Trade induced technical change? The impact of Chinese imports on technology and employment

Nicholas Bloom[1] , Mirko Draca[2] John Van Reenen[3]

[1] *Department of Economics, Stanford, Centre for Economic Performance and NBER*

[2] *Centre for Economic Performance, London School of Economics, and University College London*

[3] *Centre for Economic Performance, London School of Economics, CEPR and NBER*

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Abstract

Despite popular belief among politicians and the public, the consensus amongst empirical economists is that trade has *not* been a major cause of increased wage inequality in advanced countries and the technological and institutional change are much more important. Recent theoretical work shows how trade can induce technical change, however. Furthermore, the consensus was reached using data pre-dating the rise of China in the 1990s. In this paper, we examine the impact of the growth of Chinese imports on a panel of 30,000 establishments in 14 European countries. We find that Chinese import competition is associated with a significant increase in the adoption of new technology (measured by usage of information technology) and the generation of innovation (measured by patenting intensity). We also find that exposure to trade with China significantly increases the probability of establishment exit and reduces employment growth, but this effect is significant only for low-tech firms. The wave of Chinese trade has therefore caused a within and between plant increase in average IT intensity. Despite these effects on the intensive and extensive margins, we calculate that trade with China still only accounts for a relatively small proportion of the increase in IT intensity and patenting so does not appear to overturn the conventional wisdom that trade is less important than technical change.

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I. INTRODUCTION

A vigorous political debate is in progress over the impact of globalization on the economies of the developed world (e.g. Krugman, 2007). The growth of China looms large in these discussions, as the GDP of China has experienced tremendous growth over the last two decades, averaging some 9-10% per year in real terms. In terms of GDP at current exchange rates, China now ranks as the world's fourth largest economy. This even underestimates China's influence since much of the economy is in the non-market sector so in PPP terms, China may be second only to the United States.

The rise of China and other emerging economies such as India, Mexico and Brazil has 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, a large body of empirical evidence emerged by the early 21st Century that strongly suggested that trade was not to blame for increasing wage inequality (e.g. Desjonqueres et al, 1999). There are many pieces of evidence including the facts that, firstly, the vast majority of the increase in the aggregate share of skilled workers has occurred within industries rather than between industries (e.g. Berman et al, 1994). Basic Heckscher-Ohlin theory suggests the opposite: because the aggregate wages of skilled workers are higher, there should be a within industry shift *away* from skilled workers. Secondly, wage inequality does not seem to have systematically fallen in developing countries as Heckscher-Ohlin would predict (e.g. Berman et al, 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[1]. Fourthly, calibrated general equilibrium models and factor content approaches find only a quantitatively small role of trade[2]. Most authors do find an important role for skill biased technical change and/or institutions such as the minimum wage or labor unions (DiNardo, Fortrin, and Lemieux, 2001).

There are at least two major problems with the consensus, however. First, most of this work was done on data up to the mid 1990s, which largely predates the rise of behemoths like China. In 1996, for example, China only accounted for 3% of world exports. By 2006 this figure had tripled to over 9%. Secondly, an emerging line of theory has pointed to mechanisms whereby trade can affect the incentives to adopt and develop new technologies[3]. Thus, the finding that measure of technology such as IT are highly correlated with changing skill shares does no 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. We use an original source of data on IT usage at the establishment level matched with data on imports from China (and other nations).

Our paper partially addresses these two criticisms. We use data from the last decade to examine the role of trade in affecting technological adoption in developing countries. Using the rapid growth of Chinese imports across different industries, we examine the impact of trade on the adoption of IT across over 30,000 establishments. We distinguish the impact of trade competition on technology through an intensive and extensive margin. On the intensive margin, we find that Chinese import

[1] For example, see Machin and Van Reenen (1998). This test may not be so compelling, however, as the threat of Chinese imports can have an effect even if no import flows actually take place. Krueger (1997) however finds that although the relative prices of unskilled goods has fallen as Heckscher-Ohlin would predict, the magnitude of these changes is not large.
[2] For example, see Krugman (1995) for a GE approach, Borjas, Katz and Freeman (1997) for factor content analysis and Freeman (1995) for an overview.
[3] See inter alia Acemoglu (1999, 2002), Lloyd-Ellis (1999), Thoenig and Verdier (2003)

competition increases the IT intensity of surviving firms. On the extensive margin, we find that Chinese import competition decreases employment and survival chances of establishments and that this effect is much stronger for low-tech firms than for high tech firms. Consequently, industries that face greater competition from China will tend to upgrade their technology for reasons of selection (the low tech establishments shrink and die) and for reasons of within-establishment change (the surviving establishments invest more in IT).

