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TRADE INDUCED TECHNICAL CHANGE? THE IMPACT OF CHINESE IMPORTS ON INNOVATION, IT AND PRODUCTIVITY

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ABSTRACT

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

We examine the impact of Chinese import competition on patenting, IT, R&D and TFP using a panel of up to half a million firms over 1996-2007 across twelve European countries. We correct for endogeneity using the removal of product-specific quotas following China's entry into the World Trade Organization. Chinese import competition had two effects: first, it led to increases in R&D, patenting, IT and TFP within firms; and second it reallocated employment between firms towards more innovative and technologically advanced firms. These within and between effects were about equal in magnitude, and appear to account for around 15% of European technology upgrading between 2000-2007. Rising Chinese import competition also led to falls in employment, profits, prices and the skill share. By contrast, import competition from developed countries had no effect on innovation. We develop a simple "trapped factor" model of innovation that is consistent with these empirical findings.

JEL Classification: F14, L25, L60 and O33
Keywords: China, employment, firm survival, technical change and trade

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I. INTRODUCTION

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

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

The rise of China and other emerging economies such as India, Mexico and Brazil has also coincided with an increase in wage inequality in the United States and other developed "Northern" nations. Many authors have drawn a link between the two trends, because basic trade theory predicts that the integration of a low skill abundant developing economy with a high skill abundant developed economy will lead to an increase in the relative price of skill in the developed economy. Although this logic is compelling, the consensus among most labor economists was that trade was less important than technology in causing the large increase in US wage inequality since the late 1970s.[1]

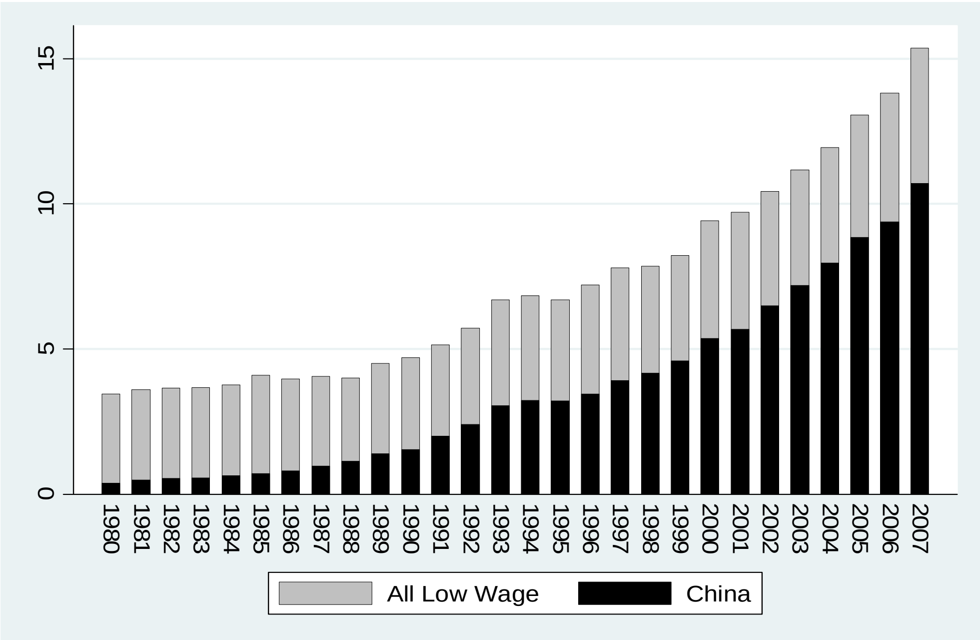
There are at least three major problems with this consensus that trade did not matter. First, most of this work used data only up to the mid 1990s, which largely predates the rise of China (see Figure 1). In the 1980s China only accounted for about 1% of total imports to the US and EU and by 1991 the figure was still only 2%. However, by 2007 China accounted for almost 11% of all imports.[2] Second, Feenstra and Hansen (1999) points to an impact of trade through

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

[2] Krugman (2008) emphasises this in his re-evaluation of the older literature. Note that Figure 1 may overestimate China's importance as import growth does not necessarily reflect value added growth. For example, although IPods are produced in China, the intellectual property is owned by Apple. However, our identification relies on *differences*

offshoring rather than final goods. Third, an emerging line of theory has pointed to mechanisms whereby trade can affect the incentives to develop and adopt new technologies. Thus, the finding that measures of technical change are highly correlated with skill upgrading does not mean trade has no role. What may be happening is that trade is stimulating technical progress, which in turn is increasing the demand for skilled labor.

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



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

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

A major empirical challenge is that there may be unobservable technology shocks correlated with the growth of Chinese imports. To tackle this endogeneity issue we implement

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.

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

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

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

We also offer some back of the envelope quantification of Chinese import effects on technical change. Over 2000-2007 China appeared to account for almost 15% of the increase in IT intensity, patenting and productivity, with this rising to almost 20% over the most recent 2004-2007 period. This suggests that trade with emerging nations such as China may now an important factor for technical change, and therefore for growth in richer countries.

To motivate the empirical framework we discuss a model, further developed in Bloom, Romer and Van Reenen (2010), that explains how trade from China drives innovation in exposed firms. The intuition relies on "trapped-factors" – that is factors of production which are costly to move between firms because of adjustment costs and sunk investment (e.g. firm-specific skills). Chinese imports reduce the relative profitability of making low-tech products but since firms cannot easily dispose of their "trapped" labor and capital, the shadow cost of innovating and producing a new good has fallen. Hence, by reducing the profitability of current low-tech products and freeing up inputs to innovate and produce new products, Chinese trade reduces the opportunity cost of innovation.

We find empirical support for two other predictions of the model. First, import competition from low wage countries like China has a greater effect on innovation than imports from high wage countries. This occurs because Chinese imports have a disproportionate effect on the profitability of low-tech products, providing greater incentives to innovate new goods. Second, firms with more trapped factors will respond more strongly to import threats.

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

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

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[3] Technological forces also have an effect on trade. For example, better communication technologies facilitate offshoring by aiding international coordination. This is another motivation for addressing the endogeneity issue.

[4] See, for example, Pavcnik (2002), Trefler (2004), Eslava, Haltiwanger and Kugler (2009), de Loecker (2007b) and Dunne, Klimek and Schmitz (2008).

[5] For low-wage countries, Bustos (2007) finds positive effects on innovation from lower export barriers for Argentinean firms and Teshima (2008) finds positive effects on process R&D from lower output tariffs for Mexican firms. The only study of Southern trade on Northern innovation is LeLarge and Nefussi (2008), who find that the R&D of French firms reacts positively to low wage country imports, although they have no external instrument.

[6] Theoretical analysis of trade and innovation is voluminous from the classic work by Grossman and Helpman (1991, 1992) and recent important contributions by Yeaple (2005) and Atkeson and Burstein (2009).

Finally, there is a large empirical literature examining the impact of competition on innovation, but a major challenge is finding quasi-experiments to identify the causal impact of competition on innovation (e.g. Aghion et al, 2005). Our paper extends this work by using China's trade growth, and particularly its entry into the WTO, as an exogenous shift in competition.

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

II. THEORY

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

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

In Bloom, Romer and Van Reenen (2010) we develop a stylized model of trade-induced innovation. The basic idea (see Appendix A for more details) is that firms can allocate factors to produce old goods or innovate and produce new goods. China can produce old goods, but cannot (as easily) innovate and produce new goods. At the beginning of the period there are factors of production employed in Northern firms making old goods (protected by trade barriers). These factors are "trapped" in the sense that workers have some firm-specific human capital and capital has firm-specific adjustment costs.

When import barriers are lowered, China starts exporting and the profitability of making old goods falls. Therefore, the opportunity cost of the trapped factors falls, reducing the costs of innovation. In addition, the fact that the opportunity costs of these factors falls means the cost of producing new goods also falls. Both effects – the reduced costs of innovation and the reduced cost of producing new goods – increases the profitability of innovation. In terms of welfare, this model suggests a benefit of lowering trade barriers against low wage countries is this will increase innovation, which is likely to be too low in equilibrium.[7]

The trapped factor approach has two additional empirical implications that we will examine. First, integration with a high wage country will not have a clearly positive effect on innovation. This is because imports from high-wage countries will not reduce the price of old goods relative to potential new goods. In our data imports from other high wage countries does not appear to stimulate innovation, consistent with the model. A second implication of the model is that all else equal firms who have more trapped factors will respond more positively to the China shock. We will use lagged TFP as a crude proxy for such trapped factors, as firms with more firm specific human capital will appear to have higher productivity than observationally equivalent firms who do not (see Appendix C). There may be other theories that can also rationalize the results of course, so we do not want to over-claim for our simple model. Nevertheless, we believe it may capture some features of the stylized facts in our data and the prior case studies[8].

B. Alternative Innovation models

There are several alternative models of how reducing trade barriers against low wage country goods could induce Northern innovation. First, lowering import barriers in general can increase competition, but we know that the effects of competition on innovation are theoretically ambiguous. Competition may foster innovation because of reduced agency costs (e.g. Schmidt, 1997), "higher stakes" (Raith, 2002) or lower cannibalization of existing profits.[9] But there is a fundamental Schumpeterian force that competition lowers price-cost margins, thereby reducing the quasi-rents from innovation. We will examine competition emanating from high wage countries and show that the main effect we identify is through low wage country competition, consistent with the trapped factor model.

