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

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September 26th 2009

Abstract
There is a popular belief that Chinese imports have devastated US and European manufacturing and contributed to rising inequality. Somewhat paradoxically, the consensus amongst empirical economists is that trade has *not* been a major cause of rising wage inequality (although this is largely based on datasets predating China's rise). We argue that both views have underestimated the positive impact of Chinese trade on technical change. We examine the impact of the growth of Chinese import competition on technical change (as measured by IT, patent counts and citations, TFP and R&D) using a panel of over to 200,000 European firms through 2007. We correct for endogeneity using quasi-experiments such as China's entry into the World Trade Organization. Chinese import competition led to both within firm technology upgrading and between firm reallocation of employment towards more technologically intensive plants. These effects account for about 15-20% of technology upgrading 2000-2007 and are growing over time. These results suggest that trade with low wage countries appear to have potentially large beneficial impacts on technical change as recent theories suggest.

JEL No. O33, F14, L25, L60,

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

Acknowledgements: We would like to thank the Economic and Social Research Council, Anglo-German Foundation, the EDS/HP Innovation Centre, the European Commission and the Alfred Sloan Foundation for their financial support. Helpful comments have been received from Steve Redding, Elhanan Helpman, our formal discussants (Oriana Bandeira, Allan Collard-Wexler, Marc Melitz, Peter Schott and Reinhilde Veugelers) and from seminar audiences in the AEA, Brussels, Berkeley, Harvard, LSE, Maryland, Minnesota, MIT, NBER Productivity Group, Princeton, San Francisco Federal Reserve Board, Stanford, SITE, Toronto, UC Davis, UCLA, Yale and ZEW. Charles Wang has provided excellent research assistance.

I. INTRODUCTION

A vigorous political debate is in progress over the impact of globalization on the economies of the developed world (e.g. Krugman, 2008). The growth of China looms large in these discussions, as the China has experienced tremendous export growth over the last two decades, averaging over 20% per year in real terms[1]. Many politicians in Europe and the US have become increasingly vocal in their opposition to increased trade with China, and the current economic downturn has increased the protectionist rhetoric in many quarters. Indeed, increasing restrictions on Chinese imports was a major issue in the 2008 US Presidential race, with the recent tariffs on Chinese tires one outcome of this.

A 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 helped induce faster technical change from both innovation and the adoption of new technologies, contributing to a growth in productivity. Several detailed case studies such as Bartel, Ichinowski and Shaw (2007) on American valve-makers or Freeman and Kleiner (2005) on footwear suggest this is an important phenomenon. The contribution of our paper is to confirm the importance of low wage country trade for technical change using hundreds of thousands of 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 writers have drawn a link between the two trends, not least because basic trade theory would predict that the integration of an economy abundant in less skilled labor with a developed economy abundant in skilled labor would lead to an increase in the relative price of skill in the developed economy. Although this logic is compelling, the consensus among empirical economists was that that trade was not the main culprit[2]. Most authors do find an important role for skill biased technical change

[1] Census foreign trade data: http://www.census.gov/foreign-trade/balance/c5700.html#questions

[2] There are many pieces of evidence (see Acemoglu, 2002 for an overview). First, the vast majority of the increase in the aggregate share of skilled workers has occurred within industries rather than between industries. Basic Heckscher-Ohlin theory suggests the opposite. Secondly, wage inequality does not seem to have systematically fallen in developing countries would predict (e.g. Berman, Bound and Griliches, 1998). Thirdly, the within industry growth of skill demand is closely correlated to measures of technology such as computer use or R&D, but largely uncorrelated with measures of trade (e.g. Autor, Katz and Krueger, 1998). Fourth, although the relative prices of unskilled goods have fallen as Heckscher-Ohlin would predict, the magnitude of these changes is not large (Krueger, 1997)). Fifth, calibrated general equilibrium models

(e.g. Machin and Van Reenen, 1998) and/or institutions such as the minimum wage or labor unions (e.g. DiNardo, Fortrin, and Lemieux, 2001). There are at least two major problems with the consensus. First, most of this work used data up 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. By 1991 the figure was still only 2%, but by 2007 China accounted for almost 11% of all imports[3]. Secondly, an emerging line of theory has pointed to mechanisms whereby trade can affect the incentives to adopt and develop new technologies[4]. Thus, the finding that measures of technology are highly correlated with changing skill shares does not mean trade has no role. What may be happening is that trade is affecting technology and this is an intervening variable in changing the demand for skilled labor.

Our paper partially addresses these two criticisms. We use data from the last decade to examine the role of trade in affecting technical change in developed countries. Using the heterogeneous and rapid growth of Chinese imports across different industries, we examine the impact of trade on innovation, technology adoption and TFP in large samples of firms. Innovation is primarily measured by patent counts, but we show similar results when using citations and R&D. We distinguish the impact of trade competition on technology through an intensive and extensive margin.

And to tackle the issue of endogeneity of Chinese imports we implement two instrumental variable strategies. First, we use China's entry into the World Trade Organization and the subsequent elimination of most quotas in the ensuing years under the Agreement on Clothing and Textiles (formerly MFA)[5]. Second, we borrow from the literature on migration which uses "ethnic enclaves" as

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and factor content approaches find only a quantitatively small role of trade (see Krugman, 1995, for a GE approach, Borjas, Katz and Freeman (1997) for factor content analysis and Freeman (1995) for an overview). Not all trade economists shared the consensus, however. For example, Feenstra and Hanson (1999) do find some role for offshoring as a mechanism to raise the demand for skilled workers.

[3] Figure 1 may overestimate China's importance as the price of the import does not necessarily reflect the value added by China. For example, although I-Pods are produced in China, the key intellectual property is owned by Apple (see Koopman, Zhi and Shang-Jin, 2008). Identification in this paper relies on differences in exposure to Chinese industries over time *across industries* so we are not solely on the absolute aggregate trends.

[4] See inter alia Acemoglu (1999, 2002), Lloyd-Ellis (1999), Thoenig and Verdier (2003)

[5] Kandilov (2008) uses China's 1980 change to be a Most Favored Nation status with the US to look at its impact on skill demand 1979-1989. He finds effects similar in magnitude to the factor content analysis of Borjas, Freeman and Katz (1997). He does not control for technology, however, so it is unclear whether the effect he identifies could be related to technical change.

an instrument by using the fact that Chinese import growth was faster where Chinese firms had already paid the sunk costs of establishing a bridgehead in Europe by the late 1990s. Both these identification strategies strengthen our main finding that trade stimulates technical change.

In our estimations we find three sets of results. First, on the intensive margin, Chinese import competition increases the innovation and IT intensity of firms *within the industry* it exports in. Firms facing higher levels of Chinese import competition take out more patents, spend more on R&D and raise their levels of IT per employee. They also raise their overall level of productivity. Second, on the extensive margin, we find that Chinese import competition has a large negative employment impact on low tech firms. That is, when Chinese trade increases within an industry the firms with lower levels of IT and innovation appear to shrink and exit the industry much more rapidly than the hi-tech firms. Third, while trade for other low wage countries seems to have a similar impact as Chinese trade, trade from developed countries does not. So the source of the trade matters for its impact on innovation.

We offer some back of the envelope quantification of the magnitude of the Chinese import effects. In the 2000-2004 period China accounts for about 15% of the increase in IT intensity, patenting and productivity. However, this rises to about 25% for the 2004-2007 period. This suggests that trade with emerging nations such as China is now an important factor for technical change and therefore for growth and inequality.

We also discuss a theoretical model, developed in Bloom, Romer and Van Reenen (2009), which explains how trade from China drives innovation in exposed firms. The intuition relies on "trapped-factors" – that is factors which are costly to move between firms because of adjustment costs and firm-specific skills. When Chinese trade rises it reduces the profitability of making low tech products, for example basic running shoes. But since firms can not easily dispose of their "trapped" labor and capital, the shadow cost of producing a new good has fallen, increasing the returns to innovation. At the same time the high-skilled labor inputs to innovation are also cheaper since they are no longer being used to produce the good, reducing the cost of innovation. Hence, by destroying the profitability of current low-tech products and freeing up inputs to innovate new hi-tech products, Chinese trade increase the profitability of innovation. For example, firms originally making basic running shoes would instead develop hi-tech training shoes with embodied microchips. And since these higher-tech products are more complex to make the firms also invest in more IT.

Our paper relates closely to a number of literatures. First, there is the literature on wage-inequality and skill-biased technical change. As noted above the work using data from the 1970s to early 1990s found that trade played very little role in explaining the changing returns to skill, arguing instead that technical change was important. We return to this using more updated data and found an important role for trade in explaining technological change since the year 2000.

Second, there is the literature on the effects of trade on productivity (e.g. Pavcnik, 2002; Goldberg and Pavcnik, 2006). Many papers have found that trade liberalization increases aggregate industry productivity, but are often unclear over the mechanism[6]. This evidence tends to be indirect as direct measures on technical change are generally unavailable at the micro-level[7]. The literature focuses on the reallocation effects (e.g. Melitz, 2003) even though within plant productivity growth is typically as large as this reallocation effect between plants. Our paper uses new data on patenting, IT and productivity to establish that trade not only drives out the low-tech establishments but also affects the incentives of incumbents to speed up technical change.

Third, there is a large theoretical literature on trade and technology. As discussed in more detail in the next section our paper supports theories arguing for an important role of trade on technical change. The fact that the positive effect is through increased low-wage country imports is rather different from the mechanisms emphasized in most theories (e.g. market size, learning or product market competition). This is why we detail the alternative “trapped factor” outlined above.

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[6] An example of empirical evidence on the joint innovation and export market participation decisions is Aw et al (2007). Theoretical analysis of trade and innovation is voluminous including recent important contributions by Costantini and Melitz (2007), Atkeson and Burstein (2009) and Yeaple (2005).

[7] For low-wage countries themselves, Bustos (2007) finds some positive effects on innovation from reductions in export barriers facing Argentinean firms and Teshima (2008) finds some positive effects on process R&D from reductions on output tariffs for Mexican firms. The only study of the effect of Southern trade on direct innovation measures is Lelarge and Nefussi (2008), They find that the R&D of French firms react positively to imports from low wage countries, although they have no external instrument.

Finally, there is a large literature examining the impact of competition on innovation, but little empirical work examining trade-induced competition from low wage countries on innovation. Despite the growing theoretical work on the impact of "Southern" trade on "Northern" countries, the limited empirical research that exists has almost entirely looked at "South" on "South" or "North" on "North" effects.[8]

The structure of the paper is as follows: Section II sketches some theoretical models, section III describes the data, Section IV describes our econometric modeling approach and section V gives the results. Some concluding comments are offered in section VI.

II THEORY

We give a brief overview of the most salient theories that motivate our empirical work. We distinguish between two broad classes of theories: "compositional" and "innovation". The compositional theories imply that lower trade costs cause plants and firms to change their product mix from an existing menu of products. In the innovation-based theories, firms actually develop new products and processes to the economy. Empirically, we will find that although there is evidence for both sets of theories, we rule out the idea that the changes we observe are purely compositional because there are positive effects of Chinese competition on measures of innovation such as patents and R&D within firms. To rationalize these results we therefore sketch a simple "trapped factors" model of innovation.

II.A Technology upgrading through compositional change

Perhaps the most simple approach is to consider a framework where there are two regional blocs (called EU and China), with the EU holding a comparative advantage in high tech goods ("machinery") and China abundant in low tech goods ("apparel"). When we move from Autarky to Free Trade the economies integrate and we will have specialization: the industries that are high tech will grow in the EU and the industries that are low tech will decline. The opposite will occur in China. A further twist is the assumption that the high tech goods require inputs that are more sophisticated and are intensive in IT usage compared to the low-tech goods.

[8] On the theory see *inter alia* Grossman and Helpman (1992), while on the empirics see for example, Trefler (2004), Bustos (2007) and Dunne, Klimek and Schmitz (2008).

This simple framework is rather unsatisfactory. For one, we know that most of the macro changes we observe (say in technology, productivity and skills) have occurred within rather than between industries. Of course, it may be that even the four-digit classification is too crude so even the between-firm shifts that we observe could be because firms are in different parts of the market within a sector. We will show, however, that China causes increased technological upgrading even *within* ongoing establishments. Consequently, we need to think of models that can explain changes for incumbents.

Multi-product firms

Bernard, Schott and Redding (2007, 2009) investigate the impact of trade liberalization in the context of heterogeneous firms producing multiple products. Their set-up is one where firms have heterogeneous ability leading to a higher productivity across all products, but also have a product-specific efficiency draw. Higher ability firms will produce more products and be larger, but all firms will specialize by having a larger share of their output devoted to their most efficient product. In the face of falling trade costs with a country like China, there will be several effects on Northern firms. First, there will be the standard shakeout effect where less productive firms shrink and exit and this will be stronger in those products where China has comparative advantage. We will investigate this empirically as our between-plant effect, i.e. is the effect of China on employment and survival rates more negative for the low-tech plants? Second, firms will specialize in products where they have greatest comparative advantage. Thus we will expect to observe (on average) a *within firm* shift to more high-tech products and away from less sophisticated products in the North. In our data, we would therefore expect to see an increase in IT usage even within plants (assuming that more high-tech products use more IT inputs). We will show that we observe product switching and within firm technology upgrading in our data consistent with this view.

Offshoring

A fall in trade costs with China will mean that producers of goods that intensively use Chinese intermediate inputs will benefit. For example, some firms may slice up the within firm supply chain for their final products and offshore more of the low-skill intensive component to China (see for example

Grossman and Rossi-Hansberg, 2007)[9]. This will have a compositional effect if the remaining activities in the home country are more technologically intensive. In addition, the cheaper intermediate inputs from China may have a beneficial effect on technical change which is distinct from the effects of Chinese import competition in the firms' final goods market. 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).

II.B The "Trapped Factor" Model of Trade-induced Innovation

As noted above we find three stylized facts in our results. First, Chinese trade directly increases the level of innovation *within the industry* that its increases its exports in. Second, Chinese exports have a negative employment impact, particularly on the most low-tech firms. And third, while imports from other low-age countries have a similar impact as Chinese imports, those from high-wage countries do not seem to induce innovation. To explain this facts in Bloom, Romer and Van Reenen (2009) we developed a stylized model of innovation.