The paper relates closely to the literature on the effects of trade on productivity (e.g. Pavnik, 2002; Goldberg and Pavnik, 2006). Many papers have found that trade liberalization increases aggregate industry productivity, but are often unclear over the mechanism. We provide evidence on one channel trade affects the incentives to adopt new technology within establishments and drives out the low tech establishments in the economy. Both these mechanisms will tend to raise aggregate labor productivity.

We offer some back of the envelope quantification of the magnitude of the Chinese import effects. Although the effects on technology are statistically significant they are not large enough to overturn the consensus that trade is a second-order factor in understanding the evolution of the overall labor market. For example, only 7% of the increase in establishment IT intensity appears to be China-related. We do find that China can account for a larger proportion of job losses – 14% overall and rising to over a fifth in the most low-tech establishments.

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

II THEORETICAL CONSIDERATIONS

Although there has been considerable discussion over the role and importance of the rise of emerging nations like China for technical change in the OECD countries, the different mechanism have rarely been spelled out clearly. In this section we give a brief overview of the most salient theories that motivates our empirical work. We distinguish between two broad classes of theories: one from the multi-product firm literature and another of truly endogenous technical change.

IIA Heterogeneous multi-product firms and comparative advantage

Perhaps the most simple approach is to consider a framework where there are two regional blocs (called EU and China), with the EU abundant in high skilled labor and the China abundant in low skilled labor. When we move from Autarky to Free Trade the economies integrate and we will have specialization: the industries that are skill intensive will grow in the EU and the industries that are unskilled intensive will decline. The opposite will occur in China. We need a plausible twist on the standard model in that we assume that production technologies requiring more skills also require more advanced technology, i.e. skills and information technology are complements (for evidence on this see Autor et al, 1998, for the US or Bond and Van Reenen, 2008, for an international survey).

Even this extended Heckscher-Ohlin framework is rather unsatisfactory. We know much trade is North-North and that China (and other emerging nations) has moved up the quality ladder over time. We also know that most of the macro changes we observe (say in technology, productivity and skills) have occurred within rather than between industries. This can be reconciled with the Heckscher- Ohlin viewpoint by observing 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. This is harder to reconcile with the evidence that there is technological upgrading *within* establishments.

To investigate this more closely we draw on the recent contributions of Bernard, Schott and Redding (2007, 2008) who 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[4] leading to 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 European firms. First, there will be the standard shakeout effect where less productive firms shrink and exit and this will be stronger in those areas where China has comparative advantage (i.e. low tech/low skilled industries). We will investigate this empirically as our between-firm effect. Second, and this is more novel, 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 our data we would therefore expect to see an increase in IT usage if this is used more intensively in the production of more sophisticated products (which is likely).

IIB Endogenous technological change

The Bernard et al (2007) framework can generate within firm changes in the technology, but this is due to a shuffling in the portfolio of products rather than the firm generating new technology. An alternative perspective is that even for a given product, firms may respond to falling trade costs with China by improving their technology. This is a more direct role for trade on technology. There are several variations of these models: market size and competition being the two most prominent.

Note that using our data on diffusion of IT, it is hard to distinguish whether Chinese import competition has a positive effect because of the product switching effects or because of faster diffusion for a given product. This is because we could not hope to perfectly observe all the heterogeneous product lines within a firm and their input requirements. We do, however, have access to patents that are a measure of *innovation* rather than diffusion. If we observe positive effects of trade on innovation, it is unlikely that this could be generated just from shifts within a given portfolio of products. Trade is actually creating new products in this case (thus closer in spirit to Grossman and Helpman, 1992).

[4] This is modeled in the manner of Hopenhayn (1992) and Melitz (2003). All firms receive a random productivity draw when they enter the industry. If this draw is below a productivity cut-off, which depends on production fixed costs, and the price-cost margin they will decide not to produce, i.e. immediately exit the industry. There are sunk costs of entry, so higher fixed costs and/or expected lower profit will reduce entry incentives.