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

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

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

A second class of models stresses the importance of trade in increasing market size that will generally foster innovation incentives (e.g. Schmookler, 1966; Krugman, 1980; Acemoglu, 2008). Lower trade costs generate a larger market size over which to spread the fixed costs of investing in new technologies[10]. We will investigate these effects by examining whether European firms' *exports to China* are associated with changes in innovation activity and show that this is not driving the imports effect we identify.

Finally, imports could enhance innovation by enabling domestic firms to access better overseas' knowledge (e.g. Coe and Helpman, 1995 or Acharya and Keller, 2008). This may occur through the imports of intermediate inputs and supply networks (e.g. Goldberg, Khandelwal, Pavcnik and Topalova, 2008a, b)[11]. These mechanisms do not seem appropriate in the Chinese context however, as European firms have (currently) a large technological lead over China[12].

C. Compositional models

Perhaps an even simpler approach is to consider a framework where we keep the menu of products fixed in the economy. When trade barriers fall between the EU/US and China, the high-tech industries will relatively grow in the EU/US (where these industries have comparative advantage) and low-tech industries will decline. 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 as a result of China. Bernard, Jenson and Schott (2006) show a similar result for US plants using indirectly proxies for technologies such as capital intensity.

But our results will show that China induces faster technical change *within firms* and *plants* that goes beyond the existing results. In principle, TFP increases could be accounted for

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

[11] A related literature typically finds that productivity rises when exporting increases (e.g. de Loecker, 2007a; Verhoogen, 2008).

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

by two factors: changes in a firm's product portfolio or offshoring. First, on product switching, Bernard, Redding and Schott (2010) investigate the impact of trade liberalization in heterogeneous multi-product firms. In the face of falling trade costs with a low wage country like China, Northern firms shift their product mix towards more high-tech products (see Bernard, Redding and Schott, 2007). We will investigate this mechanism by examining how plants change their product classes, and find some moderate evidence for this. Second, a fall in trade costs with China will mean that producers of goods that can use Chinese intermediate inputs will benefit. For example, firms may slice up the production process and offshore the low-TFP tasks to China (see for example Grossman and Rossi-Hansberg, 2008). This will have a compositional effect if the remaining activities in the home country are more technologically advanced[13]. To investigate this mechanism we will look explicitly at Chinese imports into the industry from which a firm purchases its intermediate inputs (using a method similar to Feenstra and Hansen, 1999).

Although we will show evidence that both product switching and offshoring are important in our dataset, neither can explain our core findings. In particular, the fact that we find that just over half of the increase in innovation following the fall in trade barriers against China comes from within firms (they spend more on R&D and take out more patents), implies that changing composition cannot be the whole story.

III. DATA

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

A. Patents

[13] In addition, by making it cheaper to produce new products Chinese trade may also encourage innovation. For example, the Apple IPod may never have been developed without the capacity to cheaply produce in China.

We combined Amadeus with the population of patents from the European Patent Office through matching by name. Patent counts have heterogeneous values so we also use future citations to control for patent quality in some specifications. We consider both a main sample of "patenters" - those Amadeus firms granted at least one patent since 1978 – and a wider sample where we assume that the firms for which we could not attribute any patents actually had zero patents.

B. Productivity and R&D

Amadeus contains accounting information on employment, capital, materials, wage bills and sales. We calculate TFP using firms in France, Italy, Spain and Sweden because of their universal firm coverage and inclusion of all accounting items needed to estimate "four-factor" TFP (in particular, materials), although the results are similar using the data for all 12 countries. We estimate TFP in a number of ways, but our core method is to use a version of the Olley Pakes (1996) method applied by de Loecker (2007b) to allow for trade and imperfect competition. In a first stage, we estimate production functions separately by industry across approximately 1.4 million observations to recover the parameters on the factor inputs.[14] We then estimate TFP and, in the second stage regression relate this to changes in the trade environment. As a robustness test we also allowed the production function coefficients to be different by country and at a lower level of industry aggregation with qualitatively similar regression results. Details of this procedure are contained in Appendix C.

The R&D data comes from BVD's Osiris database which provides data on publicly listed firm in Europe, covering around 4,000 manufacturing firms. Of these, 459 firms report performing R&D for 5 years or more so can be used for some of the regressions (the smaller sample means we cannot run all the analysis on these firms).

C. Information technology

Harte Hanks (HH) is a multinational company that collects IT data to sell to large IT firms (e.g. IBM, Cisco and Dell). Their data is collected for roughly 160,000 establishments across 20 European countries. HH surveys establishments annually on a rolling basis which means it provides a "snapshot" of the IT stock. The data contain detailed hardware and software information. We focus on using computers per worker (PCs plus laptops) as our main measure of

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

IT intensity because: (i) this is a physical quantity measure which is recorded in a consistent way across sites, time and countries, and (ii) this avoids the use of IT price deflators which are not harmonized across countries. In robustness tests we also use alternative measures of IT such as Enterprise Resource Planning software, Groupware and database software.

The fact that HH sells this data on to firms who use this for sales and marketing exerts a strong discipline on the data quality, as errors would be quickly picked up by clients in their sales calls. HH samples all firms with over 100 employees in each country. Thus, we do lose smaller firms, but since we focus on manufacturing the majority of employees are in these larger firms, and we find no evidence this sampling biases our results.[15]

D. UN Comtrade data

The trade information we use is sourced from the UN Comtrade data system. This is an international database of six-digit product level information (denoted HS6) 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 Feenstra et al (2005) concordance. For firms that operate across multiple four digit industries we use a weighted average of imports across all sectors a firm produces in (see Appendix B)[16].

We use the value of imports originating from China (M^{China}) as a share of total world imports (M^{World}) in a country by four-digit industry cell as our key measure of exposure to Chinese trade, following the "value share" approach outlined by Bernard, Jensen and Schott (2002, 2006); i.e. we use $IMP^{CH} = M^{China} / M^{World}$. As two alternative measures we also construct Chinese import penetration by normalizing Chinese imports either on domestic production (M^{China} / D) or on apparent consumption (domestic production less exports plus imports), M^{China} / C. For domestic production we use Eurostat's Prodcom database. Compared to Comtrade, Prodcom has no data prior to 1996, so this restricts the sample period. An added problem is that some of the underlying six-digit product data is missing (for confidentiality

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

[16] For a minority of large firms this generates a firm-specific imports measure, but the results are similar when we allocate firms to a single primary sector (compare Tables 1 and 5B, for example).

reasons as the industry-country cells are too small), so some missing values had to be imputed from more aggregated data. Although we obtain similar results with all measures (see Tables 6 and A6) we prefer the normalization on world imports which does not have these data restrictions.

E. Descriptive statistics

The rise of China's share of all imports to the US and the 12 European countries in our sample is remarkable. In 2000 only 5.8% of imports originated in China, but by 2007 this had almost doubled to 10.7%. This increase also varies widely across sectors, rising most rapidly in sectors like toys, furniture and foot ware (see Table A2).

Some basic descriptive statistics are shown in Table A1. With the exception of the survival analysis, the regression samples condition on non-missing values of our key variables over a five year period. The exact number of observations (and average firm size) differs between samples. In the sample of firms who have patented at least once since 1978 the mean number of patents per year is one and median employment is 100. When we use the entire sample of firms with accounting data the mean number of patents falls to 0.02 and median employment to 17. R&D reporting firms are the largest of all, 2,054 employees at the median with an average R&D intensive of 15% (recall these are all publicly listed firms whereas the other samples also include private firms). For plants with IT data, median employment is 140 and the average IT intensity is 0.58 computers per worker.

IV. EMPIRICAL MODELING STRATEGY

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

A. Technical change within surviving plants and firms

The basic firm-level equation for patents growth in firm *i* in industry *j* in country *k* at time *t* is:[17]

$$\Delta \ln(PATENTS)_{ijkt} = \alpha^{PAT} \Delta IMP^{CH}_{jkt-l} + \beta^{PAT} \Delta x^{PAT}_{ijkt} + \upsilon^{PAT}_{ijkt} \qquad (1)$$

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

We measure IMP^{CH}_{jkt} mainly as the proportion of imports (M) in industry j and country k that originate from China $(M^{China}_{jk} / M^{World}_{jk})$. Rapid growth in the Chinese import share is therefore used as a proxy for a rapid increase in trade competition from low wage countries. The trade-induced technical change hypothesis is that $\alpha^{PAT} > 0$, and x^{PAT}_{ijkt} are a set of control variables such as country dummies interacted with time dummies to absorb macro-economic shocks.

The specification in equation (1) is estimated in long (five year) differences to control for unobserved heterogeneity between firms (fixed effects)[18] denoted by the operator Δ. The growth of Chinese imports may still be related to unobserved shocks, υ^{PAT}_{ijkt} so we consider instrumental variables such as the removal of quotas when China joined the WTO. Note that we allow for a dynamic response in equation (1) depending on the lag length indicator l. Our baseline results will use $l = 0$ to be consistent with the other technology equations, but we show the differences in results to alternative lag lengths in sub-section V.C (see Table A5).[19]

The second technology measure we use is for the diffusion of information technology:

$$\Delta \ln(IT / N)_{ijkt} = \alpha^{IT} \Delta IMP^{CH}_{jkt} + \beta^{IT} \Delta x^{IT}_{ijkt} + \upsilon^{IT}_{ijkt} \qquad (2)$$

where IT is a measure of information technology in establishment i and N is the number of workers. To measure IT we will generally use the number of computers (personal computers plus laptops), but experiment with many other measures of ICT such as Enterprise Resource Planning software (like SAP), Databases and Groupware. Our third and fourth measures of technology are R&D and TFP, whose specifications follow (2).