The basic idea is that China can produce current low-tech goods, but can not produce (as easily) new high-tech goods. For example, China can make basic home-computers but is less effective at creating new advanced super computers. At the beginning of the period (the mid-1990s in our data) there are factors of production employed in European and US factories making low-tech good. These factors are "trapped" in the sense that they have firm-specific human capital and adjustment costs. When China starts exporting these low-tech goods to Europe and the US their price falls substantially. This induces innovation through two related channels. The first is that the opportunity cost of using these trapped factors in innovating new goods falls because their marginal revenue product in making the good falls. For example, the cost of diverting skilled workers from producing basic shoes to designing new high-tech shoes falls if the price of basic shoes falls. At the same time the capital used to make the old goods – the factories and equipment – is also trapped because of capital adjustment costs. As a result the shadow cost of using this capital to produce new high-tech goods falls as it is no longer profitable to

[9] Interestingly, increased ICT sophistication may itself be driving this increase in off-shoring, since coordinating international production will require much more extensive communication. This is one of the motivations for addressing the endogeneity issue.

make the old goods. This increases the profits from innovating as the shadow price of the cost of producing these new good falls. Hence, the fall in prices of old low-tech goods arising from Chinese imports, reduces the costs and increases the profits from innovating new high-tech goods by incumbent producers. This is consistent with our results that China increases innovation in incumbent firms, and this occurs in the industries in which its exports grow most.

Integration with a high wage country will not have this effect. This is because imports from high-wage countries will not reduce the price of old low tech good relative to new high-tech goods. If, for example, Japan can make super computers just as cheaply as home-computers there is no reason for domestic producers in Europe and the US to switch from producing home computers to super-computers. This is consistent with our results we do not fund 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. From the Social Planner's perspective there may be underinvestment in R&D and China induces greater innovation[10].

IIC Alternative models of Trade-Induced Innovation

There are many other theories that suggest mechanisms through which trade can influence innovation. We discuss some here, but none of them relate as well to our three key empirical results as our "trapped factor" model.

Imitation Threats from the South

Grossman and Helpman (1992) describe an endogenous innovation model of trade integration between South and North. Northern firms innovate and Southern firms imitate, but both activities are costly. Integration with the South tends to increase innovation in the North in their model. When the South copies Northern products and competes in world markets there is an adverse effect because the

[10] 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 to 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.

innovating firm only enjoys its monopoly rents for a shorter duration (the standard "Schumpeterian" effect). Imitation, however, tends to thin the ranks of Northern innovators which means that while the firm has a monopoly innovation it earns higher per period profits. In their basic model the second effect dominates so that Southern integration raises innovation incentives in the North. Extensions to the model to that allow Southern firms to also innovate renders the result ambiguous, since these firms may leapfrog the Northern leader. This extension effectively increased product market competition for the Northern firm, so we turn explicitly to consider competition effects next.

Product market competition

Reductions in trade barriers imply that Chinese producers are much more effective competitors because even if their products are lower quality, their lower production costs place a competitive constraint on incumbent Northern producers. It is very likely that the rise of China constitutes a trade-based competitive shock on domestic Northern producers. It is well known that theoretically the impact of competition on innovation is ambiguous. On the one hand, there may be increased managerial innovative effort because of the fear of greater bankruptcy risk, greater sensitivity of relative profits to effort, a stronger "escape competition" effect (Aghion et al, 2005), lower switchover costs (Holmes, Levine and Schmitz, 2008) and (in equilibrium) larger firm size (see Vives, 2005). On the other hand, lower profits will blunt innovation incentives for standard Schumpeterian reasons - lower rents from innovation implies less incentives to invest in R&D.

Although there is much empirical evidence on competition and technical change (e.g. Aghion et al, 2005; Blundell et al, 1999; Cohen and Levin, 1989), finding an exogenous measures of increases in competition is difficult. Our paper is distinctive in three ways; first, we argue that that China's trade growth constitutes the best recent example of a major quasi-experiment increasing competition. Secondly, previous papers have focused on competition in general rather than trade with developing countries in particular. Thirdly, the papers that have looked at trade liberalizations have tended to look at plant productivity (e.g. de Loecker, 2007b) rather than at technology per se. Thus, we believe that focusing on the rise of China is novel and interesting extension of this literature.

Market Size

An important feature distinguishing investments in technology from other inputs is the large fixed and sunk cost component that, if successful, reduces marginal costs across all other inputs. Models of endogenous growth where the incentives to invest in new technologies depend on the size of the market have been long discussed since at least Adam Smith (see also Schmookler, 1966 and Krugman, 1979) and have had a recent revival (e.g. Acemoglu, 1999, 2008). The essential idea is that greater trade generates a larger market size to spread over the fixed costs for investing in new technology. Recent work by Lelieva and Trefler (2008) has shown market size effects on Canadian firms of joining NAFTA.

Learning

Another mechanism through which imports can enhance innovation is through enabling domestic firms to gain access to better technology (e.g. Coe and Helpman, 1995). This may occur directly through the import of new varieties of intermediate inputs and through informal channels as the importing firms build up supply networks (Riviera-Batiz and Romer, 1991; Goldberg, Khandewal, Pavcnik and Topalova, 2008a, b). A related literature finds evidence that productivity rises when exporting increases (e.g. de Loecker, 2007a, Verhoogen, 2008). These mechanisms[11] do not seem appropriate in the context of China however, as European firms will be ahead of them on the technological frontier (although this may be changing in some sectors as China develops – see Schott, 2008). We examine explicitly whether exporting to China may have helped spur technical change, but (unlike imports) we do not empirically identify any significant empirical effect of exports to China on technical change.

II.D. Summary

In summary, the existing literature has suggested some mechanisms whereby trade will affect technology adoption and innovation, but these have not been systematically empirically examined. To the extent they have been looked at, the focus has been on developing rather than developed countries, on indirect measures of technology (TFP) rather than at direct measures (IT and patents) and at the macro level (nation or industry) rather than at the micro level (establishment). We have put forward a new "trapped factor" model that we believe offers insights into why Chinese imports may generate

[11] Although there are many papers which do not find a causal role for exports (e.g. MacGarvie, 2006).

greater innovation in the North. Nevertheless, the theory is ambiguous, so the effects must be examined empirically.

III. DATA

We combine datasets from multiple sources. First, we use an original source of IT data at the establishment level across many countries (Harte Hanks' CiTDB). Second, we use patenting at the European Patent office matched to firm-level accounts data. We combine these datasets with four-digit industry by country trade data from COMTRADE and other industry data sources. The advantage of having establishment/firm-level panel data on technology is that we can distinguish within and between establishment/firm-level effects of trade, which would be impossible if we had only industry level data.

IIIA Harte-Hanks IT data (HH CiTDB)

The Ci Technology Database (CiDB) is produced by the international marketing and information company Harte Hanks (HH). Harte-Hanks is a global company that collects IT data primarily for the purpose of selling on to large producers and suppliers of IT products (e.g. IBM, Dell etc). Their data is collected for roughly 160,000 establishments across 20 European countries as well as the US[12]. In Europe, HH began surveying the major Western European countries in the early 1990s, and by the late 1990s had expanded to cover the rest of Western Europe.

Harte Hanks surveys establishments on a rolling yearly basis. This means that at any given time, the data provides a "snapshot" of the stock of a firm's IT. The CiTDB contains detailed hardware, equipment and software information including PCs, many types of software, networking resources, databases, etc. We focus on using computers per worker (PCs and laptops) as our main measure of 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 controversial and are not harmonized across countries. The computers per worker measure of IT has also been used by

[12] The US branch has the longest history with the company beginning its data collection activities in the mid 1980s. The papers by Bresnahan et al (2002) and Brynjolfsson and Hitt (2003) use a sub-set of the US data, matching it to large publicly traded US firms.

other papers in the micro-literature on technological change and is highly correlated with other measures of IT use like the firm's total IT capital stock intensity (see, for example, Beaudry, Doms and Lewis, 2006, and Bloom, Sadun and Van Reenen, 2007). In robustness tests we compare econometric results using alternative measures of IT such as Enterprise Resource Planning, Groupware, databases, etc.

The fact that HH sells this data on to major firms like IBM and Cisco, who use this to target their sales efforts, exerts a strong market discipline on the data quality. If there were major discrepancies in the collected data this would rapidly be picked up by HH's clients when they placed sales calls using the survey data, and would obviously be a severe problem for HH future sales.[13] Because of this HH run extensive internal random quality checks on its own data, enabling them to ensure high levels of data accuracy.

Another valuable feature of the CiDB is its consistency of collection across countries. The data for Europe is collected via a central call centre in Dublin and this ensures that all variables are defined on an identical basis across countries. 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[14].

In terms of survey response rates HH report that large European countries (UK, France, Germany, Italy, and Spain) had a response rate of 37.2% in 2004 for firms with 100 or more employees[15]. As mentioned above, the sampling strategy followed by HH allows us to construct a measure of establishment survival. The company's policy is to continue to conduct follow up surveys with all establishments after they have entered the survey. Since the "first contact" or initial survey of an establishment is arguably the most difficult to achieve it makes sense for HH to capitalise on this sunk cost and conduct regular follow-up interviews. Hence, while the company defines no formal measure

[13] HH also refunds data-purchases for any samples with error levels above 5%

[14] It is also worth noting this survey frame is based on *firm* employment - rather than *establishment* employment - so the data contains establishments with less than 100 employees in firms with multiple establishments. In our data 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. It is also worth nothing that in the countries we study firms with over 100 employees account for over 80% of total employment in manufacturing.

[15] HH find no systematic response bias in terms of observables such as region, industry, etc.

of establishment survival in their data we able to infer exit by the disappearance of an establishment from a dataset. Practically, we classify any establishment that has not appeared in the survey for 24 months as an exit. We cross checked these assumptions against matched firms from the Amadeus database and found it to be an accurate rule in almost all cases.

IIIB Patents Data

We use the AMAPAT database (Belenzon, 2008) for our analysis. This begins with the population of patents from the European Patent Office which began in 1978. We selected corporate patents and matched them by name to the Amadeus database from Bureau Van Dijk. The latter contains close to the population of firms in our 12 European countries and includes both publicly listed and private firms (in the UK, for example, the data is lodged at Companies House and contains over 2 million firms per year). Because all firms have a four digit company code we were then able to match them to trade data at this level.

Amadeus also gives us information from the accounts of firms on items such as employment, capital, wage bills and sales, etc. But since accounting requirements differ between countries and firm size we have this information only for a sub-sample of the whole database. Consequently we report results both on the larger sample where we do not have accounting data and show robustness of the results to conditioning on other firm level variables from the accounts.

Patent counts have well-known limitations as measures of innovation, but there are no other quantitative indicators of innovative outcomes measured in a consistent way over time and across a large range of countries. We are also able to construct cite-weighted versions of patents to control for patents of different value as well as to examine whether Chinese import competition was associated with a decline in the value of patenting as indicated by patent citations[16].

IIIC. Productivity and R&D data

[16] This may be important as European firms may react to the greater risk of import competition from China by guarding their intellectual property more carefully by taking out more patents (rather than necessarily increasing the stock of knowledge). If this were the case then these patents would embody less intrinsic knowledge which would be reflected in a lower future citation count.

We calculate productivity using manufacturing firms in France, Italy, Spain and Sweden in the Amadeus dataset. We select these countries because: first, they appear to have complete coverage of their manufacturing population of firms evaluated by comparing their employment figures to those in their national Census (see Bloom, Sadun and Van Reenen, 2008); and second their accounting require reporting of sales, employment, capital and materials so we can estimate TFP controlling for four factors. In robustness tests we show our results on productivity are very similar if we use the Amadeus data for all 12 countries in our analysis, but present the baseline results for these four countries where there appears to be no selection bias in reporting. The R&D data comes from a database called Osiris, also provided by Bureau Van Dijk, which provides data on every public listed firm in Europe covering around 4,000 firms, for which 459 have R&D data for 5 years or more.

IIID. UN Comtrade Data

The trade information we use is sourced from the UN Comtrade data system. This is an international database of 6-digit product level information (denoted HS6) on all bilateral imports and exports between given pairs of countries. This data was used by Feenstra et al (2005) to construct the NBER's international trade flows database running from 1962-2000. Of course, since our interest lies in the period since 2000 we extract and build our own dataset on trade flows between China and the European countries covered in our establishment data. We aggregate from 6-digit product level to 4-digit US SIC industry level using the Feenstra et al (2005) concordance.

We use the value of imports originating from China as a share of total world imports in a country-industry cell as our key measure of exposure to Chinese trade, following the "value share" approach outlined by Bernard and Jensen (2002)[17]. As two alternative measures we also construct Chinese import penetration by normalizing Chinese imports either on domestic production or on apparent consumption (domestic production less exports plus imports). For domestic production we use Eurostat's Prodcom database. Compared to Comtrade, Prodcom has the disadvantage that there is no data prior to 1996, so this restricts the sample period, especially for the patents equation which requires long lags. It also has the problem that some of the underlying six digit product data is missing (for confidentiality reasons) so some missing values had to be imputed. Although we obtain similar results

[17] See also Bernard, Jensen and Schott (2004, 2006).

with all measures we prefer the normalization on world imports which does not have these data restrictions.

In terms of overall trends in China's trade Figure 1 shows the remarkable rise of China's share of all imports to the US and the 12 European countries in our sample. In 2000 only 5.8% of imports originated in China. By 2007 this had doubled to approximately 10.7%. Furthermore, this growth in Chinese imports also appears to be accelerating, rising from an increase of about 0.5 percentage points per annum of imports a year in the late 1990s to one percentage point a year in the 2000s. Of course, this aggregate disguises considerable heterogeneity by industry. Appendix Table A1 lists the top ten four digit industries in terms of imports from China in 1999, along with the level in 2006. The two things of note here are firstly the heterogeneity in shares that this list reveals – while the aggregate share of 10% could be considered low there are a number of industries where China has a very high share even in 1999. Secondly, these high shares are still associated with high subsequent rates of growth up to 2006. For example, China's share of SIC 3944 (games and toys) was 40% in 1999 and rose to 71% by 2006. It is this feature of high initial presence in particular industries and strong subsequent growth that we exploit for our later instrumental variable strategy. For example, the industries where China has a high import share contrast with the more capital and technologically intensive industries where its import share is typically low in both 1999 and 2006.