Market Size

Typically, the key feature distinguishing technology from other inputs is that technological investments have a fixed cost component that reduces marginal costs across all 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) but have only been formalized more recently (e.g. Acemoglu, 1999 and 2007). The essential idea is that greater trade generates a larger market size to spread over the fixed costs for investing in technology.

The empirical literature here have naturally tended to focus on the role of *exports* in affecting productivity growth and technical change as the models focus on the extension of product markets. There is abundant evidence that firms that are more productive select into export markets (e.g. Bernard and Jensen, 1999). A smaller emerging literature also finds evidence that productivity rises when exporting increases (e.g. Verhoogen, 2008, on Mexico and de Loecker, 2007, on Belgium). Bustos (2007) is unusual in examining direct measures of technology – she finds that Argentinean firms seemed to increase their investment in technologies when Brazil lowered tariffs against them. This literature seems less appropriate in our application, however, as the main effect we focus on is on the increase in Chinese imports rather than the opening up of export opportunities in China for OECD firms. Although we also look at the effect of exports to China, this is not the main policy concern in the West. Furthermore, we do not empirically identify much effect on technical change through this channel.

Product market competition

A second class of models where trade has a direct effect on the (within firm) incentives to invest in technology is when trade opening increases the degree of product market competition. Reductions in tariff rates on Chinese goods imply that Chinese producers are much more effective competitors because even if their products are lower quality, their lower prices place a competitive constraint on incumbent domestic producers. It is very likely that the rise of China constitutes a trade-based competitive shock on domestic EU producers. How will technical change react to such an increase in increase in product market competition? This is an old question in economics. Analytically we need to distinguish between establishment (selection) and within establishment effects. In terms of between-establishment effects we would expect a *selection* effect whereby the least efficient establishments shrink and exit the market in the face of tougher competition. If the low-tech firms are less efficient and productive, then this will mean an industry-wide upgrading towards more high tech firms.

The impact of competition on technological adoption and innovation within establishments is more ambiguous. On the one hand, there may be increased managerial effort because of the fear of greater bankruptcy risk (Schmidt, 1997), greater sensitivity of relative profits to effort (Raith, 2003), a stronger "escape competition" effect (Aghion et al, 2005) and (in equilibrium) larger firm size (see Vives, 2005). On the other hand, lower profits will blunt the innovation incentives for 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. Here, we are arguing that that China's trade growth constitutes the best recent example of a major quasi-experiment increasing competition. Furthermore, the focus in these papers has been on competition in general rather than trade with developing countries in particular. Finally, the papers that have looked at trade liberalizations have tended to look at firm (total factor) productivity rather than at technology and have focused on developing countries rather than developed countries (see Goldberg and Pavnik, 2006, for a survey). Thus, we believe that focusing on the rise of China is novel and interesting in extending this literature.

Learning

Another mechanism through which trade can enhance innovation is through enabling domestic firms to gain access to better technology (e.g. Coe and Helpman, 1995). This may occur through informal channels as the importing firms build up supply networks. This mechanism does 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).

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 seek to fill this gap.

III. DATA

In order to analyze the question we have to combine datasets from multiple sources. Our main database is an original source of IT data at the establishment level across many countries (Harte Hanks). We combine this with four-digit industry by country trade data from COMTRADE and to other industry data sources. The advantage of having establishment-level panel data on IT is that we can distinguish within plant and between plant effects of trade, which would be impossible if we had only industry level data on IT.

IIIA Harte-Hanks IT data (HH)

The main data that we use in this paper is constructed using the Ci Technology Database (CiDB) 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. 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 Harte-Hanks data matched to large publicly listed firms in Compustat. In Europe, the company began surveying the major Western European countries (UK, France, Germany, Italy, Spain) in the early 1990s, and by the late 1990s had expanded to cover the rest of Western Europe.

Harte Hanks surveys establishments (referred to as “sites” in the CiTB database) on a rolling basis with an average of 11 months between surveys. 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 at the establishment level. Areas covered by the survey include PCs, many types of software, networking resources, LAN, servers, storage and IT staff (including development staff such as programmers). We provide an establishment report for one establishment, Rolls Royce, as an example of the typical data provision in Appendix A1. Currently, we focus on using PC per worker as our key measure of IT intensity because this is available for all the establishments and is measured in a comparable way across time and countries. This PC per worker measure of IT has also been used by 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 (see, for example, Doms et al, 2006 and Bloom, Sadun and Van Reenen, 2007). We plan to use the more extensive information on quality and other forms of technology in future versions of the paper.

