look even stronger than OLS with the interaction remaining significant at the 5% level. The last two columns repeat the exercise for TFP and, like IT, we find the coefficient on the interaction between Chinese imports growth and lagged technology is larger in IV than OLS (albeit with a larger standard error). Panel B of Table 5 repeats the specifications using survival as the outcome. The pattern is broadly similar with the coefficients on the key interaction term all being positive (except Column (4)). The coefficients are much less precisely determined, however, with all interaction coefficients insignificant in the IV specifications.

It is worth remembering that the specifications in Table 5 are demanding. The sample is smaller than Table 4 (just clothing and textile industries) and we are instrumenting both the linear effect (as in Table 2) *and* the interaction. Despite this, the overall qualitative similarity of the IV results compared with OLS is reassuring.

4.5. *Magnitudes*

Taking all these results together we have a clear empirical picture of the role of Chinese imports in increasing technological intensity both within firms (Tables 1– 3) and between firms by reallocating to more technologically advanced firms (Tables 4 and 5). So a natural question is how large are these effects on an economy level? As Atkeson and Burstein (2010), Arkolakis *et al*. (2012), and Ossa and Hsieh (2010) have stressed, when examining general equilibrium results we have to take into account a range of broader impacts. Nevertheless, we can use the regression coefficients to perform partial equilibrium calculations to get rough magnitudes for the potential importance of China in shaping technical change.

To run our magnitude calculations we use a standard productivity decomposition following papers such as Foster *et al.* (2000), to decompose aggregate increases in productivity into a within firm term and between firm reallocation term. Formally, denoting P_t as an aggregate index of technology in a country, for example patents or TFP, the change in P_t between time t and time 0 can be decomposed as follows:

$$\begin{aligned}\Delta P_t = & \sum_{i=1}^{N} s_{i0}(p_{ijt}-p_{ijo}) + \sum_{i=1}^{N}(s_{it}-s_{i0})p_{ij0} + \sum_{i=1}^{N}(s_{it}-s_{i0})(p_{ijt}-p_{ij0}) \\ & - \sum_{i\in \text{exit}} s_{it}^{\text{exit}}(p_{ij0}^{\text{exit}}-\bar{p}_{jo}) + \sum_{i\in \text{entrant}} s_{it}^{\text{entrant}}(p_{ijt}^{\text{entrant}}-\bar{p}_{jt})\end{aligned}, \tag{4.6}$$

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

TABLE 5

Between firm effects—using quota removal as an IV for Chinese imports

Panel A: Employment

Dependent variable: Employment growth Technology variable (TECH) Estimation technique	(1) PATENTS OLS	(2) PATENTS IV	(3) IT OLS	(4) IT IV	(5) TFP OLS	(6) TFP IV
Change in Chinese imports	−1.068**	−3.266***	−1.119***	−2.746***	−0.376**	−2.041**
ΔIMP^{CH}_{jk}	(0.453)	(1.148)	(0.227)	(0.735)	(0.168)	(0.930)
Change in Chinese imports * technology at $t-5$	3.670*	3.256	1.341**	3.481**	0.110	1.058
$\Delta IMP^{CH}_{jk} * TECH_{t-5}$	(2.162)	(4.609)	(0.509)	(1.584)	(0.441)	(0.763)
Technology at $t-5$	0.445***	0.453***	0.239***	0.189***	0.113***	0.076**
$TECH_{t-5}$	(0.120)	(0.152)	(0.027)	(0.031)	(0.019)	(0.031)
First stage F-Stat (ΔIMP^{CH}_{jk})		11.7		11.6		10.45
First stage F-Stat ($\Delta IMP^{CH}_{jk} * TECH_{t-5}$)		2.8		11.7		7.66
Number of units	1,388	1,388	2,891	2,891	12,247	12,247
Number of country by industry clusters	140	140	83	83	177	177
Observations	2,377	2,377	2,891	2,891	20,625	20,625