IIIE. Descriptive Statistics

Table 1 contains some basic descriptive statistics. In the regression sample we only keep establishments with non-missing values on our key variables over a five year period. This gives us a sample of just under 23,000 establishments. Our establishments have a median (mean) employment of 140 (248). In 2000 IT intensity was 49% (about one PC and laptop for every two employees) but this rises over the next 7 years to around 58% by 2007. Employment, by contrast, fell during this period reflecting the ongoing contraction of the manufacturing sector. About 88% of establishments alive in 2000 were still alive in 2005.

In Figure 2 we plot the mean change in (within-establishment) IT intensity and ln(employment) ordered by the degree of exposure to Chinese import competition. We divide establishments into quintiles based upon the increase in Chinese import share, so that the lowest (first) quintile represents those four digit industries which had the lowest increase in Chinese imports and the highest (fifth) quintile represents those industries that had the highest increase in Chinese imports. Looking at the change in IT intensity (the first, dark shaded bar), there is a monotonic relationship between imports and technology upgrading. Although IT intensity has increased, on average in all establishments it has increased more for those establishments most exposed to an increase in trade competition (17% in the bottom quintile of Chinese import growth compared to 23% in the top quintile). By contrast, establishment job growth is almost the mirror image of the IT intensity changes. Although employment generally fell in all plants, those establishments most exposed to Chinese import competition experienced the largest falls in employment. A concern is that the IT intensity figures are simply driven by the employment changes (the denominator) rather than changes in technology. In the econometric analysis we show this is not the case by controlling for employment changes when we run IT intensity regressions.

Figure 3 probes the employment effects more deeply and shows the contrast between establishments who are in the bottom quintile of the increase in Chinese imports ("low exposure industries" in Panel A) to those in the top quintile ("high exposure industries" in Panel B). We break down the within establishment employment growth in each sector by the establishment's initial IT intensity. We see the same pattern observed in Figure 2: high exposure industries suffered greater job losses than low exposure industries. But we also see that the more IT intensive establishments were somewhat shielded from this job loss. In fact, the most IT intensive establishments (i.e. in the top quintile) in both sectors actually experienced *increases* in employment (of about 8%). The most interesting feature of Figure 3, however, is that this "protective" aspect of technology against job loss is much stronger in the industries more exposed to Chinese competition. In the low exposure industries the least IT intensive establishments had a mean job loss of about 10%. By contrast in the high exposure industries these types of establishments suffered job losses of closer to 20%. This suggests that the main effect of Chinese competition is likely to be felt by the least technologically advanced firms.

This examination of the descriptive statistics suggests an empirical modelling strategy that analyzes both the *intensive* margin of IT upgrading (how IT increases within establishments more exposed to

Chinese trade) and the *extensive* margin of industry-wide upgrading through selection effects. The latter focuses on how the less technologically advanced firms are most at risk from an increase in Chinese import competition which can cause their employment to shrink and ultimately mean that they will exit. The shakeout of these plants will mean that IT intensity rises in the industry as a whole even if no establishments were to increase their IT. We now turn explicitly to our econometric modelling strategy.

IV. EMPIRICAL MODELING STRATEGY

IVA. General Modeling Approach: Chinese import competition in the output market

Our generic industry level equations take the form:

$$\ln Y_{jkt} = \alpha IMP_{jkt}^{CH} + \beta x_{jkt} + u_{jkt} \tag{1}$$

Where Y is an indicator of technology such as IT intensity, patents or TFP (we also consider R&D) in industry j in country k at time t. IMP_{jkt}^{CH} is our measure of exposure to trade competition with China and the trade-induced technical change hypothesis is that $\alpha > 0$. We measure IMP_{jkt}^{CH} mainly as the proportion of imports (M) in industry j and country k that originate from China $(M_{jk}^{China} / M_{jk}^{World})$, where we normalize Chinese imports (M^{China}) by total imports from anywhere in the world (M^{World}). Rapid growth in the Chinese import share is therefore used as a proxy for a rapid increase in trade competition from low wage countries in the industry. The x are other observable controls.

There are two major problems with estimating equation (1). First, there is considerable unobserved heterogeneity between industries, so we will have to control for fixed effects, which we will generally do by estimating in long (five year) differences[18] denoted by the operator Δ. Second, the growth of Chinese imports may still be related to unobserved shocks, Δu_{jkt} so we will have to consider instrumental variables such as the removal of quotas when China joined the WTO.

[18] We use long-differences to mitigate the problem of attenuation bias when using first differences.

We are interested in the mechanism through which Chinese trade effects technology upgrading in an industry. Broadly, this effect can be divided into a "within" effect (incumbent firms upgrade their technology) and a "between" or reallocation effect. The reallocation effect arises because exposure to Chinese trade will (a) affect the distribution of output between surviving firms and (b) affect the type of firms who exit (and possibly enter). For the industries more exposed to Chinese imports we would expect low-tech firms to shrink and exit faster than higher tech firms.

IVB. Technical change within plants and firms

Our first firm-level equation is for IT growth:

$$\Delta \ln(IT / N)_{ijkt} = \alpha^{IT} \Delta IMP_{jkt}^{CH} + \beta^{IT} \Delta x_{ijkt}^{IT} + v_{ijkt}^{IT} \tag{2}$$

Where IT is a measure of information technology in establishment i and N is the number of workers. We will generally use the number of personal computers and laptops, but experiment with many other measures of ICT such as ERP, Databases and Groupware.

Next, consider the analogous equation to (2) for innovation (P) rather than IT diffusion (as measured by patent counts or cite-weighted patent counts):

$$\Delta \ln(Pat)_{ijkt} = \alpha^{PAT} \Delta IMP_{jkt-m}^{CH} + \beta^{PAT} \Delta x_{ijkt}^{PAT} + \upsilon_{ijkt}^{R\&D} \tag{3}$$

Note that we have lagged the Chinese import measure by m periods because of the time for increased R&D to generate innovations.[19] We will present experiments with many lag lengths and show that longer lags provide a better fit of the data (our baseline uses a three year lag).

Our third measure of innovation is R&D which we treat analogously to IT and patents:

[19] Because of the zeros in patents we normally use $\Delta\ln(1 + PAT)$. The addition of unity is arbitrary, but close to the sample mean of patents. We compare the results with the standard fixed effect count data models exploiting the moment $E(P_{ijkt} \mid X_{ijkt}) = \exp(\alpha^P IMP_{jkt-m}^{CH} + \beta^P x_{ijkt}^P + \eta_i^P)$, e.g. Blundell, Griffith and Van Reenen, 1999, which generated qualitatively similar results.

$$\Delta \ln(R\,\&\,D)_{ijkt} = \alpha^{R\&D}\Delta IMP_{jkt}^{CH} + \beta^{R*D}\Delta x_{ijkt}^{R*D} + \upsilon_{ijkt}^{R*D} \tag{4}$$

Finally, we use TFP as our third measure of "technology" (this should be regarded as a more general indicator of efficiency). We estimate this 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 (following Klette and Griliches, 1996). In a first stage we estimate production functions separately by two digit industry across 1.4m observations to recover the parameters on the factor inputs and the unobserved efficiency term. We then relate this efficiency term to changes in the environment. Details are contained in Appendix C.

$$\Delta \ln TFP_{ijkt} = \alpha^{TFP}\Delta IMP_{jkt}^{TFP} + \beta^{TFP}\Delta x_{ijkt}^{TFP} + v_{ijkt}^{TFP} \tag{5}$$

IVB. Technological upgrading through reallocation between plants and firms

The prior section examines whether Chinese import competition is associated with technological upgrading on the intensive margin – i.e. within surviving plants. We also examine whether trade affects the *extensive* margin by examining employment equations and survival equations. As discussed in the section (III), conventional models would predict that China would cause low-tech plants to shrink and die, as these are the firms competing most closely with Chinese imports.

We estimate employment growth equations of the form:

$$\Delta \ln(N)_{ijkt} = \alpha^{N}\Delta IMP_{jkt}^{CH} + \beta^{N}\Delta x_{ijkt}^{N} + \gamma^{N}[TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}] + \delta^{N}(TECH)_{ijkt-5} + v_{ijkt}^{N} \tag{6}$$

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

Equations (2)-(5) 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:

$$SURVIVAL_{ijk} = \alpha^S \Delta IMP_{jkt}^{CH} + \beta^S \Delta x_{ijkt}^S + \gamma^S [TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}] + \delta^S TECH_{ijkt-5} + v_{ijkt}^S \qquad (7)$$

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 $\alpha^s < 0$ and if high-tech plants are somewhat more protected from this effect we expect $\gamma^s > 0$.

To complete the decomposition of equation (1) 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 observed technology level as this is clearly endogenous (in equations (6) and (7) we use lagged technology variables which we claim are weakly exogenous). Consequently, we will estimate equation (7) without the technology variables for entry.

V. RESULTS

VA Industry Level Results

Table 1 presents some results on the industry-country panel formed by aggregating our micro-data. The period as a whole is 2007-1996, although there are missing years in some columns due to data availability. The first two columns are a basic sense check on the data. We find that greater Chinese imports significantly reduces prices (column (1)) and employment (column 2)) in the more affected industries. This is unsurprising, but a useful starting point[20].

The other columns show how greater Chinese imports are associated with faster technical change (as measured by IT, patents and TFP). Column (3) presents the IT equation showing that imports are associated with significantly greater IT per worker and column (4) includes employment growth as an additional control to show that this is not just driven by employment falls. Column (5) uses patent counts until 2006 and column (6) uses patents counts through 2005. In both cases trade is associated with a higher level of innovative activity. Column (7) used R&D expenditure and shows Chinese imports are associated with an increase in industry R&D expenditure, which column (8) confirms this with employment controls included. The final column shows the results for TFP with Chinese imports again entering with a strong and positive coefficient.

VB. Within Firm and Within Plant Results

Table 3 presents our key results: firm-level and plant-level measures of technical change. All columns control for fixed effects and country-specific macro shocks. Looking across all columns, it is clear that industries subject to larger increases in Chinese import competition had a significantly faster rate of technical progress across all measures and specifications. Column (1) uses IT intensity as the dependent variable and suggests that a 10 percentage point increase in Chinese import penetration is association with a 3.6% increase in IT intensity. Since employment fell in those industries more affected by Chinese trade we condition on employment in column (2), this almost halves the coefficient, although it remains positive and significant[21] implying that the positive association of IT intensity with Chinese imports does not simply reflect employment falls.

We now turn to the patent equations using the European Patent Office data matched with firm accounts. Column (3) uses the growth in patents as the dependent variable and indicates a strong

[20] Broda and Romalis (2009) claim to find (although do not report) a "strong negative correlation between the changes in prices by product module and the change in Chinese trade in that same module" in the US in recent years.
[21] This is consistent with the idea that firms offshore the low tech part of their activities in response to trade threats.

positive correlation between innovation and trade[22]. We control for employment in the next column, but unlike IT this makes little difference to the marginal effect.[23] Column (5) presents R&D results showing a significant increase in firm-level R&D expenditure associated with Chinese imports, which column (6) confirms is robust to controlling for employment. In the final column we use TFP growth as the dependent variable and also establish a positive and significant association.

As we will discuss in more detail in sub-section IVE below The magnitudes are economically important: a 10 percentage point increase in Chinese imports is associated with about a 3.6% increase in IT intensity, a 3.5% increase in patenting, a 12% increase in R&D and a 2.5% increase in TFP.

VC. Endogeneity

An obvious problem with estimating these equations is the potential endogeneity of Chinese imports. Consider equation (2) for example. If there is an unobserved technology shock to v_{ijkt} increasing the IT intensity of domestic firms in an industry country pair, Chinese imports are likely to fall. This causes a downwards bias to the estimate of α thus making it *harder* to identify the effect we are looking for. Of course, there may be counter examples. An unobserved demand shock could raise IT intensity and (for some reason) suck in more Chinese imports than other types of imports.

The fact that our variable of interest is industry-level rather than establishment-level and is in differences rather than in levels, helps mitigate the bias, but will not eliminate it. Consequently, we consider several instrumental variable strategies.

China joining the WTO as a quasi-experiment

[22] If we condition on a sub-sample of the data where we observe the lagged capital-sales ratio and lagged employment missing values on these accounting measures cause the sample to fall by almost half, but the point estimate on Chinese imports is actually higher and still significant. If we include the ln(capital/sales) ratio and ln(employment) in the regression this barely shifts the results (0.370 with a standard error of 0.125). The correlation with Chinese trade is not simply an increase in all types of capital, but seems related specifically to technical change.

[23] We also estimated negative binomial count-data models for patents including the Blundell, Griffith and Van Reenen (1999) pre-sample mean scaling controls for fixed effects and recovered similar coefficients, for example with a point-estimate (standard error) of 0.467 (0.279) for patents on the level of Chinese imports.

One identification strategy is to use the accession of China to the WTO that generated a fall in trade barriers against China for most OECD economies. We exploit the fact that quotas for textiles and clothing against China were raised very substantially (and abolished in many cases). This is because the Agreement on Textiles and Clothing (the successor to the Multi-Fiber Agreement, the MFA) had very high quotas to begin with. When China joined the WTO in December 2001, it immediately gained access to the first two waves of quota reductions from the MFA and benefited from the planned 2002 liberalization. The next liberalization in 2005 then abolished most of the remaining quotas (see Brambilla, Khandewal and Schott, 2008, for a more detailed description). Thus over the post 2000 period there was a significant relaxation of barriers to Chinese imports into Europe and (as we show) a large increase in Chinese imports in those industries most affected. Since these quotas were built up from the 1950s to protect against Japanese and India imports, and their phased abolition negotiated in advance of the Uruguay round of 1994, it seems fair to take these as exogenous. Note that we use the level of quotas against China in 2000 (prior to WTO accession) as the instrument. We could use the five-year change of these quotas, but some of the quotas remained and were re-introduced in 2006 due to domestic lobbying. The initial level of quotas should be robust to this problem.