B. Technological upgrading through reallocation between plants and firms

The prior sub-section examined whether Chinese import competition was associated with technological upgrading *within* firms. We also examine whether trade affects innovation by reallocating employment *between* firms by examining employment and survival equations. As discussed in the Section III, compositional models would predict that China would cause low-tech plants to shrink and die, as these firms are competing most closely with Chinese imports. We estimate firm employment growth equations of the form:

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[18] We use five-year long-differences to mitigate the problem of attenuation bias when using first differences. Using three-, four- or six-year differences leads to similar results.

[19] For patents, the largest effects appear after three years (see Table A5) which is consistent with the idea that most firms take a few years to obtain innovations from their increased R&D spending.

$$\Delta \ln N_{ijkt} = \alpha^N \Delta IMP_{jkt}^{CH} + \beta^N \Delta x_{ijkt}^N + \gamma^N (TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}) + \delta^N TECH_{ijkt-5} + \upsilon_{ijkt}^N \quad (3)$$

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

Equations (1)-(3) are estimated on surviving firms. However, one of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate:

$$SURVIVAL_{ijk} = \alpha^S \Delta IMP_{jkt}^{CH} + \beta^S \Delta x_{ijkt}^S + \gamma^S (TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}) + \delta^S TECH_{ijkt-5} + \upsilon_{ijkt}^S \quad (4)$$

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

To complete the analysis of between firm effects we would also need an entry equation. The fundamental problem is that there is no "initial" technology level for entering firms. We cannot use the current observed technology level ($TECH_{ijkt}$) as this is clearly endogenous (in equations (3) and (4) we use lagged technology variables under the assumption that technology is weakly exogenous). We can address the issue of entry indirectly, however, by estimating industry-level versions of (1) and (2):

$$\Delta TECH_{jkt} = \alpha \Delta IMP_{jkt}^{CH} + \beta \Delta x_{jkt} + \upsilon_{jkt} \quad (5)$$

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

V. RESULTS

A. Within firm and within plant results

Table 1 presents our key results: within firm level and within plant-level 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. Column (1) uses patents as the dependent variable and suggests that a 10 percentage point increase in Chinese import penetration is associated with a 3.2% increase in patenting.[20] Since jobs fell in those industries affected by Chinese imports (see Table 3) we control for employment in column (2) and the coefficient on imports is slightly larger.[21]

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

In column (3) of Table 1 we examine IT intensity and find a positive and significant coefficient on Chinese imports. This persists, although is smaller in magnitude when we condition on employment in column (4). 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. But in Table A4 we investigate other measures of IT – the adoption of Enterprise Resource Planning, database software, and groupware tools – and also find positive coefficients on Chinese imports.

Column (5) of Table 1 presents R&D results showing a significant increase in firm-level R&D expenditure when Chinese imports rise, which column (6) confirms is robust to controlling for employment. In the final column we use TFP growth as the dependent variable and again

[20] We also estimated negative binomial count-data models including the Blundell, Griffith and Van Reenen (1999) pre-sample mean scaling controls for fixed effects and recovered similar coefficients. For example in an equivalent specification to column (1) we obtained a coefficient (standard error) of 0.467 (0.279) on Chinese imports.

[21] 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.

establish a positive and significant association between Chinese import growth and this more general measure of efficiency.[22] As we discuss in Section VI below the magnitudes are economically as well as statistically significant: a 10 percentage point increase in Chinese imports is associated with a 3.2% increase in patenting, a 3.6% increase in IT, a 12% increase in R&D and a 2.6% increase in TFP.

B. Endogeneity: the problem of unobserved technology shocks

An obvious problem with estimating these equations is the potential endogeneity of Chinese imports due to unobserved technology shocks correlated with the growth of Chinese imports. To address this we consider two instrumental variable (IV) strategies based on China joining the WTO and initial conditions.

China joining the WTO as a quasi-experiment - One identification strategy is to use the accession of China to the WTO, which led to the abolition of import quotas on textiles and apparel. We discuss this in detail in Appendix D, but sketch the idea here. The origin of these quotas dates back to the 1950s when Britain and the US introduced quotas in response to import competition from India and Japan. Over time, this quota system was expanded to take in most developing countries, and was eventually formalized into the Multi-Fiber Agreement (MFA) in 1974. The MFA was itself integrated into GATT in 1994 as part of the Uruguay round, and when China joined the WTO in December 2001 these MFA quotas were eliminated in two waves in 2002 and 2005 (see Brambilla, Khandelwal and Schott, 2010). Since these quotas were built up from the 1950s, and their phased abolition negotiated in the late 1980s in preparation for the Uruguay Round, it seems plausible to believe their level in 2000 was exogenous with respect to future technology shocks. The level of quotas also varied seemingly randomly across four-digit industries[23] – for example, they covered 77% of cotton fabric products (SIC 2211) but only 2% of wool fabric products (2231), and covered 100% of women's dresses (2334) but only 5% of men's trousers (2325). This variation presumably reflected the historic bargaining power of the various industries in the US and UK in the 1950s and 1960s when these quotas were introduced, but are now uncorrelated to any technology trends in the industries as we show below.

When these quotas were abolished this generated a 270% increase in Chinese imports on average within the affected industries (Brambilla et al, 2010). In fact, this increase in textile and

[22] TFP is a residual after taking out labor so we do not include it on the right hand side of the equation.

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

apparel imports was so large it led the European Union to re-introduce some limited quotas after 2005.[24] Since this re-introduction was endogenous, we use the initial level of quotas in 2000 as our instrument to avoid using the potentially endogenous post-2005 quota levels. Although the quota-covered industries are considered low-tech sectors, European firms in these industries generated 21,638 patents in our sample.

Panel A of Table 2 uses this identification strategy of China's accession to the WTO.[25] 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).[26] 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 (China joined the WTO at the end of 2001). 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 positive and significant effect of Chinese imports with a higher coefficient than OLS (1.86 compared to 1.16).

Columns (4)-(6) repeats the specification but uses IT intensity instead of patents as the dependent variable. Column (4) shows that the OLS results for IT are also strong in this sector and column (5) reports that the instrument has power in the first stage. The IV results in column (6) also indicate that the OLS coefficient appeared downward biased.[27] The final three columns repeat the specification for TFP showing similar results to patents and IT. So overall there is a large OLS coefficient for patents, IT and TFP, but an even larger IV coefficient and certainly no evidence of upward bias for OLS.[28]

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

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

[26] We did not have enough observations of R&D in these industries to estimate the R&D equation.

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

[28] 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).

There are several issues with the specification. First, the regressions all use the actual flow of Chinese imports to reflect the threat of import competition. But an advantage of the IV estimates is that by replacing the actual flow of imports by the predicted flow based on quota relaxation, this more accurately reflects the *threat* of Chinese competition.[29]

Second, one could argue that firms will be adjusting their R&D earlier in response to *anticipation* of quota relaxation. However, at the time there was considerable uncertainty over whether the liberalization would actually take place. A common view was that even if there was an abolition of quotas this would be temporary, as to some extent it was with the temporary reintroduction of some quotas in 2006. We discuss this issue in more detail in Appendix D where we show that there is no significant correlation of the quota instrument with technical change or Chinese imports prior to the 2001 WTO accession.[30] This placebo experiment also addresses the concern that quota intensity is proxying some other trend correlated with Chinese import growth.

To further test for this we included lagged Chinese import growth (2000-1995) as an additional control in Table 2. The coefficients are robust to this.[31] The most rigorous test is to include lags of both technology and Chinese imports in the regression, which we do in Table A7. We use the TFP specifications as we have the largest time series of data in order to condition on the pre-policy variables. Column (1) of Table A7 repeats the specification from the final column of Table 2 Panel A. Column (2) conditions on the balanced panel where we observe firms for 10 years and shows that the results are robust even though we have only two-thirds of the industries. Column (3) includes the two pre-policy variables, the lagged growth of imports and the lagged growth of TFP. The coefficient on lagged imports is insignificant, but lagged TFP is negative and significant. Importantly, the coefficient on current Chinese import growth remains positive and significant, actually rising from 1.49 to 1.61. The negative coefficient on the lagged dependent variable is expected due to mean reversion, so we also report the results of instrumenting this with the firm's initial TFP. This reverses the sign of the coefficient on the lag, suggesting a positive relationship between past and present TFP. But again the coefficient on Chinese imports is essentially unchanged.