Panel B: Survival

Dependent variable: SURVIVAL Method Sample	(1) OLS PATENTS	(2) IV PATENTS	(3) OLS IT	(4) IV IT	(5) OLS TFP	(6) IV TFP
Change in Chinese imports	−0.182	−0.271	−0.483**	−1.162***	−0.220***	−0.308*
ΔIMP^{CH}_{jk}	(0.171)	(0.247)	(0.200)	(0.383)	(0.083)	(0.142)
Change in Chinese imports * Technology at $t-5$	0.432**	0.617*	0.175	0.163	0.209*	0.243
	(0.211)	(0.347)	(0.359)	(0.637)	(0.110)	(0.159)
Technology at $t-5$	−0.024	−0.030	0.002	−0.015	−0.017	−0.018
$TECH_{t-5}$	(0.027)	(0.032)	(0.014)	(0.018)	(0.009)	(0.012)
First stage F-Stat (ΔIMP^{CH}_{jk})		18.4		13.2		8.68
First stage F-Stat ($\Delta IMP^{CH}_{jk} * TECH_{t-5}$)		17.9		10.7		7.04
Number of industry clusters	113	113	84	84	202	202
Observations (and number of units)	1,624	1,624	5,980	5,980	11,794	11,794

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. Estimation by OLS in odd numbered columns and IV in even numbered columns. The instrument is "Quota removal" is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the four-digit industry that were covered by a quota restriction on China in 2000 (prior to China's WTO accession) that were planned to be removed by 2005 (see online Appendix C for details). We use two instruments for the two endogenous variables in the IV columns, QUOTA and QUOTA * $TECH_{t-5}$ (the F-statistics in this case is the joint test of both instruments). $\Delta IMP^{CH}$is the five-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. In Columns (1) and (2) TECH is ln[(1+ the firm's patent stock)/employment]; in Columns (3) and (4) TECH is computers per employee and in Columns (5) and (6) TECH is TFP. Twelve countries in all columns except Columns (5) and (6) which is for four countries. Sample is firms in the clothing and textile industry. Standard errors for all regressions are clustered by four-digit industry in parentheses (the quota IV does not vary across within industry across countries like the Chinese import share, which is why we take the more conservative approach compared with Table 1). In Panel A, the dependent variable is the five-year difference of ln(employment). The sample period is 2005–1996 for patents, 2007–2000 for IT, and 2005–1995 for TFP. In Panel B, the sample period is the 2000–2005 cross-section. The dependent variable is SURVIVAL which refers to whether an establishment in Columns (3) or (4) or firm (in all other columns) that was alive in 2000 was still alive in 2005. Specifically, we classify an establishment as having exited if it drops out of the panel and does not appear for four successive years in Columns (3) and (4). In the other columns SURVIVAL it is based on Amadeus company status 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.

where s_{it} is the firm share of total employment, p_{ijt} is the firm technology level, $\bar{p}_{jt}$ is the average technology level of all firms, p_{ij0}^{exit} and p_{ijt}^{entrant} are the technology levels of exiters and entrants, respectively, and the summations is over all N firms in the economy. In Equation (4.6) 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 aggregate technology from shifting employment from low-tech firms towards 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).[41] 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). We cannot directly calculate the entry component (as the pre-entry technology level of an entrants is unobservable), but we can indirectly examine the effect of entry by comparing the industry-level estimates to the four components we can identify. To calculate the decomposition in Equation (4.6) we used the parameter values from Table 1 Panel A and Table 4 Columns (2), (4), and (6).

As shown in Table 6 (with details in online Appendix D) we estimate that over the 2000–7 period Chinese imports accounted for 13.9% of the increase in aggregate patenting per worker, and approximately 13.5% each for IT intensity and TFP growth. Decomposing these we find for patents the within firm component is 5.1%, the between effect is 6.7% with the rest due to exit (2.1%). For IT and productivity, the *within c*omponent is larger (9.8% and 9.9%, respectively). We also re-calculated the magnitudes including the offshoring coefficients from Table 1 Panel D which includes offshoring. Although the overall effects on patents are not much changed, the implied effects of China on aggregate IT and TFP more than double. We can also use the IV coefficients from Tables 2 and 5, and find that the impact of Chinese import competition is much larger.[42] Hence, this implies that if anything, our baseline figures are *underestimating* the effect of China.

Finally, an alternative approach to gauging the magnitude of the within and between firm effect of China is to compare estimates at the industry level and at the firm level. The industry-level magnitudes capture both effects while the firm-level magnitudes capture only the within effects. In addition to being a cross check on the magnitudes as estimated from the full set of equations, the industry-level estimates include any effect of China on entry.[43] For example, if Chinese competition discourages entry of innovative firms within an industry, then the magnitude calculations will over-estimate the impact of trade on technical change. By contrast, the industry-level aggregates are the stock of firms so include all growth from entrants as well as survivors. We find results that are very consistent with the earlier calculations—the industry coefficients are all significant and about twice as large as the firm-level coefficients for patents and TFP (and about a 10th larger for IT).[44]

41. 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.