Table 4 uses this identification strategy of China's accession to the WTO that led to a huge fall in quotas against Chinese goods (see Appendix A)[24]. Since this is only relevant for textiles, clothing and tableware we first present the OLS results for the IT equation for these industries 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 height of quotas in the years before China joined the WTO (1999) as the external instrument. Quota reduction appears to be positive and highly significant in predicting 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 under OLS (1.9 compared to 1.3)[25]. A concern is that the height of the quota in

[24] Note that throughout the IV tables (4 and 5) we cluster by four-digit industry only, instead of four digit by country dummies as in the previous tables. We do this 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. We consider anticipation effects and other dynamic responses in the robustness tests.

[25] If we repeat the IV specification of column (3) 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 which 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

2000 is proxying some other trend correlated with Chinese import growth. To test for this we included Chinese import growth 2000-1995 as an additional control. The coefficient on this control 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).

Columns (4)-(6) implement the same identification strategy but use patents instead of IT. Column (4) shows that the OLS results for patents are also strong in this sector and column (5) reports that the instrument has power in the first stage. The IV results in the final column also indicate that the OLS coefficient appeared downward biased, although the standard error is large. The final three columns repeat the specification for TFP showing no evidence of upward bias for OLS.[26]

Initial conditions instruments

A disadvantage of the quota-based instrument is that we can only construct the instrument for the affected industries (textiles, clothing, footwear and tableware), so we consider a second identification strategy. The overall increase in Chinese imports is driven fundamentally by the opening up to the global economy because of ongoing liberalization by Chinese policy makers, so is clearly exogenous. The industries where China exported more depended on whether the industry is one in which China has 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 that China has a comparative advantage in – such as textiles, furniture and toys (see Appendix Table A1) – and so would experience much more rapid increase in import penetration in the subsequent years. Consequently, high exposure to Chinese imports in 1999 can be used (interacted with the overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($IMPS_{j99}^{CH} * \Delta M^{China}$) as an instrument for $\Delta IMPS_{jkt}^{CH}$ where

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).

[26] We do not run R&D specifications as the sample size for R&D doing publicly quoted textile and apparel firms in Europe is too small.

$IMPS^{CH}_{j99}$ is the Chinese import share in industry j in the world. Note that we do not make $IMPS^{CH}_{j99}$ specific to country k to mitigate some of the endogeneity problems with using an initial condition[27].

A priori the instrument has some credibility as Brambilla, Khandewal and Schott (2008) document evidence that Chinese imports grew faster from expansion of existing products (the "intensive margin") rather than the existence from adding new products ("the extensive margin") after 2001. A similar finding also emerged from looking over the period since 1992 in Amiti and Freund (2007). Of course this is not always the case (e.g. after NAFTA Mexico started exporting new goods to the US), which is why the first stage must be carefully examined.

So we next consider this "initial conditions" approach, which instruments with the growth of total Chinese imports into Europe interacted by the China's lagged share of imports in the (European wide) four-digit industry. Column (1) of Table 5 re-presents the basic OLS results. 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) then presents the second stage: the coefficient on Chinese imports is 0.727 (and significant at the 5% level). Columns (4) through (6) repeat the experiment for patenting (using the same specification as Table 4). In column (6) the coefficient on Chinese imports is positive and significant at the 10% level and above the OLS estimate[28]. In the final column for TFP, the IV coefficient is again above the OLS estimate, although the standard error is large (we have only 106 clusters).[29]

The downward bias on the OLS coefficients is consistent with our priors as we might expect a technology shock to give some "protection" to an establishment from Chinese imports. Taking both IV tables together, there does not appear to be evidence that we are over-estimating the effects of China on technical change by treating the growth of Chinese imports as exogenous.

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27 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. It shares the problems of course, that we are assuming that the level of imports is not correlated with unobservable future technology shocks. In order to examine this assumption we present experiments conditioning on pre-sample trends in employment, technology and skill measures.

28 Unsurprisingly the results are more precise if we use both instruments together. For example in the final column of Table 4 (IV patents) the coefficient (standard error) on patents is 2.067 (0.717).

29 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).

VD. Reallocation effects: jobs and survival

Table 6 examines reallocation effects by analyzing employment growth regressions (still of survivors). First we examine the raw correlations in column (1) suggesting a strong negative association between job growth and exposure to Chinese imports. This suggests a ten-percentage point increase in Chinese imports is associated with a 2.8% fall in employment. The interaction of Chinese trade and lagged IT intensity that enters with a positive and significant coefficient in column (2). This suggests that firms that are IT intensive are somewhat “shielded” from the effects of Chinese imports[30].

We divide our firms into five quintiles based on their lagged IT intensity and we interact these with Chinese import growth. A clear pattern emerges shown in column (3) whereby the imports effect is much weaker for the more IT intensive firms. In fact, for establishments in the top quintile of the IT intensity distribution there is no association of Chinese imports with job losses. By contrast, for those who were in the bottom quintile of the IT distribution a ten percentage point increase in Chinese imports is predicted to reduce employment by 4%. Columns (4) and (5) use patenting as the lagged technology indicator instead of IT[31]. Column (4) continues conditions the sample on firms who took out at least patent since 1978, whereas column (5) uses all firms, even those who never patent. In both columns more high tech firms were less likely to shed jobs following an increase in Chinese imports. The final column uses TFP as our technology indicator, and again finds a positive and significant interaction between imports growth and lagged TFP intensity.

Table 7 examines models of survival where we consider a cohort of firms 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 their initial characteristics. Column (1) shows that even after conditioning on (lagged) establishment size and IT intensity, establishments more exposed to Chinese imports are

[30] Note that lagged IT intensity enters with a positive and significant coefficient both with without the interaction suggesting that the more technologically advanced firms in were more likely to grow over the next five years.

[31] We construct patent stocks (PATSTOCK) using the perpetual inventory method, $PATSTOCK_t = PAT_t + (1 - \delta)*PATSTOCK_{t-1}$ where PAT is the flow of patents and δ is the depreciation rate. Following Hall, Jaffe and Trajtenberg (2005) we set $\delta = 0.15$. Even though similar results emerge from using the flow, we prefer to use the stocks as the year to year movement in patents can be very volatile.

significantly less likely to survive (i.e. more likely to exit) than those less exposed. A ten percentage point increase in Chinese imports decreases the survival probability by 1.2 percentage points. Since the average survival rate in our sample period is 88%, this represents about a 1.4% decrease in survival rates (equivalent to an 11.4% increase in exit rates), which is a non-trivial effect. Larger establishments are more likely to survive as we would expect. Column (2) includes an interaction of lagged IT intensity with Chinese imports. As with the employment equations, the low-tech firms appear most "at risk" from Chinese import competition, as the coefficient on the interaction between Chinese imports and IT intensity is positive (although it is not significant). Column (3) reports the specification where we use the quintiles of the IT intensity. This indicates that the least technologically intensive establishments in the bottom quintile (the omitted base) are significantly *less* likely to survive when Chinese imports grow than the other groups, as the coefficients on all other interactions with the higher quintiles are PC intensity are positive. We show this most clearly in column (4) where we include only the bottom quintile interaction with Chinese imports. This takes a negative and significant coefficient indicating that the effect of Chinese imports on establishment survival is confined to these low-tech firms (outside the bottom quintile of the IT intensity distribution the effect on survival is still negative, but it is small and insignificantly different from zero). Columns (5), (6) and (7) shows that there are also significant interaction effects when we use patents or TFP as alternative measure of technology. Firms with initially higher patent stocks or TFP are significantly more likely to survive when faced by a Chinese import shock[32].

VE. Magnitudes

Taking all these results together, we have a clear empirical picture of the role of Chinese imports. Increased import competition with China is associated with higher technological intensity in an industry for at least two reasons. First, there is a selection effect whereby those establishments that are less technologically advanced will suffer comparatively more from Chinese competition and tend to shrink and exit. Secondly, even within an existing establishment Chinese trade tends to be associated with faster technical change as proxied by IT diffusion and patenting activity.

[32] 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.

We use the magnitude of our coefficients to perform some “back of the envelope” calculations for how much of the empirical change in technology China could account for. This is explained in detail in Appendix B but summarized here. For IT we estimate this in two steps: first we calculate the growth in aggregate IT intensity in our sample[33], and second we apply the coefficients from our regression results to get a predicted increase in aggregate IT intensity. By comparing the aggregate increase in IT intensity and the “Chinese induced” increase in IT intensity we can crudely attribute a proportion to the impact of Chinese imports. For patents we follow a similar exercise, again calculating overall patents (in this case an estimate from official aggregate data rather than our sample data) and apply our regression coefficients to see what fraction of aggregate patent growth Chinese imports can potentially explain.

In Table 8 we calculate that over the 2007-2000 period Chinese imports appear to have accounted for about 15% of the increase in aggregate IT intensity, 23% of the increase in patents per worker and 18% of TFP growth in European manufacturing. Beyond the aggregate numbers two other results stand out. First, the impact of Chinese imports appears to be rapidly increasing over this period. For example, we estimate that Chinese imports accounted for 12% of the increase in IT over the 2000-04 period but 19% over the 2004-2007 period. One reason for this acceleration is clear in Figure 1, where we see that Chinese import growth has rapidly increased over this period, with the annualized percentage point increase in China’s share growth rate increasing from 1.35 between 1997-2000 to 2.51 between 2004-2007. Second, for patents and TFP 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, the within component is much larger. This may be because the adjustment costs of adopting IT are less than those for increasing innovative activity or TFP (e.g. if this requires extensive re-organization or improvements of managerial practices).

VF. Dynamic Selection on the unobservables

A concern with our finding that there is a significant within firm effect of Chinese trade on technical change is that there may be a form of selection bias. We certainly find evidence for (and control for)

[33] Aggregate IT intensity is the sum of PCs and laptop across all plants divided by the sum of employment across all plants in our sample. There is no official figure here and apart from the CiTDB we use there is no way to consistently calculate this aggregate number across all 12 European countries used here.

selection on the observables – high tech plants are more likely to survive in the face of a Chinese import shock (see Table 7). We control for many forms of selection bias through the fixed effects, instrumental variables and the Olley Pakes selectivity correction term. Nevertheless, a concern may be that firms in an industry heavily exposed to Chinese competition may exit non-randomly due to differential expectations about their future technical change. For example, if firms who expect to be reducing their innovative activity in the future are more likely to exit when faced with an import shock, we will generate an upwards bias on the coefficient on Chinese imports in equation (3). Alternatively, if the firms who have had a negative transitory shock (and therefore expect to be doing more innovation in the future) are more likely to exit we will generate a downwards bias on the trade coefficient.

Note that the industry level results in Table 2 are robust to this critique. We tackle the firm level problem in several ways. First, we bound the magnitude of the effects by using the fact that the IT and patents can never fall below zero. Consider a transformation so that the growth of IT intensity is defined as $\frac{(IT/N)_t - (IT/N)_{t-5}}{\frac{1}{2}\left[(IT/N)_t + (IT/N)_{t-5}\right]}$ so exiters have a value of -2. Re-estimating Table 3 column (1) using this dependent variables on the same sample of survivors gives similar results to the standard logarithmic growth version, a coefficient on Chinese imports of 0.311 with a standard error of 0.068. If we now include the exiters (increasing the sample size from 37,500 to 42,988), the coefficient (standard error) is 0.184(0.066). Therefore, even under these extreme assumptions, the lower bound of the within effect is still substantial.

A second approach is to use information on the trends in technical change. The cleanest way to do this is to consider the regressions where we use quota removal as an IV. If the firms who were more likely to have faster technical change post policy were more likely to choose to stay in the industry, we would expect to observe some systematic differences in their pre-policy trends. To do this we use the TFP specifications as we have the largest amount of data in order when conditioning on pre-policy variables. Column (1) of Table A2 repeats the specification from the final column of Table 4. 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 half the number of industries. Column (3) includes the two pre-policy variables, the lagged growth of imports and the lagged growth of TFP. Lagged imports are insignificant, but lagged TFP is negative and significant. Importantly, the coefficient on imports remains positive and significant, having fallen from 1.58 to 1.17. 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 (the moment condition of Anderson and Hsaio, 1981). This reverses the sign of the coefficient on the lag, suggesting a positive relationship between past and present TFP. The coefficient on Chinese imports is larger than the previous column and remains significant. If we treated this as a true dynamic model, the implied long-run effect in this column is larger than in the first column.

Dealing with dynamic selection is challenging, but the evidence in this sub-section strongly suggests that there is a positive statistically and economically significant causal effect of Chinese import competition on within firm technical change.

VG. General Equilibrium and Welfare

A limitation of our approach is that it is both partial equilibrium and positive – we examine whether Chinese import liberalization has caused technological upgrading rather than whether this has been on net welfare improving. Atkeson and Burstein (2009) emphasis the limitations of micro-economic studies of trade and technology because of these lacunae[34]. In particular, one might argue that Chinese trade increases the demand for innovation at the firm level, but this simply drives up the wages of R&D scientists and may lead 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 to occur. 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

[34] Their key concern is that there is an endogenous response on the entry of new product/firms which can fall after trade liberalization and this is missing from empirical studies. In fact, our analysis does specifically examine new products (patents) and finds that these increase in response to Chinese imports. Furthermore, we found no evidence that Chinese imports reduced new entry of patents – regressions of patents by entering firms on Chinese imports were positive but always insignificant. The positive net patent effect can also be seen from the industry-level results in Table 2 showing an aggregate increase in patenting activity.

require more skilled workers, but not more (inelastically supplied) scientists. Second, it is unlikely the supply curve of R&D scientists really is 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.

VI EXTENSIONS AND ROBUSTNESS

VI.A Alternative Normalizations of Chinese imports

Our key measure of Chinese import completion is the share of total imports originating in China. A disadvantage of this measure is that Chinese imports could simply displace those from other low wage countries with the aggregate amount of low wage imports remaining unchanged. 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 9 for all four endogenous variables (IT, patenting, employment and survival). Although the magnitude of the point estimates changes as the mean of the imports variable is different, the qualitative results are remarkably similar. For example, in Panel A where we use domestic production to normalize Chinese imports, there is a positive and significant correlation of Chinese imports intensity with IT in column (1) and patents in column (2). The interactions of Chinese import intensity with IT is positive and significant in the employment growth equation (column (3)) and survival (Column (4)).