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.[5] 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. This provides some advantages over alternative strategies such as (for example) harmonising government statistical register data collected by independent country level survey agencies.

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. 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.

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

Furthermore, HH only drops establishments from the survey if they die or repeatedly refuse to answer, so that the sampling frame covers all firms that have had at 100 employees in any year since the survey began.

In terms of survey response rate HH reports that for the large European countries (UK, France, Germany, Italy, and Spain) they had a response rate of 37.2% in 2004 for firms with 100 or more employees[6]. As mentioned above, the sampling strategy followed by HH allows us to construct a measure of establishment exit. 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 of establishment exit 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 36 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.

IIIC Patents Data

We use the AMAPAT database (Belenzon et al, 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 14 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.

The match 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

[6] This is close to the 44.9% response rate achieved by Bloom, Sadun and Van Reenen (2008) using a similar telephone survey technology, in which the response rate appeared to be uncorrelated with any firm-level performance characteristics. HH claim no systematic response bias and we are currently matching the HH database against the population of firms in Europe obtained from the AMADEUS database to analyze the factors determining the response rate in the HH data.

have this information only for a sub-sample of the whole database. Nevertheless, we can use this information to conduct a battery of robustness tests.

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[7].

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). To make sure that the variable is not simply proxying total trade we also consider conditioning on total imports to production as an additional control. The advantage of focusing on China is that the growth of Chinese exports is a large exogenous change facing plants.

In terms of overall trends in China's exporting activity Figure 1 shows the remarkable rise of China's share of all world exports (excluding those exports to China). Since 1996 China's share has increased from approximately 3% in the mid-1990s to almost 10% in 2006. Of course, this aggregate disguises

[7] 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.

considerable heterogeneity by industry. Appendix Table 2 lists the top ten four digit industries in terms of imports from China as share of the world's imports 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 3% to 10% could be considered low there are a number of industries where China had a high share 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[8]. For example, these industries where China has a high export share contrast with more capital and technologically intensive industries

IIIE. Other Industry Data

Finally, we combine our establishment and trade data with industry level information on production and total imports from the OECD STAN database. Data on skills (the proportion of college educated workers) are drawn from the EU KLEMS dataset (http://www.euklems.net/). Both of these datasets are defined at the 2-digit industry level with a selection of industries defined at the 3-digit level. It is relatively easy to map these into the USSIC system used in the CiTDB data from Harte-Hanks.

IIIF. Descriptive Statistics

Table 1 contains some basic descriptive statistics for the sample on which we run our technology and employment regressions. In the regression sample we only keep establishments with non-missing values on our key variables over a five year period and who are alive in 2000 or 2001. This gives us a sample of just over 20,000 establishments (we have 29,000 for the sample where we look at exits based on being alive in 2000). Our establishments have a median (mean) employment of 150 (260). In the baseline year (generally 2000, but sometimes 2001) PC intensity was 49% - about one PC for every two employees - but this rises rapidly over the next 5 years to around 58% in 2005/2006. Employment, by contrast, fell during this period which is unsurprising since the manufacturing sector has been in long-term decline in developed countries. About 11% of establishments alive in 2000 had exited by 2005.

[8] For example, these industries where China has a high export share contrast with large mass of more advanced capital intensive industries such as Fluid Power Pumps and Motors (SIC code 3594, level of 0.6% in 1999 and 0.7% in 2006) or Non-standard Internal Combustion Engines (SIC Code3519 , level of 0.7% in 1999 and 0.75% in 2006).

The most dramatic change has been in the position of China. In the baseline year only 3.4% of imports originated in China. In the next five years this rose by 2.7 percentage points – a full 79% increase in only a five year period. Thus there is a substantial increase in Chinese import competition over this period.