42. See online Table A6. About half of the increase in aggregate magnitudes is because the coefficients are larger in textiles than the overall sample and half is due to the IV coefficients being larger than the OLS coefficients.

43. Atkeson and Burstein (2010) stress this as one of the main problems with firm-level analysis of trade.

44. See online Table A5. In summary, for patents, the coefficient was 0.368 at the industry level compared with 0.171 at the firm level. For TFP the coefficients were 0.326 versus 0.262 and for IT they were 0.399 versus 0.361. The firm coefficients differ slightly from Table 1 because we allocate firms to one four-digit industry (for comparability to the industry results).

TABLE 6
Magnitudes

Panel A: Increase in patents per employee attributable to Chinese imports				
Period	Within	Between	Exit	Total
Product market	5.1	6.7	2.1	13.9
Product market + offshoring	5.8	8.6	2.7	17.1

Panel B: Increase in IT per employee attributable to Chinese imports				
Period	Within	Between	Exit	Total
Product market	9.8	3.0	0.6	13.5
Product market + offshoring	23.2	5.4	3.2	31.8

Panel C: Increase in total factor productivity attributable to Chinese imports				
Period	Within	Between	Exit	Total
Product market	9.9	2.4	0.2	13.5
Product market + offshoring	25.0	7.6	1.1	33.7

Notes: All figures are as a % of the total increase over the period 2000–2007. Panel A reports the share of aggregate patents per worker accounted for by China, Panel B the increase in IT per worker and Panel C the increase in total factor productivity. In each panel the first row (Product Market) uses the coefficients from Tables 1 and 4 to impute the within, between, and total impacts of Chinese import competition on technological as discussed in Section 4.5 and detailed in online Appendix D. The second row also includes the effects of offshoring (see sub-section 5.3).

5. EXTENSIONS AND ROBUSTNESS

5.1. *Dynamic selection bias*

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

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

Table 7 implements this bounds method.[45] We first report the baseline results of Panel A of Table 1 Column (1) and then report the results for the worst-case lower bounds in Column (2). Note that as well as additional observations on our surviving 8,480 firms we also obtain additional firms as we now can construct a five-year difference even for firms with less than five years of actual patenting data by giving them zeros for the years after they exit. Dropping firms

45. This worse-case bounds approach cannot be implemented for the TFP equation as it does not have a lower bound of zero.

TABLE 7
Assessing dynamic selection bias in the patents equation

Estimator Method	(1) Five-year long differences Baseline	(2) Five-year long differences Worst-case Lower Bound	(3) Fixed effects Negative Binomial Baseline	(4) Fixed effects Negative Binomial Worst-case Lower Bound
Change in Chinese imports	0.321***	0.271***		
$\Delta\left(M_{jk}^{\text{China}}/M_{jk}^{\text{World}}\right)$	(0.102)	(0.098)		
Level of Chinese imports			0.398***	0.395***
$\left(M_{jk}^{\text{China}}/M_{jk}^{\text{World}}\right)$			(0.168)	(0.166)
Number of clusters	1,578	1,662	1,578	1,620
Number of firms	8,480	8,732	8,480	8,732
Number of observations	30,277	31,272	74,038	74,486

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

with less than five years of data is another possible source of selection bias that is addressed by this method.[46] Our results appear to be robust to these potential selection bias problems as the coefficient on Chinese imports in Column (2) remains positive and significant and has fallen only by less than one-sixth, from 0.321 to 0.271.

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

Column (3) of Table 7 implements the Negative Binomial model and shows that the coefficient on imports is positive and significant that is if anything slightly higher than the long-differenced results. Column (4) shows, and the worst-case lower bounds are again not much lower than the baseline, with the effect falling only slightly from 0.398 to 0.395.[47] We conclude from Table 7

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

47. We obtain similar results if we implement this approach on the textiles sub-sample in Column (3) of Table 2. The OLS coefficient (standard error) in Column (1) of Table 2 fell to 1.131 (0.369) and the IV estimate fell to 1.767 (0.965).