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

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

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

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 2005 and 2000, sectors in which China was already exporting strongly in 1999 are likely to be those where China had a comparative advantage – such as textiles, furniture and toys – and are also the sectors which experienced much more rapid increase in import penetration in the subsequent years (see Appendix Table A2). Consequently, high exposure to Chinese imports in 1999 can be used (interacted with the exogenous overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($IMP^{CH}_{jt-6} * \Delta M^{China}_{t}$) as an instrument for ΔIMP^{CH}_{jkt} where IMP^{CH}_{jt-6} is the Chinese import share in industry *j* in the EU and US. Note that we do not make IMP^{CH}_{jt-6} specific to country *k* to mitigate some of the potential endogeneity problems with initial conditions.[32]

A priori, the instrument has some credibility. Amiti and Freund (2010) show that over the 1997 to 2005 period at least three quarters of the aggregate growth of Chinese imports was from the expansion of existing products rather than from adding new products. Similarly, Brambilla et al (2010) find this was true when focusing on textiles and clothing after 2001.[33]

Column (1) of Table 2 panel B re-presents the basic OLS results for patents. Column (2) presents the first stage for the instrumental variable regressions. The instrument is strongly correlated with the endogenous variable, the growth of Chinese import intensity. Column (3) presents the second stage: the coefficient on Chinese imports is 0.495 and significant.[34] Columns (4) through (6) repeat the experiment for IT. In column (6) the coefficient on Chinese imports is positive and significant and above the OLS estimate. In the final column (9) for TFP, the IV

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

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

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

coefficient is again above the OLS estimate.[35] Taking Table 2 as a whole, there is no evidence that we are under-estimating the effects of China on technical change in the OLS estimates in Table 1. If anything, we may be too conservative.[36]

Controlling for technology shocks using industry trends. A third way to control for unobservable technology shocks is to include industry trends. We do this in Panel C of Table 2 by including a set of three-digit industry dummies in the growth specifications. In column (1) we reproduce the baseline specification for patents and column (2) includes the industry trends. We repeat this for each of the technology variables. Although the magnitude of the coefficient on Chinese imports is smaller in all cases the coefficient remains significant at the 10% level or greater. Note that the industry dummies 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 severely exacerbating any attenuation bias. The coefficient on imports is identified from (i) multi-product firms who face differential industry effects in addition to their primary sector; (ii) different cross country import growth within the same industry and (iii) variation within a four digit industry across three digit industries[37]. The continued importance of the trade variable even after this tough test is remarkable.

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

C. Reallocation effects: jobs and survival

Table 3 examines reallocation effects by analyzing employment growth in Panel A and survival in Panel B. Starting with employment growth in Panel A we first examine the basic associations in column (1), which suggest a strong negative effect of Chinese imports - a 10 percentage point increase in imports is associated with a 3.5% fall in employment. In addition, high-tech firms (as

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

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

[37] One can switch off this source of variation though including four digit industry trends with little change to the results. The coefficient (standard errors) in the patent, IT and TFP regressions are 0.185(0.125), 0.177(0.080) and 0.232(0.064) when four digit industry trends are included. A fourth source of identification is the acceleration of import growth and technology

indicated by a high level of lagged patents per worker) were more likely to grow. Most importantly, the interaction of Chinese trade and lagged patent stock enters with a positive and significant coefficient in column (2). This suggests that more high-tech firms are somewhat shielded from the effects of Chinese imports. In columns (3) and (4) we repeat the estimates but for the "patenters" sample rather than all firms (i.e. those firms who had at least one patent since 1978) and find a similar result that firms with a high lagged patent stock had less job falls following a Chinese import shock.[38] In columns (5) and (6) we run similar employment estimations using the initial level of IT and TFP and again find similar positive interaction terms, suggesting high-tech firms are somewhat protected from the effects of Chinese import competition.

We also examined the dynamic effects of Chinese imports on employment and compared this to the impact on technology. Table A5 explores the timing for patents by moving from a lag-length of 5 years in column (1) to a lag-length of zero years in column (6) as in our baseline model. Chinese imports appear to have the largest impact on patents after about three years. Panel B of Table A5 shows the same results for employment, where we see the largest impact for Chinese imports is contemporaneously. This is consistent with the idea that firms respond to Chinese imports by cutting employment while also initiating new R&D projects. These R&D projects appear to take around three years on average to produce innovations that are sufficiently developed to be patented.

Panel B of Table 3 examines survival. We consider a cohort of firms and plants alive in 2000 and model the subsequent probability that they survived until 2005 as a function of the growth of industry-wide Chinese imports and the initial technology levels. Column (1) shows firms facing higher rates of Chinese import growth are less likely to survive - a ten percentage point increase in Chinese imports decreases the survival probability by 1.2 percentage points. Since the mean exit rate in our sample period is 7-percentage point this represents a 17% increase in exit rates. Column (2) analyzes the interaction term between Chinese import growth and lagged patents and finds again a positive "shielding" effect – firms with a low initial patent stock have a significantly higher change of exiting when faced by an influx of Chinese imports. In columns (3) and (4) we re-estimate these specifications using only patenting firms and again

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

find a significant positive interaction between lagged patent stocks and Chinese imports[39]. Columns (5) and (6) shows that there are also positive interaction effects when we use IT or TFP as alternative measures of technology, although these are not significant at the 5% level. Further investigation reveals that the main effect is coming from firms in the bottom quintile of the technology distribution who were significantly more likely to exit because of Chinese import competition.[40] These findings on the impact of low wage country imports on reallocation is consistent with those found in US manufacturing establishments in Bernard, Jensen and Schott (2006) using indirect measures of technology (capital intensity and skills) for the pre-1997 period.

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

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

A. Magnitudes

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

In Table 4 we see that over the 2000-2007 period Chinese imports appear to have accounted for about 14.7% of the increase in aggregate patenting per worker, 14.1% of the increase in IT intensity and 11.8% of TFP growth in European manufacturing. The predicted

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

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

impact of Chinese imports appears to increase over this period. For example, we estimate that Chinese imports accounted for 13.9% of the increase in patents per employee over the 2000-04 period but 18.7% over the 2004-2007 period. The reason for this acceleration is clear in Figure 1, where Chinese import growth has rapidly increased over this period. Table 4 also shows for patents the contributions of the within and between components are roughly equal which is consistent with the literature on trade liberalization (e.g. Pavcnik, 2002). For IT and productivity, the within component is much larger. One possible explanation is because the adjustment costs are lower in response to the more gradual growth of Chinese imports over the 2000's compared to the "shock" trade liberalizations examined in places like Chile and Columbia.

B. Industry level results

In Table 5 we re-estimate our technology regressions at the industry level in Panel A and at the firm level in Panel B.[41] This provides another approach to comparing the within firm and between firm magnitudes of the impact of trade with China, since the industry level magnitudes capture both effects while the firm level magnitudes capture only the within effects. In addition to being a cross check on the magnitudes as estimated from the full set of equations, the industry-level estimates include any effect of China on entry.[42] For example, if Chinese competition discourages entry of innovative firms within an industry, then the calculations in Table 4 will over-estimate the impact of trade on technical change.

Table 5 starts by examining outcomes where we expect Chinese trade to have a negative impact: prices, employment and profitability. We use producer prices as a dependent variable in column (1) of Panel A (there is no firm-level price data) and observe that Chinese imports are associated with large falls in prices in the most affected industries, consistent with Broda and Romalis, 2009. Column (2) uses employment as the dependent variable and shows a larger negative effect at the industry level (Panel A) than the firm level (Panel B) consistent with the evidence from Table 3 that there is a trade effect on exit probabilities. Column (3) contains the results for profitability (profits before tax, interest and dividends divided by revenue) and shows that industry and firm profits have fallen significantly (the smaller firm-level coefficient is the

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

[42] Atkeson and Burstein (2009) stress this as one of the main problems with firm-level analysis of trade. See also Arkolakis, Costinot and Rodríguez-Clare (2010).

usual selection effect due to the least profitable firms being the first to exit). This negative profitability effect is important, as it is consistent with the idea that Chinese imports are causing an increase in competitive pressure in the industry (as assumed in the "trapped factor" model). If Chinese import share was instead only proxying some greater ability to offshore (which if properly measured it should not as these are Chinese imports in the firm's *output* market not its *input* market), then we would expect the coefficient to be positive as this should enhance rather than inhibit profitability. We discuss offshoring in more detail in sub-section VII.D below.

In columns (4) to (10) of Table 5 we show results for our technology measures - patents, IT, R&D and TFP. At the industry level (Panel A) we find that Chinese import competition is significantly associated with increases in all of these measures of technology. In Panel B columns (4) to (10) confirm that the firm level results show similar strong associations between Chinese import growth and technology, but with magnitudes between one-half to two-thirds of those at the industry level, broadly consistent with the share of the within firm component shown in the Table 4 magnitude calculations. This suggests that any entry effects omitted from the firm-level results, but included in the industry level results, must be relatively small given the similarity of the magnitudes.[43]

C. Dynamic selection on the unobservables?

One concern with our finding of positive effects of Chinese import competition on technical change is that there may be a form of dynamic selection bias. For example, it may be that only firms which know they are technologically improving stay in the industry in the face of Chinese import shock, generating our positive coefficient. Note that our industry-level results in Panel A of Table 5 are robust to this critique, but dynamic selection would mean that we allocate too much of this aggregate industry effect to the within firm component and too little to the reallocation component.

We can tackle the problem in two ways. First, we can condition on lags of technology as discussed in sub-section V.B and Table A7 where we showed that our results are robust to this experiment. Second, we can place an upper bound on the magnitude of the dynamic selection effects by exploiting the fact that the number of patents and computers can never fall below zero. Implementing this idea for the specification of column (1) in Table 1 leads to only a slight

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

decrease in the implied effect for patents. The lower bound coefficient (standard error) of the China effect is 0.412(0.158) compared to an "upper bound" of 0.417(0.158)[44]. The IT equation we estimate a lower bound coefficient (standard error) of China of 0.274 (0.056) compared to a coefficient (standard error) of 0.380 (0.086) on the normal sample of column (2) Table 1.[45] This is a more substantial reduction, due to the higher exit rates of plants (the IT sample) than firms. However, even under these extreme assumptions, the lower bound of the within effect is still substantial.