In Figure 2 we plot the mean change in (within-establishment) IT intensity and log employment ordered by the degree of exposure to Chinese import competition. We divide establishments into quintiles based upon the increase in Chinese import penetration, 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 PC 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") to those in the top quintile ("high exposure industries"). 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 where 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 MODELLING STRATEGY

IVA. Information Technology

We consider three basic equations to empirically examine the role of Chinese import competition. Consider the basic technology intensity equation:

$$\ln(IT/N)_{ijkt} = \alpha IMPS_{jkt} + \beta x_{ijkt} + u_{ijkt} \tag{1}$$

Where IT is a measure of information technology in establishment i in four digit industry j in country k at time t. We will generally use the number of personal computers (PCs), but experiment with many other measures of IT such as the quality of PCs and other types of IT (like servers and software applications). $IMPS$ is our measure of exposure to competition to China, N is the number of workers, x_{ijkt} is a vector of controls and u_{ijkt} is an error term whose properties we discuss below. We measure $IMPS$ mainly as the proportion of imports in industry j and country k that are from

China $(M_{jk}^{China} / M_{jk}^{World})$, where normalize M^{China} by total imports from anywhere in the world, M^{World}. This follows Bernard et al (2004, 2006) and can be justified by the idea that the growth in Chinese imports is the most important increase in trade competition facing OECD producers. Rapid growth in Chinese import share is therefore used as a proxy for a rapid increase in trade competition in the industry. The vector x_{ijkt} includes controls for many other factors such as the type of establishment (e.g. single site or multi-plant), overall import intensity, skills, etc. We model the error term, u_{ijkt} as consisting of a fixed effect, a time effect and a random component, and estimate equation (1) as:

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

Where Δ denotes the long (five-year) difference operator[9]. Our interpretation of the trade-induced technical change hypothesis is essentially that $\alpha > 0$.

Equation (2) examines whether Chinese import competition is associated with technological upgrading on the intensive margin – i.e. within surviving firms. We also examine whether trade affects the extensive margin by examining employment equations and exit equations.

We estimate an employment growth equation of the form:

$$\Delta \ln(N)_{ijkt} = \alpha^n \Delta IMPS_{jkt} + \beta^n \Delta x_{ijkt}^n + v_{ijkt}^n \tag{3}$$

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. $\alpha^n < 0$). We are particularly interested in whether trade has a larger effect on lower tech firms, so to capture this we include the interaction of *IMPS* with lagged (IT / N) and estimate specifications of the form:

[9] We use long-differences to mitigate the problem of attenuation bias when using first differences (see Mairesse and Griliches, 1998, for example).

$$\Delta \ln(N)_{ijkt} = \alpha^n \Delta IMPS_{jkt} + \beta^n \Delta x_{ijkt}^n + \gamma^n [(IT/N)_{ijkt-5} * \Delta IMPS_{jkt}] + \delta^n (IT/N)_{ijkt-5} + v_{ijkt}^n \quad (4)$$

If Chinese trade has a disproportionately negative effect on low-tech firms we would expect $\gamma^n > 0$. Equations (2) and (4) are long differenced specifications on surviving firms. However, one of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate a third equation:

$$SURVIVAL_{ijk} = \alpha^x \Delta IMPS_{jkt} + \beta^x \Delta x_{ijkt}^x + v_{ijkt}^x \quad (5)$$

which is defined on a cohort of establishments who were alive in 2000. We follow these establishments over the subsequent five years and define $SURVIVAL_{ijk}$ = 1 if the establishment has remained alive until 2005 and zero otherwise. If Chinese imports do reduce survival probabilities we expect $\alpha^x < 0$.

Analogously to the employment equation we also estimate:

$$SURVIVAL_{ijk} = \alpha^x \Delta IMPS_{jkt} + \beta^x \Delta x_{ijkt}^x + \gamma^x [(IT/N)_{ijkt-5} * \Delta IMPS_{jkt}] + \delta^x (IT/N)_{ijkt-5} + v_{ijkt}^x \quad (6)$$

Where we expect that the effect of Chinese imports will have the most negative effect on low-tech establishments so $\gamma^x > 0$.

IVB. Innovation

Consider the analogous equation to (1) for innovation (as measured by patent counts or cite-weighted patent counts) rather than diffusion of IT:

$$\exp(I_{ijkt}) = \theta_1 IMPS_{jkt-l} + \theta_2 x_{ijkt} + \eta_i + \varepsilon_{ijkt} \quad (7)$$