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

5.2. *Initial conditions as instrumental variables*

A disadvantage of the quota-based instrument is that we can only construct the instrument for the affected industries (textiles and clothing), so we consider a second identification strategy. The overall increase in Chinese imports is driven by the exogenous liberalization being pursued by Chinese policy makers. The industries where China exports grew more depended on whether the industry is one in which China had a comparative advantage. For example, if we consider the growth of Chinese imports in Europe between 2000 and 2005, sectors in which China was already exporting strongly in 1999 are likely to be those where 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. Consequently, high exposure to Chinese imports in 1999 can potentially be used (interacted with the exogenous overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($\text{IMP}^{\text{CH}}_{jt-6} * \Delta M^{\text{China}}_{t}$) as an instrument for $\Delta\text{IMP}^{\text{CH}}_{jkt}$, where $\text{IMP}^{\text{CH}}_{jt-6}$ is the Chinese import share in industry j in the EU and US.[48]

Using this initial conditions IV strategy generated similar qualitative results to the quota instrument as shown in Table 8. Panel A has the within-firm technology results. The first stage is very strong in all cases (see even numbered columns). The coefficient on Chinese imports is positive, significant, and larger in the IV specifications compared with the OLS specifications across all three technology equations, just as it was for the quota IV.[49] Panel B has the between firm employment regressions. Again, the first stages are strong, the coefficients on the interactions all remain positive and are significant at the 5% level for two of the three technology variables. Panel C repeats the analysis for survival and also finds qualitatively similar results to OLS, although the smaller sample sizes mean that the first stages are weaker.

5.3. *Other robustness tests*

We considered a wide range of other robustness tests on the results, the main ones of which are reported here (also online Appendix E for more details).

Low-wage versus high-wage country trade—We define low-wage countries as those countries with GDP per capita less than 5% of that in the US between 1972 and 2001. On this definition, the increase in non-Chinese low-wage imports (as a proportion of all imports) 1996–2007 was close to zero (0.005), whereas China's growth was substantial (see Figure 1). Using the normalization by domestic production (Table 1 Panel C) we found that in the technology equations the coefficient on all low-wage countries was essentially the same as the coefficient on China. We interpret this

48. Note that we do not make $\text{IMP}^{\text{CH}}_{jt-6}$ specific to country k to mitigate some of the potential endogeneity problems with initial conditions. A priori, the instrument has credibility. Amiti and Freund (2010) show that over the 1997–2005 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. The concern is that the initial conditions may not be excludable from the second stage, however. This may be because the initial level of Chinese imports is correlated with an unobservable industry characteristic that affects subsequent technology growth.

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

TABLE 8
Using "initial conditions" as an instrumental variable

Panel A: Within firm technology equations

Dependent variable	(1) Δln(PATENTS)	(2) Δln(PATENTS)	(3) Δln(IT/N)	(4) Δln(IT/N)	(5) ΔTFP	(6) ΔTFP
Method	OLS	IV	OLS	IV	OLS	IV
Change in Chinese imports	0.321***	0.494**	0.361***	0.593***	0.257***	0.507*
	(0.117)	(0.224)	(0.076)	(0.252)	(0.087)	(0.283)
Initial condition IV						
First-stage F-statistic		95.1		38.7		14.5
Sample period	2005–1996	2005–1996	2007–2000	2007–2000	2005–1996	2005–1996
Number of units	8,480	8,480	22,957	22,957	89,369	89,369
Number of industry clusters	304	304	371	371	354	354
Observations	30,277	30,277	37,500	37,500	292,167	292,167