VI.B. Imports from low wage countries vs. imports from high wage countries

We focus on China as a canonical example of import competition from low wage countries. Over the last decade the increase in low wage imports is overwhelmingly dominated by China. We use the definition of a low wage country from Bernard et al (2006) 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) between 1996 and 2007 was close to zero (0.005) whereas China's growth was substantial (see Figure 1). Furthermore, analysis of the imports shares reveals that 91% of the variance of industry by country growth of low wage imports is accounted for by China.

Table 10 presents some analysis of this using the import penetration measure from Table 9 Panel A (normalizing imports on domestic production). In Panel A we report the results from the IT regressions. Column (1) simply shows what we have already seen – Chinese import penetration is associated with significantly greater IT intensity. Column (2) includes the non-Chinese low wage country import penetration measure. This attracts a positive coefficient as expected but is insignificant. We include all low wage country import penetration instead of just China in column (3) and obtain very similar results to column (1).

Column (4) includes the growth of imports from high wage countries. The coefficient is positive but insignificant and easily dominated by Chinese imports when this is included in column (5). Column (6) uses total import penetration that is positive but again dominated by China in column (7). A concern is that the endogeneity bias may be greater for high wage imports than Chinese imports. We followed Bertrand (2004) and used trade weighted exchange rates as an instrument. These were very significant in the first stage, but made the other trade results even weaker. For example, using column (6) we found that the coefficient on all imports fell to -0.099 with a standard error of 0.173 when it was instrumented.

Table 10 strongly suggests then, that China is a good experiment as a shock increase in trade competition from a low wage country. Competition from low wage countries appears to stimulate faster technical change for our European firms. Import competition from richer countries does not appear to stimulate faster technical change.

VI.C Skill Demand

In Table 11 we look at the impact of Chinese imports on relative skill demand. To do this we build up SIC 3-digit panel on the share of the wage-bill going to college educated workers using the UK Labor Force Survey. We use UK data because we can not easily get hold of Labor Force surveys for other European countries. Since the impact of China is relatively common across Europe we think the UK results should be broadly representative for the rest of Europe.

In column (1) we see that Chinese imports are associated with a relatively faster increase in the wage-bill share going to college educated workers, suggesting Chinese trade raises the demand for more educated workers. In column (2) we see the standard result that IT is also associated with an increase in the share of wages for college workers. Interestingly, putting both variables into the regression in column (3) shows that both IT and Chinese imports are significant, although with both lower coefficients, suggesting part of the association of IT with skilled workers may be a proxy for the impact of developing country trade. In column (4) we re-estimate this by OLS using the textile and apparel sample, and in columns (5) and (6) report the IV results which appear to support a causal impact of Chinese import competition on the demand for skilled workers. This is consistent with the notion outlined in theory section that Chinese trade leads European firms to switch from the production of older low-tech goods to the design and production of newer high-tech goods, which is likely to increase the relative demand for skilled workers.

VI.D Offshoring and outsourcing

We have focused on China's effect through competition in the final goods market. However, an alternative way in which China could affect technical progress is through allowing Western firms to buy cheaper intermediate inputs from China and allow the offshoring of low value added parts of the production chain[35]. We investigate this by adapting the offshoring measure of Feenstra and Hansen (1999) for China, so we have a measure of the proportion of intermediate inputs that are offshored to China.

Column (1) of Table 12 includes this offshoring measure in the IT equation. It enters with a positive coefficient indicating that there may be some effect here (since the mean of the offshoring variable is smaller than that of Chinese imports, the implied effect is of a similar order of magnitude). However, when we control for employment in column (2) the coefficient on offshoring becomes zero. One interpretation of this is that offshoring is associated with reductions in employment in low-tech tasks and this can raise IT intensity through a compositional change. Despite all this, the Chinese import variable remains positive and highly significant in all specifications, suggesting the effects we identify

[35] The role of intermediate inputs has been stressed (in a developing country context) by Amiti and Konings (2006) and Goldberg et al, 2008b).

are not purely from offshoring of inputs. In column (3) we look at the impact of this offshoring measure on patents and find no impact, suggesting that while the offshoring may reduce the employment in low-tech tasks it does not impact overall levels of innovation.

VI.E Product and Industry Switching

The leading "compositional" theory we discussed in the theory section was the hypothesis that in the face of Chinese import competition, European firms change their product mix. To investigate this idea we can examine whether a plant changes its primary four digit industrial sector in the CiTDB data. On average 11% of plants switch industries over a five year period, a substantial number that is consistent with some evidence from recent papers[36]. We examine first whether trade with low wage countries like China is associated with switching and second, whether this switching can account for much of the faster technical change induced by trade.

Table 13 begins by regressing a dummy for switching on Chinese imports and the usual controls. Industries more exposed to China were significantly more likely to switch industries. This is consistent with the evidence from US plants in Bernard et al (2006). In column (2) we include a control for lagged IT intensity which reduces the probability of switching, but only slightly reduces the coefficient on Chinese imports. Column (3) includes employment growth that has little impact. The second half of the Table uses IT intensity growth as the dependent variable. Column (4) shows that switching is indeed associated with greater use of IT, but the magnitude of the effect is small: plants who switched industries had a 2.5% faster growth in IT intensity than those who did not. Column (5) displays the standard regression for this sample showing the positive relationship between IT intensity and Chinese imports for the sub-sample where we have switching data. Column (6) includes the switching dummy. This reduces the coefficient on imports by only a small amount. A similar story is evident when we include employment growth in the final two columns.

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[36] For example, Bernard, Schott and Redding (2009) on the US, Goldberg et al (2008a,b) for India and Manova and Zhang (2008) for China. Bernard et al (2006) found that 8% of manufacturing plants switched four digit industries over a five year period. Our higher number probably reflects the fact that our plants are larger on average than their sample.

Our data does not allow us to observe product switching at a more disaggregate level. Bernard et al (2009, Table 5) show that in US manufacturing firms three quarters of the firms who switched (five digit) products did so across a four digit industry. If we run column (5) on those plants who did not switch industries, the Chinese imports effect remains strong (0.474 with a standard error of 0.082). This could still conceivably be driven by the small percentage of plants who switched five-digit sector within a four sector, but it seems unlikely that the compositional story can explain all the effects we observe. This evidence plus the direct impact of Chinese trade on patents suggests that innovation of new products is likely to be the main factor in accounting for the effect of Chinese trade.

VI.F Exports to China

We have focused on imports from China as driving changes in technology, but as discussed earlier exports may also have an effect. 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 14 presents the results. In the IT equation the exports variable has a positive coefficient as we might expect, but it is insignificant. The coefficient is also negative and insignificant in the other three equations. 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 behind the European technology frontier.

VI.G Limitations with Patents as a measure of Innovation: Do Chinese imports induce greater protection of Intellectual Property?

Patents have limitations as a measure of innovation. For example, an alternative interpretation of the patents equation could be that the increased threat of China causes firms to take out more intellectual property protection. Rather than increasing innovation, firms could simply be employing more patent lawyers more to keep out Chinese imports. Of course our RD results in Tables 2 and 3 suggest Chinese trade is also leading firms to increase R&D expenditure, but nevertheless we implement two tests for the adequacy of patents as an indicator of innovation.

First, we constructed a measure of future citations per patent and regressed this on Chinese imports in Table A3. We would expect to see the number of cites per patent falling if China was inducing firms to take out more patents to protect marginal innovations. Inspection of Table A3, however, shows that the coefficient on China is actually positive rather than negative (although insignificant) in all columns.

Second, we examined the dynamic effects of Chinese imports. Table A4 explores alternative timing assumptions of the way imports affect technical change. Because we only have IT data post 1999 in Harte Hanks, we are rather limited in our ability to investigate this. For patents, by contrast, we have a much longer time series so we can estimate the long-differenced equation allowing Chinese imports to affect patents at different lag lengths. Column (1) of Panel A reports results with a 5-year lag, with the lag-length falling by one year per column as we move across to Column (6). So, for example, column (2) for example uses a four year lag of Chinese imports, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-4}$ and column (6) the contemporaneous value, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t}$. If our results spuriously reflected legal inducement or more generally some unobservable shock simultaneously increasing patenting and imports we would expect the contemporaneous effect to be stronger. In fact, the opposite is the case: the coefficient on imports systematically falls as we approach the current year. This is consistent with the view that firms take time to adjust their innovation activities in response to a shock.

Panel B of Table A4 shows the same results for employment. To keep the sample similar to Panel A we use the Amadeus firm-level employment numbers rather than the plant-level employment numbers presented already in Table 6. We see a quite different pattern to patents. Growth of imports five or four years earlier are not significantly related to job losses whereas there is a significant relationship in years that are more recent. This is exactly what we would expect as adjustment costs for labor are much lower than they are for innovation. Overall, the dynamic patterns look economically sensible.

In short, the results on R&D, citations and dynamics seem consistent with the patents results that Chinese trade stimulates more innovation amongst European firms.

VI.H Alternative measures of IT diffusion

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. We also investigated the introduction of three other types of IT software available in CiTDB in Table A5. Although, none of these has the same continuous metric they are important parts of corporate computing. Enterprise Resource Planning (ERP) provided by companies such as SAP is a major way in which firms use software to systematize their data. Chinese imports are positively associated with the introduction of ERP in column (1) and the difference is particularly marked between the lowest decile of Chinese important growth and the higher deciles (see columns (2) and (3)). A similar finding emerges in the next three columns when we examine the introduction of major database software. Finally, the last three columns look at groupware tools (which enable workers to use networking to organize meetings and projects). Here the main difference is between the top quintile of import growth and the others.

VI.G Human capital and fixed capital

Another issue relates to capital. If Chinese imports are displacing firms with the lowest skills and these are the establishments with the lowest IT intensity, then our results could simply reflect the fact that we have not controlled properly for skills. This hypothesis is quite consistent with our argument: if there is complementarity between skills and technology, then trade will have an effect via this route and this is still an interesting finding. Nevertheless, there may be some direct effect of trade even controlling for skills.

In Table A6 we include the growth of industry wages as a proxy for skills changes in column (2). The variable enters with a positive and significant coefficient, but it does not change the coefficient on Chinese imports very much (see column (1)). When we control for employment the coefficient on the skills proxy is insignificant. We also obtained a direct measure of skills – the proportion of college educated workers in the three-digit industry from EU KLEMS. The coefficient was also positive, but had little effect on the Chinese imports term. A second issue is whether technical change simply reflects a more general upgrading of the capital stock. To check on this we included the growth of the industry level capital-worker ratio in columns (3) and (4). As with human capital, the variable does enter positively but is insignificant and barely affects the Chinese trade coefficient.

VII. CONCLUSIONS

In this paper we have re-examined the impact of trade on technical change in 12 European countries. Our motivation for this is that the rise of China 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. Our results suggest that increased import competition with China has been caused a significant technological upgrading in European firms through both faster diffusion and innovation. This has occurred *within* as well as between establishments and firms.

The results are easy to summarize. First, patenting, IT and TFP have risen in manufacturing firms who where more exposed to increases in Chinese imports. Second, in sectors more exposed to Chinese imports, jobs and survival fall in low tech firms (as measured by patents, IT or TFP), but are relatively protected in high tech firms. This finding is consistent with those found in US manufacturing establishments in Bernard, Jensen and Schott (2004, 2006) using indirect measures of technology for the pre-1997 period. These results appear to be robust to many tests, including treating trade as endogenous using China's accession to the WTO in 2001. In terms of magnitudes, China could account for around 15-20% of the overall technical change in Europe 2000-2007. Its effect also appears to be increasing over time.

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 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. Thirdly, we want to complement our European analysis with a similar exercise in the US where we have also recently accessed the Harte Hanks IT data. We have a longer time span for the US, so we can do more analysis of pre-sample trends.

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APPENDIX A: THE TEXTILE AND CLOTHING QUOTA RELAXATION

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 (2007) 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". Nevertheless, these were much lower than the pre-existing quotas. 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

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 IT equation 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 all world imports per SIC4 industry. 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 still remaining in 2006 are endogenous as they were the result of lobbying by the effected sectors. The fill rates for most quotas were high for China implying that these constraints were binding. 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 1970s under the Uruguay Round that makes them likely to be exogenous to any post 2000 actual (or anticipated) shocks. To be specific, in the regression sample of Table 4 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.

Table A7 provides some additional checks on the validity of the quota instrument. 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 (all regressions include country by year effects).

Column (1) includes simply the height of the quota in 2000, and the positive coefficient on this variable indicates that industries where quotas where high had faster growth in Chinese imports throughout the period. This is a worry, because maybe we are just picking up a long-term trend unrelated to quota removal. Column (2) then interacts the quota variable with a policy dummy equal to one after China joined the WTO in 2001. This is our instrument. 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 B: CALCULATING MAGNITUDES

The magnitudes in Table 8 are presented as attempts to quantify the potential contribution of Chinese imports to increase IT intensity and increased patenting in European manufacturing firms.

To undertake this quantification for IT requires two steps:

1) Calculating the employment weighted growth in IT intensity in our sample. This was done by comparing the employment weighted IT intensity at the end period with the beginning period. The employment weighted IT intensity is calculated as the sum of all computers and laptops dived by the sum of all employees in our regression sample at each point of time.
2) Calculating the Chinese import "contribution" to this increase in IT intensity. This is calculated using the coefficients from Tables 3, 6 and 7 multiplied by the actual Chinese import growth rates and IT intensity rates (for interactions) to generate a predicted change in IT intensity arising from changing Chinese imports.

The share of the increase in IT intensity that China accounts for is then simply the ratio from (2) divided by (1) for each period.

The method for TFP is analogous to that for IT intensity.

To undertake this quantification for patents also requires two steps:

1) Calculating the total increase in patenting over our sample period. The natural analog to IT would be to look at the increase in patents in our dataset over this period. However, our firms in total do not have a rising number of patents 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 instead we use the aggregate growth rate 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.[37]

2) Calculating the Chinese contribution to this increase in Patenting. Again, this is calculated using the coefficients from Tables 3, 6 and 7 multiplied by the actual Chinese import growth rates to generate a predicted change in Patenting intensity arising from changing Chinese imports.

The share of the increase in patents that China accounts for is then simply the ratio from (2) divided by (1) for each period.