D. General equilibrium and Welfare

We cannot jump to premature welfare conclusions from the results in the paper. Recent theoretical work has shown how improvements in aggregate productivity through reallocation effects have an unclear relationship with welfare. Arkolakis et al (2008, 2010) argue that the standard gains to trade summarized in the ratio of exports to GDP are not fundamentally altered in a wide class of models that allow for heterogeneous firms. Atkeson and Burstein (2010) argue that lowering trade costs may lead to the exit of low productivity domestic firms, but it will deter product innovation through new entry. In Ossa and Hsieh (2010) the reduction of barriers to Chinese imports raises average European firm productivity (as we find), but lowers the average quality of Chinese exporters to the EU. 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).

Our empirical models are indeed partial equilibrium and do not capture all of the complex welfare effects of trade with China. Nevertheless, we think that our results are suggestive of a positive aggregate effect of Chinese trade on innovation as implied by standard endogenous growth models (such as the trapped factor model of Bloom, Romer and Van Reenen, 2010 building on Romer and Riviera-Batiz, 1992)[46]. First, the within firm effects of Chinese imports

[44] The "unbounded" numbers differ from Table 1 because we can only compute death rates accurately for firms through 2005, so we use only the 2000-2005 long-difference for this analysis (consistent with the sample in Table 3 columns (3) and (4)).

[45] Since we estimate IT intensity in logarithms there is a discontinuity at zero. So instead we estimate the growth of IT intensity as $[(IT/N)_t - (IT/N)_{t-5}]/0.5*\left[(IT/N)_t + (IT/N)_{t-5}\right]$ which is why the results differ slightly from Table 1.

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

on innovation is at least as large as the more controversial between firm-reallocation effects (see Table 4). Second, we find the *volume* of an explicit measure of innovation (patents and R&D) increases in the affected firms. It is not simply that patents per worker or average TFP increases: total innovation in the affected firms and industries expands when they face more exogenous Chinese import threats (i.e. we see our effects even when we do not control for changes in industry size in Tables 1). Finally, we explicitly show that innovation of new entrants does not significantly decline. For example, the net effect of China (including all entry effects) is on average positive in the industry-level analysis of Table 5.

General equilibrium effects could offset or reinforce the pro-innovation effects we identify from reduced trade costs with China. But to generate a credible negative aggregate effect on innovation such a model would have to be consistent with an increase in the volume of industry-wide innovation, most of which is coming from incumbent firms[47].

What our results do 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. This exercise also gives magnitudes for some of the effects one might anticipate at the macro level.

VII. EXTENSIONS AND ROBUSTNESS

In Section II we discussed several models of trade induced technical change. The trapped factor model, amongst others, suggested that innovation should rise when faced by greater import competition and should occur for firms facing the largest trade shock. The trapped factor model also implied that the innovation response should be weaker for import competition from high

[47] Another argument is that although that Chinese trade increases the demand for innovation this simply drives up the wages of R&D scientists leading to no net increase in innovation. Under this interpretation, the fact that all our regressions include a full set of time (interacted by country) dummies disguises this. A full analysis of this is outside the scope of the paper, but we believe that the concern of fully offsetting increases in R&D prices is unlikely. First, much of the improvements we identify do not require large increases in R&D scientists – the incremental changes in IT, TFP and patenting may require more skilled workers, but not more (inelastically supplied) scientists. Second, it is unlikely the supply curve of R&D scientists is completely vertical – workers for innovation-related tasks can be imported from overseas and redeployed from other activities. Bloom, Griffith and Van Reenen (2002), for example, showed that the number of R&D employees rose in countries that introduced fiscal incentives for R&D even in the short-run. Nevertheless, when going from our results to an aggregate impact other general equilibrium effects would also have to be taken into account.

wage countries, and larger for firms more subject to the trapped factor problem. We investigate these further implications in the next two sub-sections, examine skills as another outcome in sub-section C and finally examine three alternative theories of Section II relating to offshoring, product switching and export-led innovation.

A. Low wage vs. high wage country trade

Our key measure of Chinese import competition is the share of total imports originating in China. An alternative approach is to normalize Chinese imports by a measure of domestic activity such as production or apparent consumption. These alternative normalizations are presented in Table A6 for patenting, IT, TFP, employment and survival. Although the magnitude of the coefficients changes as the mean of the imports variable is different, the qualitative and quantitative results are remarkably similar.[48]

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

Table 6 presents some analysis of using measures of Chinese imports normalized by domestic production. The dependent variable is the change in patents in Panel A, the change in IT in Panel B and the change in TFP in Panel C. Column (1) simply shows what we have already seen – Chinese import penetration is associated with significantly greater technical change. Column (2) includes the non-Chinese low wage country import penetration measure. The coefficient is insignificantly different from the Chinese imports coefficient in all panels. When we include all low wage country import penetration instead of just China in column (3) we obtain similar coefficients to those in column (1), with a positive and significant coefficient for all three technology measures. We conclude that China is qualitatively no different from other low wage countries - it is just the largest trade shock from low wage countries in recent decades.

Column (4) of Table 6 includes the growth of imports from high wage countries. The coefficient is positive in all panels, but insignificant. High wage imports are also easily

[48] For example, a one standard deviation increase in the import share in Table 1 column (1) is associated with a 10% increase in patenting. By contrast, a one standard deviation increase in the import share in column (1) of Panel B in Table A6 is associated with a 14% increase in patenting.

dominated by Chinese imports when both are included in column (5). Column (6) uses total import penetration that is positive but again dominated by China in column (7). One concern is that the endogeneity bias may be greater for high wage country imports than Chinese imports. We followed Bertrand (2004) and used trade-weighted exchange rates as an instrument that, although generally significant in the first stages, did not qualitatively change any of our results.[49]

Taken as whole Table 6 strongly suggests that China is a good experiment of a low wage country trade shock. Import competition from low wage countries appears to stimulate faster technical change, whereas import competition from richer countries does not. According to our model, this is because imports from the South make the production of low-tech goods less profitable and increases incentives to move up the quality ladder. Rich country imports are more likely to be higher tech goods that for Schumpeterian reasons may offset any pro-innovation effects of competition.

B. Heterogeneity: The effect of Chinese imports is stronger for high TFP firms

In Section II we suggested that firms with "trapped factors" (e.g. due to firm-specific human capital) may be less likely to innovate until a shock such as the reduction of trade barriers against Chinese goods lowers the opportunity cost of innovating. A simple test of this idea is to analyze whether the effect of import competition on innovation is greater for firms who have higher past TFP (a proxy for the quasi-rents earned by trapped factors, see Appendix C).

Table 7 presents the patent equations for the sample where we can construct TFP. Even though the sample is smaller, the effect of Chinese import competition is similar to that in the overall sample in Table 1 (0.28 vs. 0.32). We then include the firm's initial TFP in column (2) which, in line with the trapped factor model, is negatively correlated with subsequent patent growth (the opportunity cost of innovating is higher for firms with more trapped factors). Column (3) includes the crucial interaction term between import growth and initial TFP. As the model predicts, there is a significant and positive interaction suggesting that high TFP firms are

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

more likely to respond by innovating when faced by a Chinese import shock than low productivity firms.

This result has the same flavor as Aghion et al (2005) that the innovation in firms nearer the technology frontier responds more positively to competition, than low TFP firms. Unlike Aghion et al, however, we find no evidence of an inverted "U" which may be because we focus on competition from less developed countries who are near the bottom of the quality ladder, rather than an increase in general competition.[50]

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

C. Skill demand

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

In column (1) of Table 8 we see that Chinese imports are associated with an increase in the wage-bill share of college educated workers, suggesting Chinese trade raises the demand for skills. In column (2) we see the standard result that IT is also associated with an increase in the share of wages for college workers. Including both variables into the regression in column (3) shows that both IT and Chinese imports are significant, although both have lower coefficients, suggesting part of the association of IT with skilled workers may be a proxy for the impact of developing country trade[51]. In column (4) we re-estimate this specification by OLS using the textile and apparel sample, and in column (5) report the IV results that support a causal impact of

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

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

Chinese import competition on the demand for skilled workers. This is consistent with the model that Chinese trade leads firms to switch from producing older low-tech goods to the design and manufacture of new goods, which is likely to increase the demand for skilled workers.

D. Offshoring

We have focused on China's effect through competition in the final goods market, but an alternative way in which China could affect technical progress is through allowing Western firms to buy cheaper intermediate inputs and offshore low value added parts of the production chain.[52] We investigate this by adapting the offshoring measure of Feenstra and Hansen (1999) for China, which uses the input-output tables to measure for each industry the share of Chinese inputs in total imported inputs[53].

Column (1) of Table 9 includes this China offshoring measure in the patent equation. It enters with a positive but insignificant coefficient. Interestingly, in columns (2) and (3) we look at IT and TFP and *do* find a significant positive impact of offshoring. 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 (exactly the same as Table 9). 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.[54] Output quotas remained positive and significant in all three specifications.

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

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[52] Intermediate inputs are stressed (in a developing country context) by Amiti and Konings (2006) and Goldberg et al, 2008b).