We have lagged the Chinese import measure to reflect the fact that it will take some time before a firm alters its research behaviour in response to trade and again, there will be a lag (denoted *l*) between the research input and the innovation output. We will present experiments with many lag lengths and show that longer lags provide a better fit of the data (our baseline uses five year lags to be consistent with the long-differences). Because we have a much longer time series of patents (back to 1978) than we do of IT so we are able to estimate equation (7) in a way that exploits this information more efficiently. Since patents are non-zero integers the standard approach would be to utilize count data models (see Blundell, Griffith and Van Reenen, 1999, for examples of these applied to innovation equations with fixed effects and dynamics). We will do this, but including the fixed effects in a count data model is much more complicated than a linear model. Consequently, we will also present simpler models of the long differences in the same way as equation (2):

$$\Delta \ln(1+I)_{ijkt} = \theta_1 \Delta IMPS_{jkt-1} + \theta_2 \Delta x_{ijkt} + e_{ijk}^{D} \tag{8}$$

We will also present the within groups version of equation (7) by:

$$\ln(1+I)_{ijkt} = \theta_1 IMPS_{jkt-1} + \theta_2 \Delta x_{ijkt} + \eta_i + e_{ijk}^{W} \tag{9}$$

Equation (9) exploits the fact that we have a longer run of data for patents than for the information technology measures.

IVC. Endogeneity

An obvious problem with estimating these equations is endogeneity of Chinese imports. Consider equation (2) for example. If there is an unobserved technology shock increases the IT intensity of domestic firms in an industry country pair, Chinese imports are likely to fall. This will mean that there will be a downwards bias to the estimate of α thus making it *harder* to identify the effect we are looking for.

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. The overall increase in Chinese exports is driven fundamentally by the opening up to the global economy because of ongoing liberalization by Chinese policy makers, so is clearly exogenous. We argue that this overall increase will have a differential effect by industry depending on whether the industry is one in which China has a comparative advantage. Industries 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 A2) – and so would experience much more rapid increase in import penetration in the subsequent 5 years. Consequently, high exposure to Chinese imports in 1999 can be used (interacted with overall Chinese trade growth in the world, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($IMPS_{j99} * \Delta M^{China}$) as an instrument for $\Delta IMPS_{jkt}$ where $IMPS_{j99}$ is the Chinese import share in industry *j* in the world (not specific to country *k*).

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.

A related criticism of our use of the quantity flow is the key trade variable is that what matters is not the actual flow of imports but the *threat* of the flow of imports. Thus, domestic producers may react to the increased threat of competition even if no increase in trade is observed. The use of instrumental variables obviously captures this as we use the predicted increase (rather than the actual increase) so long as our IV strategy is valid and that future threats are positively correlated with initial levels of Chinese import penetration. An alternative strategy is to use Chinese import prices rather than flows as this will correctly reflect the threat. We follow the strategy of Bertrand (2004) and OECD (2007) and use the industry import-weighted exchange rates where we use 1999 industry weights and the contemporaneous aggregate exchange rates.

A third identification strategy is to use the accession of China to the WTO that generated a fall in tariff barriers in many OECD economies. This disproportionately affected some industries (such as textiles in the EU) generating a large surge in Chinese imports. A fourth strategy is to use the difference in transportation costs between China and European locations. These do not vary over time but can be interacted with the overall growth of Chinese exports to generate some cross regional variation.

Our main focus in this version of the paper is on the first identification strategy, but preliminary investigation of the other IV strategies appears to give qualitatively similar results.

V. RESULTS

VA. Main Results

IT Intensity Equations

Table 2 presents the results for the technology equations where we regress the five-year growth rate of PCs per worker on the five-year growth of Chinese imports (as a proportion of total imports) in the firm's four-digit sector in the same country. Column (1) has no controls and simply shows that there is a strong and positive association in the data. This is also illustrated in Figure 4 which shows the non-parametric regression of column (1) confirming an upward sloping relationship. Establishments that faced increased exposure to Chinese imports have had a significant increase in technological intensity: a ten-percentage point increase in trade with China is associated with a 5% increase in PC intensity. Column (2) includes a full set of country by year interactions and column (3) includes some establishment type controls, such as whether the establishment is part of a multi-plant firm. These experiments reduce the coefficient on Chinese imports only slightly. The dependent variable normalizes PCs by the number of workers so a concern may be that the result is driven by the effect of Chinese imports on reducing jobs (see next table), rather than by increasing PCs. Consequently, column (4) simply includes the growth of employment as an additional control. This enters negatively suggesting that the elasticity of PCs with respect to employment is less than unity (0.348)[10]. Nevertheless, there remains a significant and positive association of IT intensity with Chinese imports suggesting that the Chinese import coefficient does not simply reflect employment falls. The final

[10] The negative coefficient on employment suggests that a doubling of output is associated with less than a doubling of the PC stock. But there could also be an element of division bias as employment also enters the numerator of the dependent variable.

column runs the estimation on 2005 only so we only have a single year (of long-differences) to show that the effect is robust in the smaller sample.