APPENDIX C: PRODUCTION FUNCTION ESTIMATION

The Olley-Pakes Approach

Consider the basic production function as:

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

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.

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

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

[37] 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.

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

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 can approximate this function with a series estimator or non-parametric approximation 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 $S_{it} = 0$.

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

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

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

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

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

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

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 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) emphasises, 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 (see Klette and Griliches, 1996). 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.[38]

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.

[38] We assume that two-thirds of sales are in primary industries 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.

TABLE 1: DESCRIPTIVE STATISTICS

Variable	Mean (standard deviation)
IT regression sample	
Number of Employees	248.3
	(566.1)
Number of Employees at Median	140.0
	-
5-year Change in ln(Employment)	-0.058
	(0.409)
IT Intensity at (t-5)	0.494
	(0.355)
IT Intensity	0.580
	(0.385)
5-year Change in ln(IT Intensity)	0.183
	(0.544)
Level of Chinese Import Share (unweighted average across establishments)	0.066
	(0.102)
Plant Survival (% firms surviving from 2000-2005)	0.879
	(0.326)
Industry switchers (% plants switching four digit sector in five year period)	0.112
	(0.316)
Patents regression sample	
Number of Patents (per firm-year)	0.698
	(5.07)
Employment	655.2
	(3,384)
R&D regression sample	
R&D/Sales ratio	0.051
	(0.238)
Employment	16,044
	(44,981)
TFP estimation sample	
Employment	43.4
	(365.9)
Number of Firms (in TFP sample)	211,436
Number of Observations (in TFP sample)	1,409,613

Notes: Standard deviations in parentheses. Data is from HH/CiTDB except TFP sample (from AMADEUS data used to calculate TFP) and patents (from AMAPAT European Patent Office data matched to AMADEUS firm accounts). IT intensity is PCs plus laptops per worker.

TABLE 2: INDUSTRY LEVEL ANALSYIS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	**Δln(Employment)**	**Δln(Prices)**	**Δln(IT/N)**	**Δln(IT/N)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**Δln(R&D)**	**Δln(R&D)**	**Δln(TFP)**
Change in Chinese Imports	-0.411***	-0.453**	0.399***	0.354***	0.610***	0.628***	2.145*	1.791**	0.447***
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	(0.133)	(0.217)	(0.120)	(0.120)	(0.182)	(0.181)	(1.186)	(0.829)	(0.132)
Change in				-0.088***		0.042***			
Employment				(0.013)		(0.010)			
Change in log(Production)								-0.297	
								(0.403)	
Years	2005-1996	2006-2000	2007-2000	2007-2000	2005-1996	2005-1996	2007-2000	2007-2000	2005-1996
Country-Industry pairs	1,913	130	2,902	2,902	1,571	1,571	151	151	411
Observations	8,788	259	7,409	7,409	7,022	7,022	322	322	2,549

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Regressions estimated at the country-industry cell level. Coefficients estimated by OLS in five-year differences with standard errors (clustered by industry-country pair) in parentheses below coefficients. Chinese imports are measured by the value share of Chinese imports in total imports. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK in all columns except (3) which only includes France, Italy, Spain and Sweden (where we have good data on material inputs). All columns include country-year effects. Columns (2) is producer prices and is measured at the two-digit level. Columns (7) and (8) 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 SIC 2-digit level. In column (9) productivity is estimated using the de Loecker (2007b) version of the Olley-Pakes method separately for each two digit industry (see text).

TABLE 3: TECHNICAL CHANGE WITHIN INCUMBENT FIRMS AND PLANTS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	**Δln(IT/N)**	**Δln(IT/N)**	**Δln(PATENTS)**	**Δln(PATENTS)**	**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	0.361***	0.195***	0.352***	0.356***	1.213**	1.545***	0.245**
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	(0.076)	(0.068)	(0.088)	(0.122)	(0.549)	(0.330)	(0.101)
Change in Employment		-0.617***		0.011		0.558***	
		(0.010)		(0.007)		(0.043)	
Sample period	2007-2000	2007-2000	2005-1996	2005-1996	2007-1996	2007-1996	2005-1996
Number of Units	22,957	22,957	8,991	6,758	459	459	89,869
Country-Industry cells	2,816	2,816	1,718	1,531	196	196	405
Observations	37,500	37,500	30,608	20,238	1,626	1,626	293,314

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2007-2000 (so first 5-year difference is 2005-2000). Estimation is by OLS with standard errors clustered by country by four digit industry pair in parentheses (except columns (5) to (7) which are three-digit industry by country). All changes are in five-year differences, e.g. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. All columns includes a full set of country by year dummies. Imports are current except for patents where we use t-3. Δln(PATENTS) is the change in ln(1+PATENTS). 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 where we have good data on material inputs.. Dummies for establishment type (Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch) included in columns (1) and (2). In column (7) TFP is estimated using the de Loecker (2007b) version of the Olley-Pakes (1996) method separately for each two digit industry based on 1.4m underlying observations.

TABLE 4: INSTRUMENTAL VARIABLE ESTIMATES USING CHANGES IN EU TEXTILE AND CLOTHING QUOTAS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	$\Delta \ln(IT/N)$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta \ln(IT/N)$	$\Delta PATENTS$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta PATENTS$	$\Delta \ln TFP$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta \ln TFP$
	OLS	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**
Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	1.284*** (0.172)		1.851*** (0.400)				0.829*** (0.303)		1.490*** (0.608)
Change Chinese Imports (t-3) $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$				1.294*** (0.478)		3.933 (2.382)			
Quotas removal		0.088*** (0.019)			0.034*** (0.015)			0.088*** (0.011)	
Sample period	2005-2000	2005-2000	2005-2000	2005-1999	2005-1999	2005-1999	2005-1999	2005-1999	2005-1999
Number of units	2,891	2,891	2,891	1,810	1,810	1,810	12,470	12,470	12,470
Number of industry clusters	83	83	83	81	81	81	200	200	200
Observations	2,891	2,891	2,891	3,339	3,339	3,339	21,007	21,007	21,007

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Standard errors for all regressions are clustered by four-digit industry in parentheses. $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quota removal is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the 4 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 B for details). Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls included in columns (1)-(3) are dummies for establishment type: Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch. All specifications include country by year effects.

TABLE 5: INSTRUMENTAL VARIABLE ESTIMATES USING "INITIAL CONDITIONS"

	INFORMATION TECHNOLOGY			PATENTING ACTIVITY			TOTAL FACTOR PRODUCTIVITY		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	$\Delta\ln(IT/N)$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta\ln(IT/N)$	$\Delta PATENTS$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta PATENTS$	$\Delta\ln TFP$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta\ln TFP$
Method	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**
$\Delta M^{China} * \left(M_j^{China}/M_j^{World}\right)_{t-6}$									
Change in Chinese Imports	0.361***		0.593***				0.245**		0.298
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	(0.106)		(0.252)				(0.121)		(0.279)
Change in Chinese Import at (t-3)				0.342***		0.409**			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$				(0.110)		(0.205)			
Chinese imports in EU SIC4*		0.124***			0.112***			0.093***	
EU wide Chinese import growth		(0.002)			(0.001)			(0.018)	
Sample period	2007-2000	2007-2000	2007-2000	2005-1996	2005-1996	2005-1996	2005-1996	2005-1996	2005-1996
Number of Units	22,957	22,957	22,957	8,991	8,991	8,991	89,869	89,869	89,869
Number of industry clusters	371	371	371	356	356	356	106	106	106
Observations	37,500	37,500	37,500	30,608	30,608	30,608	293,314	293,314	293,314

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Standard errors are clustered by four-digit industry in parentheses). $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The instrumental variable is the share of Chinese imports in all imports in an industry across the whole of the Europe and the US (in a base year) interacted with the aggregate growth in Chinese imports in Europe and the US. The base year is (t-6). Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Columns (1)-(3) include dummies for establishment type: Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch. All columns include country by year effects.

TABLE 6: EMPLOYMENT EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	HH	HH	HH	Patenting firms	All Firms	TFP
Dependent Variable	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$
Change in Chinese Imports	-0.277***	-0.379***	-0.396***	-0.336***	-0.290***	-0.497***
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	(0.074)	(0.105)	(0.120)	(0.111)	(0.068)	(0.132)
Change Chinese Imports*IT intensity (t-5)		0.385**				
		(0.157)				
IT Intensity		0.230***				
$(IT/N)_{t-5}$		(0.010)				
ln(Patent stock per worker at t-5)*Change in Chinese imports				2.240***	1.997**	
$(PATSTOCK/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				(0.854)	(0.834)	
ln(Patent stock per worker at t-5)				0.408***	0.435***	
$(PATSTOCK/N)_{t-5}$				(0.059)	(0.057)	
Total Factor Productivity*Change in Chinese Imports						1.692***
$TFP_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$						(0.643)
Total Factor Productivity						0.228***
TFP_{t-5}						(0.023)
Highest Quintile of $(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.514***			
			(0.159)			
2nd Highest Quintile of IT $* \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.362***			
			(0.139)			
3rd Highest Quintile of IT $* \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.009			
			(0.174)			
4th Highest Quintile of IT $* \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.165			
			(0.126)			
Number of Units	22,957	22,957	22,957	6,795	176,504	89,869
Number of country-industry pairs	2,816	2,816	2,816	1,532	2,927	405
Observations	37,500	37,500	37,500	21,315	505,889	293,447

Notes to Table 6: *** 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. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. $PATSTOCK$ is ln[(1+ the firm's patent stock)/employment]. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. In column (5) only patenting firms (defined as a firm that had at least one European patent since 1978) are included, while in column (6) all firms from these countries are included. Site type controls include dummies Divisional HQ, a Divisional Branch, Enterprise HQ or a Standalone Branch. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline IT intensity. Note that linear quintile terms are included in column (4) but not reported in the table. Sample period is 2000 to 2007 for columns (1)-(3) and 1996-2005 for columns (4) - (6). "Number of units" is defined as number of plants in columns (1)-(4) and number of firms in columns (5) - (7). All columns include country by year effects.

Notes to Table 7 below: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four-digit industry in parentheses. The dependent variable (*SURVIVAL*) refers to whether an establishment that was alive in 2000 was still alive in 2005 for the HH sample in columns (1) –(4). In the other columns it is based on AMADEUS company status for the (see Data Appendix) and is defined on the basis of whether a firms alive in 1999 or 2000 was dead by 2005. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline IT . Note that linear quintile terms are included in the column (3) regression but not reported in the table. *PATSTOCK* is ln[(1+ the firm's patent stock)/employment]. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK (except final columns that includes only France, Italy, Spain and Sweden). Site type controls included in columns (1)-(4) are dummies for establishment type and include Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch. "Number of units" is defined as number of establishments in columns (1)-(4) and firms in all other columns (5) and (6). All regressions include country by year effects and ln(employment) in the initial year.

TABLE 7: SURVIVAL EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	HH IT data	HH IT data	HH IT data	HH IT data	Patenting firms	All firms	TFP
Dependent Variable: SURVIVAL							
Change in Chinese Imports	-0.118**	-0.182**	-0.274***	-0.060	-0.053	-0.113***	-0.225***
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	(0.047)	(0.072)	(0.098)	(0.049)	(0.044)	(0.025)	(0.070)
IT intensity (t-5)*Change in Chinese Imports		0.137					
$(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$		(0.112)					
Lowest Quintile IT intensity (t-5)*Change in Chinese Imports				-0.214**			
Quintile $1[(IT/N)_{t-5}] * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				(0.102)			
IT Intensity at (t-5)	0.001	-0.002					
$(IT/N)_{t-5}$	(0.006)	(0.006)					
Lowest Quintile of IT intensity at (t-5)				-0.018**			
				(0.006)			
Patent stock * Change in Chinese Imports					0.171**	0.194*	
$PATSTOCK_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$					(0.081)	(0.111)	
ln(Patent stock/employees) at (t-5)					-0.007	0.034***	
$PATSTOCK_{t-5}$					(0.009)	(0.009)	
Total Factor Productivity at t-5*Change Chinese Imports							0.267***
$TFP_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$							(0.076)
Total Factor Productivity							-0.005
TFP_{t-5}							(0.004)
Highest Quintile of $(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.201				
			(0.138)				
2nd Highest Quintile of $(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.272**				
			(0.124)				
3rd Highest Quintile of $(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.135				
			(0.137)				
4th Highest Quintile of $(IT/N)_{t-5} * \Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.238**				
			(0.104)				
Number of Country by industry pairs	2,863	2,863	2,863	2,863	1,434	2,896	405
Number of Units and observations	28,624	28,624	28,624	28,624	6,848	122,336	313,796

Notes to Table 7 on the page above:

TABLE 8: "BACK OF THE ENVELOPE" MAGNITUDES

(A) 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	11.1	3.1	1.2	15.4
2000-04	9.2	2.3	0.9	12.4
2004-07	13.7	4.0	1.6	19.3

(B) 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	10.8	10.0	1.8	22.6
2000-04	8.3	8.4	1.4	18.1
2004-07	14.3	11.2	2.2	27.6

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

Period	Within	Between	Exit	Total
2000-07	10.4	6.7	1.3	18.4
2000-04	6.2	4.1	0.8	11.1
2004-07	16.0	10.2	2.0	28.2

Notes: The top panel reports the share of aggregate IT intensity accounted for by China, the middle panel the increase in patents/employee and the bottom panel the increase in 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 2.0% (the average TFP growth in manufacturing). The coefficients that are used are: Table 3 Column (1) for IT within, Table 6 column (2) for IT between and Table 7 column (2) for IT exit. Table 3 Column (3) for patents within, Table 6 column (5) for patents between, and Table 7 column (6) for patents exit. Table 3 Column (7) for TFP within, Table 6 column (6) for TFP between, and Table 7 column (7) for TFP exit.