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

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

overseas to China. Throughout Table 9, the share of Chinese imports in the final goods market (our baseline measure) remains positive and significant with only slightly lower coefficients.[55]

E. Product and industry switching

A leading compositional theory we discussed in the theory section was that in the face of Chinese import competition; European firms change their product mix. To investigate this we examine whether a plant changes its primary four-digit industrial sector in the HH data, which has accurate four-digit industry data going back to 1996 (the other datasets do not have such reliable information on the changes in industry affiliation). On average 11% of plants switch industries over a five-year period, a substantial number that is consistent with evidence from recent papers.[56]

Table 10 begins by regressing a dummy for switching on Chinese imports and the usual controls, finding plants in industries exposed to China were more likely to switch industries. Column (2) includes a control for lagged IT intensity that reduces the probability of switching, but only slightly reduces the coefficient on Chinese imports. Column (3) includes employment growth, which has little impact. The second half of Table 10 uses IT intensity growth as the dependent variable. Column (4) shows that switching is indeed associated with greater use of IT, but the magnitude of the effect is small: plants who switched industries had a 2.5% faster growth in IT intensity than those who did not. Column (5) displays the standard regression for this sample, showing the positive relationship between IT intensity and Chinese imports for the sub-sample where we have switching data. Most importantly, column (6) includes the switching dummy; this reduces the coefficient on Chinese imports, but only by a small amount. A similar story is evident when we include employment growth in the final column. So industry switching is statistically significant but cannot account for much of Chinese import effects.

One limitation of this analysis is that our data does not allow us to observe product switching at a more disaggregate level. Bernard et al (2010, Table 5) show, however, that in US manufacturing firms three quarters of the firms who switched (five-digit) products did so across a four-digit industry. If we run column (5) on those plants who did not switch industries, the

[55] This is compared to the baseline results in columns (1), (3) and (7) in Table 1 for patents, IT and TFP. The coefficient estimates in Table 9 imply a one standard deviation increase in offshoring has a similar marginal effect on IT and TFP (0.014 and 0.008 respectively) to a one standard deviation increase in Chinese imports (0.014 and 0.007 respectively).

[56] For example, Bernard, Redding and Schott (2010) on the US, Goldberg et al (2008a, b). Bernard et al (2006) found that 8% of their sample of US manufacturing plants switched four-digit industries over a five-year period.

Chinese imports effect remains strong (0.474 with a standard error of 0.082). This could still conceivably be driven by the small percentage of plants who switched five-digit sector within a four sector, but it seems unlikely given the small effect of controlling for four-digit switching on the Chinese imports coefficient.

F. Exports to China

We have focused on imports from China as driving changes in technology but as discussed in Section II, exports may also have an impact through market size effects. Comtrade allows us to construct variable reflecting exports to China (as a proportion of total exports in the industry-country pair) in an analogous way to imports. Table A8 presents the results, and shows that in every column of results exports are not significant. This is unsurprising as most of the theories of export-led productivity growth focus on exporting to *developed* countries rather than emerging economies, like China. It is unclear what benefit there is to learning, for example, from China that is usually thought of as being behind the European technology frontier. And in terms of market size, China's share of the total world exports produced by European manufacturers is still relatively small at around 1.3%, so is not likely to drive technology change in the North.

VIII. CONCLUSIONS

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

The results are easy to summarize. First, TFP and absolute levels of patenting, R&D and IT have risen in firms who were more exposed to increases in Chinese imports (the within firm effect). Second, in sectors more exposed to Chinese imports, jobs and survival rate fell in low-tech firms (measured by indicators such as IT and patenting intensity), but are relatively protected in high-tech firms (the between firm effect). Both within and between firm effects generate technological upgrading.

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

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

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TABLE 1: TECHNICAL CHANGE WITHIN INCUMBENT FIRMS AND PLANTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(IT/N)**	**Δln(IT/N)**	**Δln(R&D)**	**Δln(R&D)**	**ΔTFP**
Estimation method	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**	**5 year diffs**
Change in Chinese Imports ΔIMP_{jk}^{CH}	0.321*** (0.102)	0.387*** (0.134)	0.361** (0.076)	0.195*** (0.067)	1.213** (0.549)	1.545*** (0.330)	0.257*** (0.072)
Change in Employment $\Delta \ln N$		0.015* (0.008)		-0.617*** (0.010)		0.558*** (0.043)	
Sample period	2005-1996	2005-1996	2007-2000	2007-2000	2007-1996	2007-1996	2005-1996
Number of Units	8,480	7,030	22,957	22,957	459	459	89,369
Number of country by industry clusters	1,578	1,464	2,816	2,816	196	196	1,210
Observations	30,277	22,938	37,500	37,500	1,626	1,626	292,167

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country by four-digit industry pair in parentheses (except columns (5) and (6) which are three-digit industry by country). All changes are in five-year differences, e.g. ΔIMP_{jk}^{CH} represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. All columns include a full set of country by year dummies. *Δln(PATENTS)* is the change in *ln(1+PAT), PAT* = count of patents. *IT/N* is the number of computers per worker. *R&D* is expenditure on research and development. TFP is estimated using the de Loecker (2007b) version of the Olley-Pakes (1996) method separately for each industry based on 1.4m underlying observations (see Appendix C).The 12 countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK for all columns except (7) 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 columns (3) and (4). Units are firms in all columns except (3) and (4) where it refers to plants.

TABLE 2: CONTROLING FOR UNOBSERVED TECHNOLOGY SHOCKS

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

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

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

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

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

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

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. In all panels A we use the same specifications as Table 1columns (1), (3) and (7) but estimate by instrumental variables (IV). In Panel A the IV is "Quota removal" is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the four-digit industry that were covered by a quota restriction on China in 2000 (prior to China's WTO accession) that were planned to be removed by 2005 (see the Appendix D for details). Sample only includes textiles and apparel. In **Panel B** the IV is the share of Chinese imports in all imports in an industry across the whole of the Europe and the US (6 years earlier) interacted with the aggregate growth in Chinese imports in Europe and the. The base year is (t-6). **Panel C** reproduces the baseline OLS regressions in columns (1), (3) and (5) and then includes a full set of three-digit dummies in columns (2), (4) and (6). Since these specifications are differences this is equivalent to including three digit trends in the levels specification. The number of units is the number of firms in all columns except the IT specification where it is the number of plants. All columns include country by year effects. Standard errors for all regressions are clustered by four-digit industry in parentheses in panels A and B and by four-digit industry by country pairs in Panel C.

TABLE 3: EMPLOYMENT AND EXIT

PANEL A: EMPLOYMENT

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

PANEL B: EXIT

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

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

TABLE 4: APPROXIMATE MAGNITUDES

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

Period	Within	Between	Exit	Total
2000-07	5.8	6.3	2.5	14.7
2000-05	4.9	6.4	2.5	13.9
2004-07	7.2	8.4	3.2	18.7

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

Period	Within	Between	Exit	Total
2000-07	9.8	3.1	1.2	14.1
2000-05	9.2	2.9	1.2	13.3
2004-07	12.3	4.2	1.7	18.1

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

Period	Within	Between	Exit	Total
2000-07	8.1	3.4	0.3	11.8
2000-05	7.8	3.3	0.3	11.4
2004-07	10.3	4.5	0.4	15.2

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

TABLE 5: COMPARING INDUSTRY LEVEL REGRESSIONS TO FIRM LEVEL REGRESSIONS

PANEL A. INDUSTRY-COUNTRY LEVEL

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

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

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

Notes: Panel A is aggregated to the industry by country level and panel B is the firm level equivalent specification with firms allocated to a single industry, except columns (6) and (7) which are plant level. *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Coefficients estimated by OLS in five-year differences with standard errors (clustered by industry-country pair) in parentheses below coefficients. Chinese imports are measured by the value share of Chinese imports in total imports. There are 12 countries in all columns except (10) which only includes France, Italy, Spain and Sweden (where we have good data on intermediate inputs) and (3) which is based on Germany, France, Finland, France, Spain and Sweden (where gross profit information is available). All columns include country-year effects. The dependent variable in column (1) is producer prices and is measured at the two-digit level. In column (3) the dependent variable is (pre-tax and interest) profits rates. Columns (8) and (9) in Panel A use industry R&D data from the OECD STAN database and includes Germany, Denmark, Spain, Finland, France, the UK, Italy, Norway and Sweden, and is run at the two-digit level. In column (10) productivity is estimated using the de Loecker (2007b) version of the Olley-Pakes method separately for each two-digit industry (see text). All firms are allocated to a single four-digit industry unless otherwise stated (i.e. we do not use the multiple-industry information exploited in the other tables) in order to make the two Panels comparable.

TABLE 6: LOW WAGE COUNTRY AND HIGH WAGE COUNTRY IMPORTS

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

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

PANEL B: DEPENDENT VARIABLE IS CHANGE IN IT INTENSITY

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

PANEL C: DEPENDENT VARIABLE IS CHANGE IN TOTAL FACTOR PRODUCTIVITY

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

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

TABLE 7: HETEROGENEITY - THE CHINA EFFECT ON INNOVATION IS GREATER FOR FIRMS WITH HIGH LAGGED TFP

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(PATENTS)	(3) Δln(PATENTS)
Change in Chinese Imports	0.284*	0.343**	-2.466***
ΔIMP_{jk}^{CH}	(0.157)	(0.153)	(0.848)
Change in Chinese Imports *TFP			1.464***
ΔIMP_{jk}^{CH} *TFP_{t-5}			(0.462)
Total Factor Productivity		-0.232***	-0.287***
TFP_{t-5}		(0.046)	(0.050)
Number of units	5,014	5,014	5,014
Number of industry-country clusters	1,148	1,148	1,148
Observations	14,500	14,500	14,500

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four-digit industry cell in parentheses. 12 countries.