Panel B: Employment

Dependent variable: Employment growth	(1)	(2)	(3)	(4)	(5)	(6)
Technology variable (TECH)	PATENTS	PATENTS	IT	IT	TFP	TFP
Method	OLS	IV	OLS	IV	OLS	IV
Change in Chinese imports	−0.434***	−0.734***	−0.379***	−1.070***	−0.377***	−2.039***
ΔIMP^{CH}_{jk}	(0.137)	(0.313)	(0.130)	(0.258)	(0.108)	(0.761)
Change in Chinese imports * technology at $t-5$	1.434**	0.876	0.385**	1.473***	0.795**	2.443***
ΔIMP^{CH}_{jk} * $TECH_{t-5}$	(0.560)	(1.634)	(0.180)	(0.587)	(0.347)	(0.732)
Technology at $t-5$	0.348***	0.365***	0.230***	0.199***	0.136***	0.103***
$TECH_{t-5}$	(0.049)	(0.071)	(0.01)	(0.020)	(0.013)	(0.021)
First stage for (ΔIMP^{CH}_{jk}), F-stat		39.3		22.6		15.6
First stage for (ΔIMP^{CH}_{jk} * $TECH_{t-5}$), F-Stat		31.8		24.2		13.3
Number of units	6,335	6,335	22,957	22,957	89,369	89,369
Industry clusters	300	300	371	371	354	354
Observations	19,844	19,844	37,500	37,500	292,167	292,167

(*continued*)

to mean 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.[50]

By contrast, the coefficient on the growth of imports from high-wage countries is always insignificant either by itself or when Chinese imports are included in the technology equations. 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. 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.

Heterogeneity of the China effect on innovation—We examined the extent to which the China effect was heterogeneous across countries and industries. The coefficients were surprisingly stable across countries and we cannot statistically reject homogeneity of the coefficients across countries. For example, the F-statistics [p-values] for testing the joint significance of country interaction terms in our main technology regressions were: 0.84 [0.592], 1.53 [0.115], and 0.20 [0.659] (for patents, ICT, and TFP, respectively). More interestingly, there did appear to be some systematic

50. Having said this, the Chinese imports variable tends to dominate the other low-wage country imports statistically, so we cannot draw very strong conclusions here. Detailed results are in in online Appendix E.

TABLE 8
Continued

Panel C: Survival						
Dependent variable: Survival	(1)	(2)	(3)	(4)	(5)	(6)
Technology variable (TECH)	PATENTS	PATENTS	IT	IT	TFP	TFP
Method	OLS	IV	OLS	IV	OLS	IV
Change in Chinese imports	−0.078	−0.428	−0.182**	−0.797***	−0.208***	−0.955***
ΔIMP_{jk}^{CH}	(0.051)	(0.454)	(0.077)	(0.275)	(0.067)	(0.317)
Change in Chinese imports * technology at $t-5$	0.260**	0.793	0.137	0.490	0.110**	0.314**
ΔIMP_{jk}^{CH} * $TECH_{t-5}$	(0.114)	(0.494)	(0.117)	(0.471)	(0.055)	(0.159)
Technology at $t-5$	−0.005	−0.022	−0.002	−0.014	−0.004	−0.010
$TECH_{t-5}$	(0.009)	(0.016)	(0.007)	(0.014)	(0.003)	(0.006)
First stage for (ΔIMP_{jk}^{CH}), F-Statistic		12.52		7.86		2.94
First stage for (ΔIMP_{jk}^{CH} * $TECH_{t-5}$), F-Stat		15.56		7.73		2.97
Industry clusters	328	328	372	372	379	379
Observations (and number of units)	7,928	7,928	28,624	28,624	60,883	60,883

Notes: *** denotes 1% significance; ** denotes 5% significance; and * denotes 10% significance. In Panel A we use the same specifications as Table 1 Panel A from Columns (1), (3), and (5) but estimate by instrumental variables (IV) in the even numbered columns. Similarly in Panels B and C we use Table 4 Panel A and B, respectively (columns (2), (4), and (6)), for the odd numbered columns in Table 8. IV equivalents are in even numbered columns. The Initial Conditions IV is the share of Chinese imports (in all imports) in the four-digit industry across the whole of the Europe and the US (six years earlier) interacted with the aggregate growth in Chinese imports in Europe. In Panels B and C we have two instruments: the linear initial conditions and the initial conditions interacted with $TECH_{t-5}$ (the F-statistics in this case is the joint test of both instruments). The number of units is the number of firms in all columns except the IT specification where it is the number of plants. All columns include country by year effects. Standard errors for all regressions are clustered by four-digit industry in parentheses.

differences across industries that had higher industry-specific "wage rents" and/or higher lagged TFP responded more to the China shock than those that did not. This appears broadly consistent with the trapped factor model of Bloom *et al.* (2015), although of course there are alternative explanations.[51]

China's effect on skill demand—We estimated industry-level skill demand equations (online Table A10) and found evidence to suggest Chinese imports are associated with a significant increase in the wage-bill share of college-educated workers, consistent with the idea of trade integration with low-wage countries reducing the relative demand for less-skilled workers.[52] We suggest that trade is having an indirect effect on skill demand through inducing faster technical change which, in turn, increases the relative demand for human capital.