TABLE 9: ALTERNATIVE MEASURES OF THE CHANGE IN CHINESE IMPORTS

Panel A: Chinese Imports Normalized by Domestic Production

Dependent Variable:	(1) $\Delta \ln(IT/N)$	(2) $\Delta PATENTS$	(3) ΔTFP	(4) $\Delta \ln N$	(5) $SURVIVAL$
Change in Chinese Imports (over production)	0.053**		0.406***	-0.192***	-0.060***
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$	(0.024)		(0.088)	(0.043)	(0.022)
Change in firm employment	-0.625***				
$\Delta \ln N$	(0.011)				
Change in Chinese Imports (t-3)		0.163**			
$\Delta\left(M_{jk}^{China}/D_{jk}\right)_{t-3}$		(0.063)			
Change Chinese Imports*IT Intensity (t-5)				0.138**	
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$* $(IT/N)_{t-5}$				(0.057)	
Change Chinese Imports*Lowest Quintile IT (t-5)					-0.128**
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$* $Q1(IT/N)_{t-5}$					(0.051)
IT Intensity (t-5)				0.248***	
$(IT/N)_{t-5}$				(0.011)	
Lowest quintile of IT Intensity (t-5)					-0.014**
$Q1(IT/N)_{t-5}$					(0.006)
Number of Units	20,106	7,683	87,046	20,106	25,130
Number of industry-country clusters	2,480	1,393	378	2,480	2,528
Observations	31,820	14,000	261,967	31,820	25,130

Panel B: Chinese Imports Normalized by Apparent Consumption

Dependent Variable:	(1) $\Delta \ln(IT/N)$	(2) $\Delta PATENTS$	(3) ΔTFP	(4) $\Delta \ln N$	(5) $SURVIVAL$
Change Chinese Imports (/apparent consumption)	0.169*		0.276***	-0.192***	-0.191***
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$	(0.089)		(0.025)	(0.043)	(0.063)
Change in firm employment	-0.623***				
$\Delta \ln N$	(0.011)				
Change in Chinese Imports (t-3)		0.338***			
$\Delta\left(M_{jk}^{China}/D_{jk}\right)_{t-3}$		(0.130)			
Change Chinese Imports*IT Intensity (t-5)				0.631***	
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$* $(IT/N)_{t-5}$				(0.198)	
Change Chinese Imports*Lowest Quintile IT (t-5)					-0.333**
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$* $Q1(IT/N)_{t-5}$					(0.140)
IT Intensity (t-5)				0.241***	
$(IT/N)_{t-5}$				(0.011)	
Lowest quintile of IT Intensity (t-5)					-0.013**
$Q1(IT/N)_{t-5}$					(0.006)
Number of Units	19,793	7,597	87,046	19,793	24,495
Number of industry-country clusters	2,406	1,346	378	2,406	2,387
Observations	31,225	13,698	261,967	31,225	24,495

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 Eurostats' Prodcom database. Sample period is 2000 to 2007 for the IT equation and 1996-2005 for patents equations.

TABLE 10: LOW WAGE COUNTRY AND HIGH WAGE COUNTRY IMPORTS

Panel A: Dependent Variable is Change in IT Intensity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports $\Delta\left(M_{jk}^{China} / D_{jk}\right)$	0.053** (0.024)	0.048* (0.026)			0.050* (0.026)		0.047* (0.027)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)$		0.028 (0.042)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)$			0.051** (0.023)				
Change in High Wage Imports $\Delta\left(M_{jk}^{High} / D_{jk}\right)$				0.009 (0.008)	0.004 (0.009)		
Change in World Imports $\Delta\left(M_{jk} / D_{jk}\right)$						0.012 (0.008)	0.005 (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 B: Dependent Variable is Change in Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports $\Delta\left(M_{jk}^{China} / D_{jk}\right)_{t-3}$	0.163*** (0.060)	0.163*** (0.060)					0.180*** (0.068)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)_{t-3}$		0.009 (0.028)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)_{t-3}$			0.149*** (0.051)		0.154*** (0.056)		
Change in High Wage Imports $\Delta\left(M_{jk}^{High} / D_{jk}\right)_{t-3}$				-0.017* (0.009)			
Change in World Imports $\Delta\left(M_{jk} / D_{jk}\right)_{t-3}$						-0.012 (0.009)	-0.016 (0.009)
Number of Firms	7,683	7,683	7,683	7,683	7,683	7,683	7,683
Number of industry-country clusters	1,393	1,393	1,393	1,393	1,393	1,393	1,393
Number of Observations	14,000	14,000	14,000	14,000	14,000	14,000	14,000

Panel C: Dependent Variable is Change in Total Factor Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Chinese Imports $\Delta\left(M_{jk}^{China} / D_{jk}\right)$	0.406*** (0.088)	0.511*** (0.154)			0.411*** (0.092)		0.422*** (0.099)
Change in Non-China Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)$		-0.087 (0.081)					
Change in All Low Wage Imports $\Delta\left(M_{jk}^{Low} / D_{jk}\right)$			0.215*** (0.050)				
Change in High Wage Imports $\Delta\left(M_{jk}^{High} / D_{jk}\right)$				0.023 (0.017)	-0.004 (0.015)		
Change in World Imports $\Delta\left(M_{jk} / D_{jk}\right)$						0.034** (0.015)	-0.006 (0.014)
Number of Firms	87,046	87,046	87,046	87,046	87,046	87,046	87,046
Number of industry-country clusters	378	378	378	378	378	378	378
Number of Observations	261,967	261,967	261,967	261,967	261,967	261,967	261,967

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 A we include "Site type dummies and employment growth as additional controls. Sample period is 2000 to 2007 for panel A and 1996-2005 for panels B and C.

TABLE 11: SKILL DEMAND

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	**Δ(Wage Bill Share of College Educated)**	**Δ(Wage Bill Share of College Educated)**	**Δ(Wage Bill Share of College Educated)**	**Δ(Wage Bill Share of College Educated)**	**Δ(Wage Bill Share of College Educated)**	**Δ(Wage Bill Share of College Educated)**
Sample	**All**	**All**	**All**	**Textiles & Apparel**	**Textiles & Apparel**	**Textiles & Apparel**
Method	**OLS**	**OLS**	**OLS**	**OLS**	**IV**	**IV**
Change in Chinese Imports	0.144***		0.099**	0.166***	0.227***	0.176*
$\Delta\left(M_{jk}^{China} / D_{jk}\right)$	(0.035)		(0.043)	(0.030)	(0.053)	(0.092)
Change in IT intensity		0.081**	0.050*			0.045
$\Delta \ln(IT / N)$		(0.024)	(0.026)			(0.048)
P-value of Test of joint significance Of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ and $\Delta \ln(IT / N)$			0.000			0.000
F-test of excluded IV in first stage					9.21	6.83
Years	2006-1999	2006-1999	2006-1999	2006-1999	2006-1999	2006-1999
Industry Clusters	72	72	74	17	17	17
Observations	204	204	204	48	48	48

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 three-digit industry panel for the UK between 2000 and 2007 (based on aggregating up different year of the UK Labor Force Survey). The dependent variable is the five year difference in the wage bill share of college educated workers. All manufacturing industries in columns (1)- (3) and textiles and clothing industries sub-sample in columns (4)-(6). IV regressions use Quota removal (the height of the quota in the three-digit industry in 2000 prior to China's 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 12: OFFSHORING, IT AND INNOVATION

Dependent Variable	(1) $\Delta \ln(IT / N)$	(2) $\Delta \ln(IT / N)$	(3) $\Delta PATENTS$
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.364***	0.220***	
Change in Chinese Imports	(0.090)	(0.082)	
$\Delta OFFSHORE$	0.865	-0.021	
Change in Chinese Imports in source industries	(0.569)	(0.501)	
$\Delta \ln N$		-0.617***	
Change in employment		(0.010)	
$\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-3}$			0.371***
Level of Chinese Imports (t-3)			(0.093)
$OFFSHORE_{t-3}$			-0.760
Level of Chinese Imports in source industries (t-3)			(1.089)
Country Year Effects	Yes	Yes	Yes
Site-Type Controls	Yes	Yes	n/a
Number of units	21,093	21,093	8,991
Observations	28,231	28,231	30,608

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. There are 2,816 distinct country by industry pairs. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls are dummies for establishment type; these are Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch. "Number of units" represents the number of establishments for columns (1)-(2) and the number of companies for column (3).

TABLE 13 INDUSTRY/PRODUCT SWITCHING AND TECHNICAL CHANGE

Dependent Variable:	**Switched Industry**	**Switched Industry**	**Switched Industry**	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Chinese Imports	0.138***	0.132***	0.131***		0.469***	0.466***	0.247***	0.244***
	(0.050)	(0.050)	(0.050)		(0.083)	(0.083)	(0.081)	(0.081)
IT intensity (t-5)		-0.018**	-0.018**					
		(0.007)	(0.008)					
Industry Switching				0.025***		0.023*		0.018*
				(0.012)		(0.012)		(0.011)
Employment growth			-0.002				-0.619***	-0.619***
			(0.006)				(0.011)	(0.011)
Observations	32,917	32,917	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. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. All regressions include country-year effects and site-type controls. Sample period is 2000 to 2007.

TABLE 14: EXPORTS TO CHINA

Dependent Variable	$\Delta \ln(IT/N)$ (1)	$\Delta PATENTS$ (2)	$\Delta \ln TFP$ (3)	$\Delta \ln N$ (4)	Survival (5)
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ Change in Chinese Imports	0.196*** (0.068)		0.269** (0.107)	-0.205*** (0.105)	-0.123* (0.065)
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$ Change in Chinese Imports (t-3)		0.352*** (0.107)			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$ Change Chinese Imports* IT Intensity at (t-5)					
$\Delta\left(X_{jk}^{China}/X_{jk}^{World}\right)$ Change in Exports to China	0.028 (0.098)		0.046 (0.250)	-0.058 (0.099)	0.094 (0.056)
$\Delta\left(X_{jk}^{China}/X_{jk}^{World}\right)_{t-3}$ Change in Exports to China (t-3)		-0.843*** (0.328)			
$\Delta \ln N$ 5-year change in ln(Employment)	-0.617*** (0.010)				
Number of Units	22,957	7,834	89,080	22,957	24,847
Number of Industry-country clusters	2,816	1,478	397	2,816	2,593
Number of Observations	37,500	13,929	271,367	37,500	24,847

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK.

TABLE A1: CHINA'S SHARE OF GLOBAL IMPORTS – TOP TEN INDUSTRIES, 1999-2006

Top Ten Industries in 1999		China's Share of Global Imports $\left(M_j^{China} / M_j^{World}\right)$		
Industry Description	Industry Code	1999	2006	Change 1999-2006
1. Dolls and Stuffed Toys	3942	0.801	0.859	0.058
2. Drapery Hardware and Window Blinds and Shades	2591	0.526	0.545	0.019
3. Leather Gloves and Mittens	3151	0.505	0.593	0.088
4. Rubber and Plastics Footwear	3021	0.500	0.602	0.103
5. Women's Handbags and Purses	3171	0.456	0.515	0.059
6. Manufacturing Industries, Not Elsewhere Classified	3999	0.438	0.535	0.097
7. Luggage	3161	0.428	0.686	0.259
8. Personal Leather Goods	3172	0.406	0.451	0.045
9. Leather and Sheep-Lined Clothing	2386	0.399	0.490	0.092
10. Games, Toys, and Children's Vehicles, Except Dolls and Bicycles	3944	0.398	0.710	0.312
All Industries		0.054	0.108	0.054
(standard-deviation)	-	(0.098)	(0.154)	(0.049)

Notes: Calculated using product-level UN Comtrade data aggregated to 4-digit US SIC codes. There are 430 4-digit industries in our dataset. China's global hare of all imports $\left(M_j^{China} / M_j^{World}\right)_{1999}$ is the proportion of imports from China in industry *j* as a share of imports from the rest of the world in industry *j*. All available countries in the UN Comtrade dataset are used. Manufacturing industries (not elsewhere classified) includes many miscellaneous goods such as hairdressing equipment, tobacco pipes, cigarette holders, artificial flower arrangements, and amusement or arcade machines.

TABLE A2: DYNAMIC SELECTION? CHECKING PRE-POLICY TFP TRENDS

	(1)	(2)	(3)	(4)
Dependent Variable	ΔTFP	ΔTFP	ΔTFP	ΔTFP
Method	IV	IV	IV	IV
Δ Chinese Imports	1.490***	1.580***	1.172**	1.255***
	(0.460)	(0.420)	(0.458)	(0.448)
ΔTFP(t-5)			-0.242***	0.429***
			(0.032)	(0.086)
ΔChinese Imports(t-5)			-0.095	-0.197
			(0.549)	(0.589)
Endogenous right-hand side variables	Chinese Imports	Chinese Imports	Chinese Imports	Chinese Imports, ΔTFP(t-5)
Number of units	12,470	3,050	3,050	3,050
Number of clusters	200	92	92	92
Observations	21,007	3,050	3,050	3,050

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by four digit industry in parentheses. These are estimates from the textile and apparel industries following Table 3. Five-year differences covering the period 1999-2005. Estimation by five year differences. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quota removal is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the 4 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 A for details). In columns (1)-(3) we use quota removal to instrument Chinese imports. In column (4) we also use $\ln TFP_{t-10}$ as an instrument for $\Delta \ln TFP_{t-5}$. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK.

TABLE A3:
NO FALLS IN CITATIONS PER PATENTS AS A RESULT OF CHINESE IMPORTS

	(1)	(2)	(3)
Dependent Variable	**Δ(CITES)**	**Δ (CITES)**	**Δ (CITES/PATENT)**
Change in Chinese Imports at (t-3)	0.245***	0.093*	0.071***
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-3}$	(0.067)	(0.054)	(0.026)
Growth of PATENTS		0.432***	
$\Delta PATENTS$		(0.015)	
Number of industry-country clusters	1,781	1,781	1,781
Number of Firms	8,991	8,991	8,991
Observations	30,608	30,608	30,608

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. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 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. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Sample period is 1996 to 2006.