Employment Equation

Table 3 starts to examine the extensive margin by examining employment growth (still of survivors). The specifications follow those in Table 2. 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 3.4% fall in employment. Including year by country dummies (column (2)) and other controls (column (3)) weakens the results only slightly. In column (4), we include lagged PC intensity as an extra control. This enters with a positive and significant coefficient suggesting that the more technologically advanced firms in 2000 were more likely to grow over the next 5 to 6 years.

In column (5) of Table 3 we include an interaction between lagged IT intensity and the growth of Chinese imports. The interaction is positive and significant at the 10% level. This suggests that firms that are IT intensive are somewhat “shielded” from the effects of Chinese imports. This is made even clearer in the next column when we divide our firms into five quintiles groups based on their lagged IT intensity and we interact these with Chinese import growth. A clear pattern emerges whereby the imports effect is much weaker for the more IT intensive firms. In fact, for establishments in the top quintile 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%. The final two columns show the results are just as strong if we look at 2005 alone.

Plant Survival Equations

Tables 2 and 3 conditioned on establishments who survived at least five years. Table 4 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 PC intensity, establishments more exposed to Chinese imports are 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 88.6%, 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 and more IT intensive 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 instead of the linear 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 the final column 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).

Innovation Equations

We now turn to the innovation equations (as measured by patent counts) using our AMAPAT database matching the European Patent Office information with firm accounts. Column (1) of Table 5 presents the empirical analogue of equation (9) where we regress the number of patents against the level of Chinese imports (lagged five years) and a full set of industry by country effects (as well as the country by year effects). There is a positive and significant relationship between these two variables: a 10 percentage point increase in Chinese imports is associated with a 3% increase in patenting. Column (2) then includes a full set of firm dummies (instead of just the industry by country dummies) and shows that the relationship remains robust. Column (3) conditions on a sub-sample of the data where we observe the lagged capital-sales ratio and lagged employment. Missing values on these accounting measures means the sample falls by almost half, but the point estimate on Chinese imports is actually higher (0.349) and still significant. In column (4) we include capital intensity and employment in the regression, but this barely shifts the results. Column (5) includes lagged sales instead which reduces the coefficient to 0.3. In the final column, we present the empirical analogue to equation (8) and estimate in long (five yearly) differences. Although the sample is much reduced (to about 22,731 observations) the coefficient on Chinese imports is remarkably similar (0.366) to the previous column and remains highly significant.

Summary

Taking Tables 2 through 5 together, we have a clear empirical picture of the role of Chinese imports. Increased import competition with China is associated with increased IT intensity in an industry for at least two reasons. First, there is a selection effect whereby those establishments that are less IT intensive 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 technological upgrading. The latter is more surprising and consistent with models of trade-induced technological change. Moreover, Chinese trade is associated not only with faster diffusion of IT but also with a greater speed of innovation as indicated by a significant increase in patenting following Chinese import growth in previous years. There appears, therefore, to be strong support for the trade induced technical change hypothesis from our data. We now consider the robustness of these results.

VB. Instrumental Variable Results

An obvious concern with the OLS regressions is that there is endogeneity bias on the Chinese import coefficient. *A priori* the sign of the bias is ambiguous. In the technology equation, the bias is likely to be negative as a positive technology shock is likely to make the industry more productive and less at risk from an influx of Chinese imports. This would make it harder to identify the positive effect we find. For the employment equation, a positive supply shock would increase employment and probably reduce imports that could generate a negative bias – possibly explaining the negative coefficient that we find. For example, Chinese imports may be attracted to those industries that are already in decline in the developed countries. On the other hand, a demand shock would increase jobs and suck in more imports that would bias the coefficient away from zero. In addition, classical measurement error will attenuate the coefficients towards zero.