TABLE 8: RELATIVE DEMAND FOR COLLEGE EDUCATED WORKERS

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

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

TABLE 9: OFFSHORING

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

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

TABLE 10: INDUSTRY/PRODUCT SWITCHING AND TECHNICAL CHANGE

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

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

APPENDIX A: A TRAPPED FACTOR MODEL OF INNOVATION

We formulate a simple model that could rationalize our result (see Bloom, Romer and Van Reenen, 2010 for details). Productive factors can be used to produce current goods or be used to innovate (losing a period of production). The basic idea is that there are some factors of production that are partially "trapped" due to sunk costs. With a low wage country trade shock, the opportunity cost of using these factors in innovating new goods falls as demand for the old product has been reduced, so the factors may be redeployed in innovating rather than continuing to produce the old good. As a simple example, if skilled workers are no longer used to make a low-tech product but are partly trapped within firms (for example due to firm specific human capital) they will be cheaper to deploy in designing and building a new high-tech product.

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

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

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

Interestingly, in this model integration with a high wage country will not have this effect, as workers in these countries are paid a similar wage and old products can still be profitably produced. This is consistent with our results as we do not find any effect of imports from high wage countries on innovation. In terms of welfare, this model suggests a new benefit in addition to the usual consumer benefits of lower prices when integrating with China if there is underinvestment in R&D. [57]

APPENDIX B: DATA

Datasources

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

Amadeus Accounting Data - The Amadeus data is provided by the private sector company Bureau Van Dijk, BVD. It has panel data on all European countries' company accounts. It includes private and publicly listed incorporated firms (i.e. not sole proprietors or partnerships). The accounting data includes variables such as employment, sales, capital, profits, materials and wage bills. The data goes back to the late 1970s for some countries, but is only comprehensive across a range of countries since the late 1990s. We use successive cohorts of the Amadeus DVDs because although all firms are meant to be kept for at least 10 years after exiting, this rule is sometimes violated. Although Amadeus is a reasonably comprehensive list of names (and locations, industries and owners) for the 12 countries we study, the accounting items listed are limited by national regulations. For example, profits are generally required to be disclosed by all firms, but employment is sometimes

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

a voluntary item for smaller firms; some countries (e.g. France) insist on wider disclosure of data than others (e.g. Germany) and disclosure is greater for public firms than private firms. In the regressions (such as the patents regressions), we consider results without and with these accounting items to check against selection bias. Our current version of the Amadeus data is only complete through 2005 (due to lags in reporting of accounts). In terms of cleaning the accounts variables are winsorized at the 1st and 99th percentiles. The profit/sales variable winsorized between -1 and +1. Amadeus tracks the number of six digit "primary" and "secondary" four digit sectors that a firm operates in. We give primary sectors a two-third weight and secondary sectors a one third weight (results are robust to alternative weighting schemes) and weight equally within these groups (Amadeus does not report the split of sales across the four digit sectors). Using this firm-specific imports measures gives similar results to allocating all firms to their primary four-digit sector (compare Tables 1 and 5B).

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

In principle, a firm in Amadeus that was not matched to the EPO has taken out no patents. Nevertheless, there is a concern that we may have missed out some of the patenting activity by some firms due to the matching procedure as we were quite conservative (we only made a match if we were quite sure that the patent did belong to the Amadeus firm). We consider a narrow sample where we only keep firms if they have made at least one patent since 1978 ("patenters sample") and a wider sample where we assume that firms who we could not match really did zero patents. The analysis of patenting equations (e.g. Table 1) just uses the patenters' sample (there is no variation in the non-patenters sample) whereas the employment and survival equations (Table 3) consider both samples.

When constructing *PATSTOCK*, the patent stock, (Table 3) we follow Blundell et al (1999) and estimate these by perpetual inventory methods using a depreciation (ϑ) rate of 15%. $PATSTOCK_{it} = PAT_{it} + (1-\vartheta)PATSTOCK_{it-1}$ where PAT_{it} is the count of patents of firm *i* in period *t* and ϑ=0.15.

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

R&D - Research and Development expenditure are taken from BVD's Osiris database. These are publicly listed firms (so a sub-set of Amadeus) but Osiris contains a wider range of accounting items that Amadeus does not include, such as R&D. R&D is not a mandatory item to disclose for all publicly listed firms in Europe. Typically only the larger firms are required to disclose this item, although rules are stricter in some countries than others (e.g. in the UK under the SSAP(13) Revised accounting standard disclosure of R&D is mandatory for medium sized and larger firms).

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

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

UN Comtrade - Our study uses data at the HS6 product level taken from the UN Comtrade online database. We use standard concordances of HS6-SIC4 (e.g. Feenstra et al, 2005) to aggregate to the four-digit industry level. We calculate a "value share" measure of import penetration as per Bernard, Redding and Schott (2006) where the value of Chinese imports for a given country-SIC4 cell is normalized by the value of total world imports flowing into the same cell.

Eurostat Prodcom Production database - In Table A6 we use measures of four-digit industry-level production to normalize our imports variable. This measure of domestic production is constructed from the Eurostat Prodcom dataset. Prodcom is an eight-digit product level database of production across EU members reported at up to a quarterly level. We use annual measures of production. The first four digits of the Prodcom product code correspond to the four-digit NACE classification system. We construct a concordance between the NACE codes and US SIC, after which we aggregate the production figures to the SIC4 level. In the final step of constructing the data we compare the estimated value of production by industry-country cell to the value of exports reported in Comtrade for the same industry-country cell. In cases where the value of exports exceeds the estimated value of production from Prodcom we use the exports number as our lower bound estimate of production. This problem occurs in a limited number of cases and is due to confidentiality restrictions on the reporting of data for small industry-country cells in Prodcom.

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

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

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

Constructing industry codes

The HH plant level data (used for IT) only has a single four-digit SIC code, but this does change between years so can be used to look at product switching. The Osiris data (used for R&D) only has a primary three-digit code. The Amadeus data (used for the patents, TFP and employment equations) has multiple four-digit industry codes which we can exploit to construct a weighted average of industry level imports variable to compare to the single industry code. Unfortunately, the industry data is not updated regularly so it is not reliable as a time series measure of industry switching.

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

For the multiple industry import measure we use the 2003 cross-section to define a baseline set of primary and secondary four-digit industry codes for each firm. We assign a two-thirds weight to the primary codes and one-third to the secondary codes to calculate a multiple four-digit measure of import penetration (the results are not sensitive to the exact weights used). We take the arithmetic mean within sets of primary and secondary codes, that is, we weight industries equally. We follow the same procedure for calculating import penetration for the alternative normalizations presented in Tables 6 and A6. In our data the median firm had one primary industry, the average firm 1.93 and the maximum was 10, only 19% of firms reported any secondary industry code with a mean of 2.68 and maximum of 11).

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

APPENDIX C: PRODUCTION FUNCTION ESTIMATION

The Basic Olley-Pakes Approach

Consider the basic production function as:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

So returning to the second stage coefficient of interest:

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

Including the shocks we have:

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

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

Our Implementation of Olley and Pakes

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

Following de Loecker (2007b) we use a modified version of the Olley and Pakes (1996) approach. We allow endogeneity of the variable factor inputs (labor, capital and materials) using a control function approach and for selection through a non-parametric correction (in practice we use a second order series estimator). In addition we allow the trade variables to enter directly into the non-parametric controls for endogeneity and selectivity. As de Loecker (2007b) emphasizes, it is important to allow for this in order for the estimator to be consistent when the trade environment changes. We allow for imperfect competition by assuming that there is monopolistic competition which implies that the coefficients on the production function are a mix between the technological parameters and a mark-up term. The latter is identified from the coefficient on an additional control for industry output in the production function. Since some firms produce in multiple industries the relevant output term is firm-specific depending on the firm's distribution across industries. We exploit the fact that Amadeus reports the number of primary and secondary four-digit industries a firm operates in to construct this.[58]

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

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

Measured TFP as an indicator of Trapped Factors

In the trapped factor model, some firms have firm-specific inputs that generate higher productivity (e.g. workers with firm specific skills. Following the notation of Appendices A and B, normalize $\underline{\theta}$=1 so labor services, *L*, are $U_i + \overline{\theta}_i S_i$. "True" TFP is therefore:

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

Denote measured TFP as MFP where

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

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

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

If there are no trapped factors then $\overline{\theta}_i = 1$ and measured and true TFP are the same. Firms which have more trapped factors, $\overline{\theta}_i > 1$, however, will have a higher level of *MFP*. Thus the level of MFP for a firm is correlated with the magnitude of the trapped factors.

[58] We assume that two-thirds of sales are in primary industries and one third in secondary industries. Within these categories we assume that it is distributed equally across the industries listed. Ideally we would use the exact distribution of sales across all industries, but this data is not available.

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

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

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

Construction of the Instrument
For each four-digit industry we calculated the proportion of product categories that were covered by a quota in each year (data on the amount produced in each industry is not available so we use a simple mean proportion of products). For the five-year change in imports 2005 to 2000 in the technology equations we use the quota variable in 2000 immediately prior to China's WTO entry. Specifically, this proportion represents the share of all quota-affected HS6 products in the four-digit industry (we weight each HS6 in an industry by its 2000 import value). The idea is that the market expected at this point all the quotas to be lifted. Using the actual change renders similar results, but there is a concern that the quotas remaining in 2006 are endogenous as they were the result of lobbying by the effected sectors. The "fill rates" (the proportion of actual imports divided by the quota) for most quotas were close to 100% for China in the late 1990s implying that these constraints were binding[59]. This also limits anticipation effects, although to the extent that they exist this will make it harder for us to identify a first stage. The products upon which the quotas were set were determined in the 1950s to 1970s (Spinanger, 1999) which makes them likely to be exogenous to any post 2000 actual (or anticipated) shocks. To be specific, in the regression sample of Table 2 Panel A we use US SIC4 two-digit industries 22, 23, 28, 30 and three-digit industries 314 and 326. We show that the results are robust to dropping all four-digit industries within this group with zero quotas against China in 2000 and dropping the tableware and footwear quotas.