TABLE A4: DYNAMICS OF THE EFEFCT OF CHINA ON PATENTS AND EMPLOYMENT

(A) PATENTS

Dependent Variable	$\Delta PATENTS$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
5-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$	0.418*** (0.119)					
4-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-4}$		0.375*** (0.099)				
3-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$			0.349*** (0.088)			
2-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-2}$				0.243*** (0.075)		
1-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-1}$					0.176*** (0.065)	
Contemporaneous change in Chinese Imports						0.138* (0.072)
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	8,814	8,899	8,986	9,027	9,027	9,027
Observations	21,560	26,663	30,592	32,076	32,079	32,081

(B) EMPLOYMENT

Dependent Variable	$\Delta \ln N$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
5-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$	0.137 (0.161)					
4-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-4}$		-0.011 (0.125)				
3-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$			-0.179 (0.131)			
2-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-2}$				-0.242** (0.125)		
1-year lag of Change in Chinese Imports $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-1}$					-0.215** (0.107)	
Contemporaneous change in Chinese Imports						-0.211*
5-year lag of Change in Chinese Imports						(0.112)
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	6,224	6,611	6,756	6,794	6,794	6,795
Observations	13,764	17,300	20,236	21,314	21,314	21,315

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. There are 2,225 distinct sic4-country clusters. All columns estimated as 5-year differences (DIFFS) .Mc/Mw represents the 5-year change in Chinese imports. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Sample period is 1996 to 2005.

TABLE A5: ALTERNATIVE IT ADOPTION AND CHANGES IN CHINESE IMPORTS, 2000-2006.

	(A) *ΔEnterprise Resource Planning*			*(B)* *ΔDatabase*			*(C)* *ΔGroupware*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Change in Chinese Imports	0.040			0.002			0.249***		
	(0.034)			(0.070)			(0.083)		
Highest Quintile for Change in Chinese Imports		0.013***			0.020**			0.034**	
		(0.005)			(0.010)			(0.014)	
2nd Highest Quintile of Change in Chinese Imports		0.006			0.030***			0.021	
		(0.005)			(0.010)			(0.013)	
3rd Highest Quintile for Change in Chinese Imports		0.014***			0.043***			-0.008	
		(0.005)			(0.010)			(0.013)	
4th Highest Quintile for Change in Chinese Imports		0.010**			0.024***			-0.018	
		(0.005)			(0.011)			(0.013)	
Lowest Quintile for Change in Chinese Imports			-0.011***			-0.028**			-0.000
			(0.004)			(0.009)			(0.001)
$\Delta \ln N$	0.005	0.005		0.021***	0.021***	0.023***	0.001	0.002	0.000
	(0.004)	(0.004)		(0.008)	(0.008)	(0.001)	(0.009)	(0.009)	(0.009)
Site-Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. 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 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK

TABLE A6: ROBUSTNESS TO WAGE AND CAPITAL CONTROLS

Dependent Variable	$\Delta \ln(IT/N)$			
	(1)	(2)	(3)	(4)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Change in Chinese Imports	0.401*** (0.100)	0.222*** (0.084)	0.222** (0.084)	0.235*** (0.080)
$\Delta \ln(W)_{jk}$ Change in industry wages	0.194** (0.099)	0.111 (0.084)		
$\Delta \ln(K/N)_{jk}$ Change in industry capital/employee				0.029 (0.046)
$\Delta \ln N$ Change in firm employment		-0.659*** (0.031)	-0.622*** (0.016)	-0.619*** (0.035)
Country-Year Effects	Yes	Yes	Yes	Yes
Site-Type Controls	Yes	Yes	Yes	Yes
Number of plants	7,578	7,578	7,578	6,782
Observations	7,578	7,578	7,578	6,782

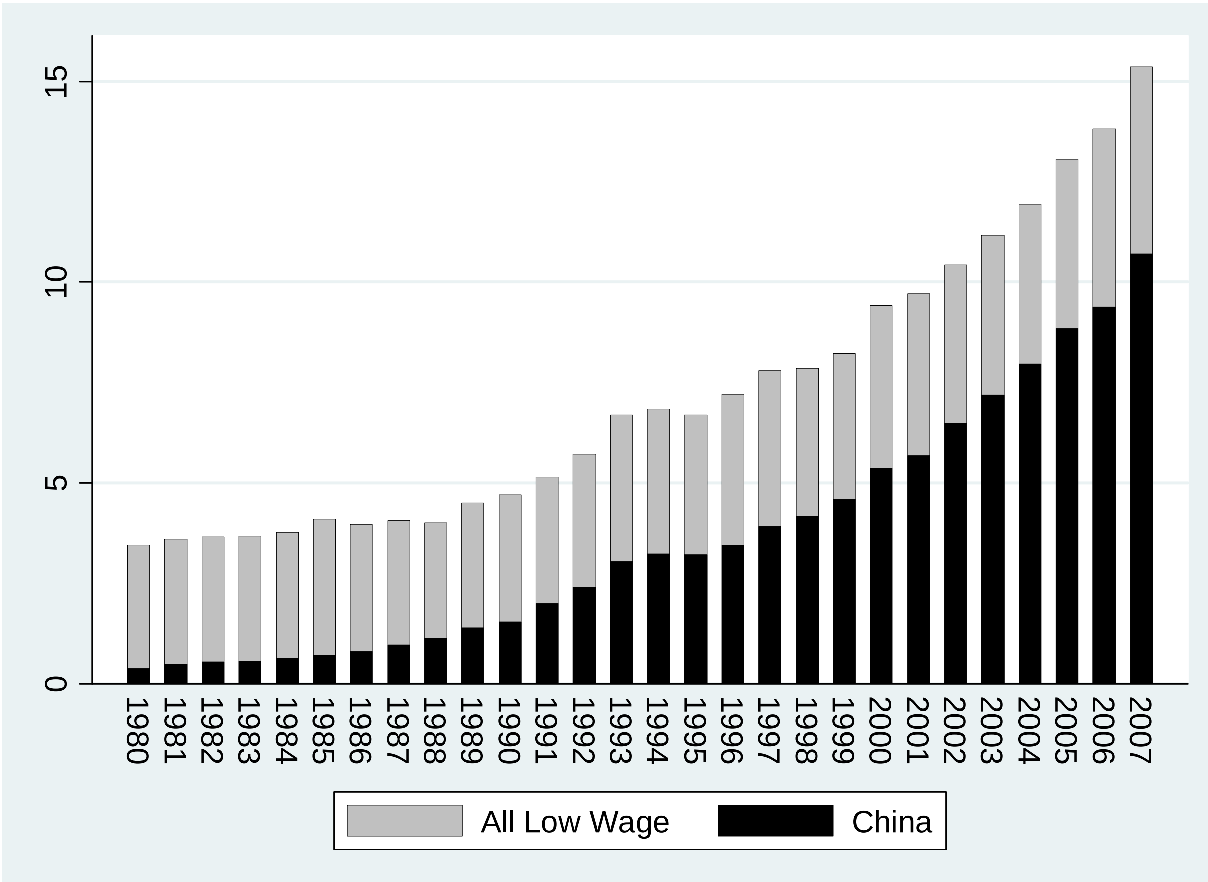
Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. $\Delta(W)_{jk}$ is the five-year change in the mean industry wage calculated from the full AMADEUS company database with full details given in the Data Appendix. $\Delta(K/N)_{jk}$ is the 5-year change in capital per employee also calculated from Amadeus. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. All regressions include country-year effects and site-type controls. "Site type controls" are dummies for establishment type: a Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch. Sample period is 2000 to 2007.

TABLE A7: THE QUOTA INSTRUMENT IS UNCORRELATED WITH THE GROWTH IN CHINESE IMPORTS PRIOR TO THE ACESSION TO THE WTO

	(1)	(2)	(3)
Dependent Variable	$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$
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

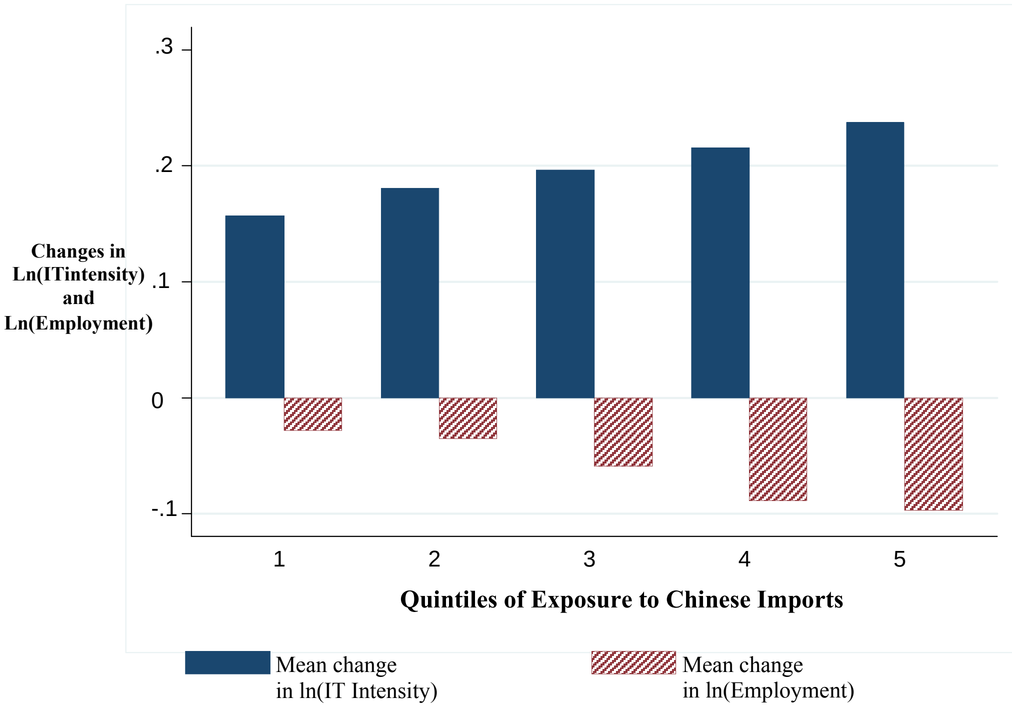
Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by four digit industry pair in parentheses. This data is a four-digit industry by country panel between 1990 and 2007. Only textiles and clothing industries sub-sample. 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's joining the WTO. "Post WTO" is a dummy equal to unity after 2001 (and zero before).

FIGURE 1: SHARE OF ALL IMPORTS IN THE EU AND US FROM CHINA AND ALL LOW WAGE COUNTRIES



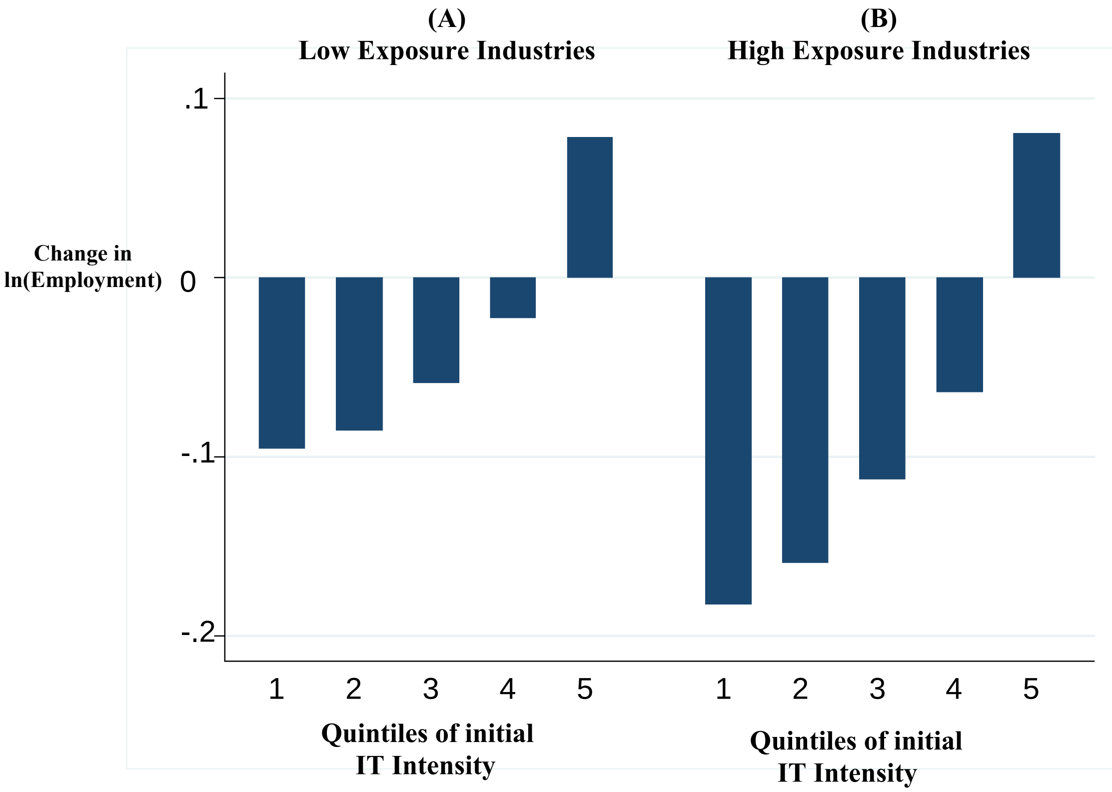
Notes: Calculated using UN Comtrade data. Low wage countries list taken from Bernard, Jensen and Schott (2006) and are defined as countries <5% GDP/capita relative to the US 1972-2001.

FIGURE 2: CHANGES IN IT INTENSITY AND EMPLOYMENT BY EXPOSURE TO CHINESE IMPORTS, 2000-2006



Notes: Calculated using regression sample of 27,354 observations for two waves of 5-year differences occurring in 2005 and 2006. The "Quintiles of Exposure to Chinese Imports" along the horizontal axis are classified according to the distribution of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$, the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The quintiles are ordered from 1 (lowest exposure) to 5 (highest exposure). The vertical axis measures $\Delta \ln(IT / N)$, the 5-year change in ln(IT intensity) and $\Delta \ln(N)$, the five year change in log (Employment).

FIGURE 3: CHANGES IN LN(EMPLOYMENT) BY INITIAL IT INTENSITY 2000-2006, HIGH VERSUS LOW EXPOSURE INDUSTRIES



Notes: Calculated using 27,354 observations in 2005 and 2006. "Low Exposure" industries in panel (A) defined as observations falling in the lowest quintile (Panel A) of the distribution of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$, the five year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. "High exposure" industries in panel (B) defined as observations classified in the highest quintile of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$. The horizontal axis then classifies observations according to $(IT/N)_{t-5}$ their initial level of IT intensity, going from the lowest quintile (labeled "1") to the highest quintile (labeled "5").