Product and industry switching—A leading compositional theory was that in the face of Chinese import competition European firms change their product mix. We do find evidence for substantial switching (online Table A11), especially in sectors more exposed to the China shock consistent with Bernard *et al.* (2010). However, this only accounts for a small fraction of the correlation of Chinese imports and technological upgrading.

51. Another angle we investigate is whether there is a stronger effect of trade on quality upgrading for firms closer to the quality frontier. Following Khandelwal (2010) we tried interacting imports with his average length of a quality ladder in the industry. The interactions typically went in the expected direction, but were insignificant.

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

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

6. CONCLUSIONS

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

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

These results appear to be robust to many tests, including treating imports as endogenous using China's accession to the WTO in 2001 which lead to differential abolition of quotas across industries. In terms of magnitudes, China could account for around 14% of the overall technical change in Europe between 2000 and 2007. These are likely to be underestimates as we also identify a similar sized role for offshoring to China in increasing TFP and IT adoption (although not for innovation) and obtain much larger effects under IV. This suggests that increased import competition with China has caused a significant technological upgrading in European firms in the affected industries through both faster diffusion and innovation.In terms of policy, our results imply that reducing import barriers against low-wage countries such as China may bring important welfare gains through technical change. A caveat to this optimistic view is that our empirical models are partial equilibrium and do not capture all of the complex welfare effects of trade with China.[53] What we directly estimate is the impact of increasing trade on innovation on an industry-by-industry basis. This is directly relevant for typical trade policy question, such as the costs of putting quotas on imports in any particular industry.

There are several directions this work could be taken. First, we would like to investigate more deeply the impact of low-wage countries on the labour market, using worker-level data on the non-employment spells and subsequent wages of individuals most affected by Chinese trade. Much of the distributional impact depends on the speed at which the reallocation process takes place. Second, it would be valuable to complement our European analysis with a similar exercise in other countries. In particular, in the US which faced a much more dramatic increase in Chinese import competition, and also in developing countries which are technologically closer to China,

53. In Ossa and Hsieh (2010) the reduction of barriers to Chinese imports raises average European firm productivity (as we find), but lowers the average quality of Chinese exporters to the EU. Arkolakis *et al.* (2008, 2012) argue that the standard gains to trade summarized in the ratio of exports to GDP are not fundamentally altered in a wide class of models that allow for heterogeneous firms, but Melitz and Redding (2013) dispute this. More subtly, the innovation response in rich countries in sectors where China has comparative advantage (like textiles) might reduce the standard Ricardian gains from trade (Levchenko and Zhang, 2010).

so could potentially both have experienced more negative impacts. Third, we would like to further develop our trapped factor model, to see how important it is in explaining trade effects compared with the more conventional market size and competition effects. Finally, it would be helpful to structurally extend the analysis to take into account general equilibrium effects.

Acknowledgments. This is a revised version of Bloom *et al.* (2011). We would like to thank the Economic and Social Research Council and the National Science Foundation for their financial support. Extremely helpful comments have been received from Stephane Bonhomme and three anonymous referees. We would also like to thank Steve Redding, our formal discussants (Oriana Bandiera, Natalie Chen, Andreas Moxnes, Allan Collard-Wexler, Francesco Daveri, Fritz Foley, Andrei Levchenko, Marc Melitz, Ralph Ossa, Peter Schott, Jason Snyder, Stephen Terry, and Reinhilde Veugelers) and from seminar participants in Aarhus, AEA, Austrian Central Bank, Brussels, Berkeley, Boston University, Brown, CEMFI, Colorado, Duke, Georgetown, Harvard, Houston, LSE, Mannheim, Maryland, Minnesota, MIT, NBER, NYU Stern, OECD, Penn State, Princeton, PSE, Queen's, San Francisco Fed, Sciences Po, SITE, Stanford, Southampton, Texas, Toronto, UC Davis, UCLA, UCSC, Venice, Warwick, World Bank, Yale, ZEW, and Zurich.

Supplementary Data

Supplementary materials are available at *Review of Economic Studies* online.

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