Anticipation of China's Accession to WTO? Problems and solutions
Even if there was an unanticipated component of the China shock, since firms knew China was going to join the WTO in 2001 does this invalidate the instrument? In a stylized way one can imagine two points at which firms will react. There is an "announcement" effect on the day China's accession is determined (Costantini and Melitz, 2007, emphasis this) and an "accession" effect when China joins. For the instrument to have power in the first stage (which it does empirically), all we need is that there was some uncertainty over the effects of the accession or that firms do not fully adjust between announcement date and accession. The instrument could still be invalid, however, because the increase in technological investments (or imports) prior to accession as a result of announcement may be correlated with post-accession investments (or imports).

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

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

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

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

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

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

There are several ways to tackle the potential problem of anticipation effects. A direct method is to explicitly estimate the dynamic model of equation (D1). This is demanding in data terms, because we need to use firms where we observe ten full years of technology data. There are too few firms to accomplish this task for IT and patents. But it is possible to do this for TFP and we reported the results in Table A7 and discussed in sub-section VC. We found that our results were completely robust to using the alternative dynamic specification of (D2).

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

We turn to pre-policy import trends in Table A9. We use the country by four-digit industry level information over the 1990-2007 period (we do not need technical change measures for this experiment so can use a longer period) and show regressions where the five year growth in Chinese imports is the dependent variable. Column (1) includes simply the quota (in 2000), and the positive coefficient on this variable indicates that industries where quotas were high had faster growth in Chinese imports throughout the period. Column (2) then interacts the quota variable with a policy dummy equal to one after China joined the WTO in 2001. The coefficient on this interaction is large and statistically significant, whereas the linear term on quota is small and statistically insignificant. The coefficients suggest that prior to China's joining the WTO in 2001 industries with high quotas (i.e. where all products where subject to some form of quota restriction) had 0.002 percentage point growth a year in Chinese imports (this is consistent with increases in the "fill rates" of quotas over this period as China grew). After China joined the WTO and quotas were relaxed this rose by 0.84 (= 4.2/5) percentage points per annum, a substantial amount. Column (3) includes an even more rigorous specification where we include industry dummies, allowing for industry trends over time. The coefficient on the policy-based instrumental variable remains significant with a similar magnitude of 0.04, implying that there was an increase in the Chinese growth trend post 2001.

APPENDIX E: CALCULATING MAGNITUDES

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

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

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

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

where $\overline{p}_{jt}$ is the average technology level of all firms in industry *j* year *t*, p_{ij0}^{exit} is the technology level of an exiter, $p_{ijt}^{entrant}$ is the technology level of an entrant and the summations are over the *N* firms in the economy. In this breakdown in equation (E2) the first term is the *within* effect (the increase in technology holding firm size constant), the second term is the *between* component (the increase in technology from shifting employment from low-tech to high-tech firms), the third term is the *cross* effect (the correlation of the increase in technology within firms and their change in employment share)[60]. The fourth term is the *exit* component (the impact of the relative technology level of exiting firms versus incumbent firms) and the final term the *entry* component (the impact of technology level of entering firms versus incumbent firms). As noted in the text, we cannot directly model entrants because we do not observe their lagged technology levels. In the paper we can indirectly examine the effect of entry by comparing the industry level estimates to the four components we can identify.

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

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

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

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

Where α^N is the coefficient on Chinese imports in the employment growth equation (equation (3) in the main text) and γ^{NP} the coefficient on Chinese imports interacted with the technology variable. The values of these are -0.352 and 1.546 respectively from column (2) in Table 3 Panel A. N_{i0} is employment in the firm[61].

[60] 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.
[61] Note that we re-weight employment throughout the calculations so that the regression sample is representative of the entire population of Amadeus firms. This avoids any differences in data sampling or matching rates affecting the aggregate calculations.

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

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

Given these equations we can then quantify the share of technical change predicted to arise from Chinese imports as the ratio $\Delta P_t^{China} / \Delta P_t$. Similarly, we can identify the contribution of each component. To calculate ΔP_t for IT intensity we calculate the total increase in technology in our sample firms, that is, the change in the weighted mean we observe in our sample. For patents we cannot use our sample because of: (i) delays in the provision of firms accounts (we match to firm accounts and some of these are not available yet for 2005/06 due to reporting delays) and (ii) processing delays at the European Patent Office since we only use granted patents (dated by their year of application). As a result we use instead the aggregate growth of the US Patent Office (which provides long-run total patent numbers) over the proceeding 10 years (1996-2005), which is 2.2%. This growth rate of total patents is stable over long-run periods, for example being 2.4% over the proceeding 20 years period of 1986 to 2005.[62] Similarly, for TFP we use 2% as our measure of the growth rate of TFP growth in manufacturing in recent years.[63]

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

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

TABLE A1: DESCRIPTIVE STATISTICS

Variable	**Mean**	Standard Deviation	Median	Minimum	Maximum
Patenters sample - Firms with at least one EPO patent since 1978					
Number of Patents (per firm-year)	1.022	10.40	0	0	882
Employment	739.5	6526.7	100	1	463,561
Number of Observations	30,277				
IT sample (Harte-Hanks)					
Number of Employees	248.3	566.1	140	1	50,000
IT Intensity	0.580	0.385	0.398	0.05	2.00
Industry switchers (% plants switching four-digit sector in five year period)	0.112	0.316			
Number of Observations	37,500				
R&D sample (Osiris)					
R&D/Sales ratio	0.152	0.888	0.034	0.001	17.3
Employment	17,230	46,422	2054	4	464,841
Number of Observations	1,626				
TFP sample (Amadeus)					
Employment	79.4	333.9	30	10	84,252
Number of Firms (in TFP sample)	89,369				
Number of Observations	292,167				
Employment sample (Amadeus)					
Number of Patents (per firm-year)	0.019	5.741	0	0	882
Employment	99.95	1,504.9	17	1	372,056
Number of Observations	581,474				

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

TABLE A2: CHINA'S SHARE OF GLOBAL IMPORTS – TOP TEN INDUSTRIES, 1999-2007

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

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

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

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

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

TABLE A4: ALTERNATIVE IT ADOPTION MEASURES

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

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

TABLE A5: DYNAMICS OF THE EFFECT OF CHINA ON PATENTS AND EMPLOYMENT

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

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

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

TABLE A6 : ALTERNATIVE MEASURES OF THE CHANGE IN CHINESE IMPORTS

PANEL A: CHINESE IMPORTS NORMALIZED BY DOMESTIC PRODUCTION

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(IT/N)	(3) Δln(TFP)	(4) Δln(N)	(5) SURVIVAL
Change in Chinese Imports (over production)	0.142***	0.053**	0.065***	-0.232***	-0.103***
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$	(0.048)	(0.024)	(0.020)	(0.033)	(0.017)
Change in firm employment		-0.625***			
$\Delta \ln N$		(0.011)			
Change in Chinese imports*ln(Patent stock per worker at t-5)				0.507	0.456***
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$ *(PATSTOCK/N)$_{t-5}$				(0.431)	(0.111)
ln(Patent stock per worker at t-5)				0.503***	0.041***
(PATSTOCK/N)$_{t-5}$				(0.054)	(0.009)
Number of Units	8,474	20,106	89,369	189,309	488,270
Number of industry-country clusters	1,575	2,480	1,210	3,115	3,335
Observations	30,221	31,820	293,167	579,818	488,270

PANEL B: CHINESE IMPORTS NORMALIZED BY APPARENT CONSUMPTION

Dependent Variable:	(1) Δln(PATENTS)	(2) Δln(IT/N)	(3) Δln(TFP)	(4) Δln(N)	(5) SURVIVAL
Change Chinese Imports (over apparent consumption)	0.349***	0.169*	0.045**	-0.477***	-0.203***
$\Delta\left(M_{jk}^{China}/C_{jk}\right)$	(0.122)	(0.089)	(0.019)	(0.078)	(0.034)
Change in firm employment		-0.623***			
$\Delta \ln N$		(0.011)			
Change in Chinese imports*ln(Patent stock per worker at t-5)				1.385	0.476***
$\Delta\left(M_{jk}^{China}/C_{jk}\right)$ **(PATSTOCK/N)$_{t-5}$*				(1.238)	(0.187)
ln(Patent stock per worker at t-5)				0.490***	0.041***
(PATSTOCK/N)$_{t-5}$				(0.078)	(0.009)
Number of Units	8,474	19,793	89,369	189,309	488,270
Number of industry-country clusters	1,575	2,406	1,210	3,115	3,335
Observations	30,221	31,225	293,167	579,818	488,270

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

TABLE A7: DYNAMIC SELECTION? CHECKING PRE-POLICY TFP TRENDS

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

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

TABLE A8: EXPORTS TO CHINA

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

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

TABLE A9: THE QUOTA INSTRUMENT IS UNCORRELATED WITH THE GROWTH IN CHINESE IMPORTS PRIOR TO THE ACCESSION TO THE WTO

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

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