As discussed above we attempt to deal with this problem by using instrumental variables. We first consider as an instrument the growth of total Chinese exports in the world interacted by the China's lagged share of imports in the (European wide) four-digit industry. The growth of Chinese exports in aggregate is due to the opening up of the Chinese economy and general global economic growth. It is likely that the industries where Chinese imports grew most strongly are those where Chinese firms had already established some presence. Column (1) of Table 6 presents the first stage for the instrumental variable regressions. The instrument is strongly correlated with the endogenous variable, the growth of Chinese import intensity (coefficient of 0.261 and standard error of 0.004[11]). Column (2) then presents the second stage. The coefficient on Chinese imports is 0.343 (and significant at the 5% level) compared to 0.241 for OLS. This bias is consistent with our priors as we might expect a technology shock to give some "protection" to an establishment from Chinese imports, but the difference between the OLS and 2SLS results is not significant.

Column (3) of Table 6 presents the first stage for the employment growth regressions and again shows that our instrument has considerable power. Column (4) presents the 2SLS results and shows that the coefficient on Chinese imports is -0.476 compared to -0.256 in OLS. Column (4) examines the interaction specification: the key interaction remains significant at the 5% level. The coefficients on the key variables are larger in absolute magnitude than in the OLS specifications, possibly because the IV estimator corrects the downward attenuation bias present in the OLS estimator.

Columns (5) through (7) of Table 6 report the survival equation. Column (5) reports the first stage that shows that the instrument is powerful in predicting the endogenous variable. Column (6) reports the first exit equation with only the linear effect of Chinese imports. The coefficient on Chinese imports has risen to 0.313 compared to 0.178 under OLS. Similarly, to the jobs and technology equation, OLS tends to under-estimate the effects of Chinese imports. Finally, in column (7) we present the exit equation with an additional interaction between the lowest quintile of lagged IT intensity and Chinese import growth estimated by 2SLS. The coefficient is negative, but not significant at conventional levels.

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[11] Note that throughout this table we cluster by four-digit industry only, instead of four digit by country dummies as in the previous tables. We do this in order to be conservative as the instrument has not country-specific variation (unlike the endogenous variable).

With the exception of the final column, the instrumental variable results in Table 6 appear to support the OLS results presented earlier. There does not appear to be a large endogeneity bias on the coefficients on Chinese imports or their interactions and, to the extent, this does exist, treating Chinese imports as endogenous makes the results stronger[12].

VC. Robustness Tests

We report some further robustness tests in Table 7 looking at total imports, exports to China and skills. We present all results for our three key outcomes: IT intensity in columns (1)-(4), employment in columns (5) to (8) and plant survival in columns (9) to (12).

Total imports

First, we consider the role of imports as a whole, rather than Chinese imports *per se*. Recall that we focus on Chinese imports as we believe this constitutes the most plausible "trade shock" due to China's accession to the WTO in 2001 and the ongoing liberalization of the Chinese economy. We include the ratio of total imports to production $\Delta\left(M_{jk}^{World}/Y_{jk}\right)$ in addition to our key Chinese imports term, $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$[13]. Since the production data is taken from the OECD's STAN database we lose a few observations due to problems of industry matching so the sample falls from 27,354 to 23,803. Columns (1), (5) and (9) simply confirm that the baseline results for technology, employment and exit respectively are robust to estimation on this sub-sample. In columns (2), (6) and (10) we see that the total imports variable has expected signs in all three equations. It has a positive correlation with IT upgrading and exit probabilities and a negative association with employment growth. However, the coefficient is not significant at conventional levels. More importantly, the coefficient on Chinese trade although reduced marginally in absolute value remains significant at the 5% level in all three columns.

Exports

[12] We also used the IV strategy on patenting with similar results. For example, the coefficient on imports rises from 0.326 to 0.349 and remains significant at the 5% level using the third lag of the growth of Chinese imports.

[13] We also considered other variants of this measure such as disaggregating imports from non-OECD countries and normalizing on value added instead of production. These produced similar results.

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 a variable reflecting exports to China (as a proportion of total exports in the industry-country pair) in an analogous way to imports. This variable was insignificant in all regressions – see columns (3), (7) and (11). 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.

Human and physical capital

A third issue relates to skills. If Chinese imports are displacing firms with the lowest skills and these are also 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, so one way to examine this is also to include a measure of human capital in the regressions. We turn to the EU KLEMs database that contains a measure of the proportion of skilled workers in the industry. We use the growth of the share of college-educated workers in the wage bill (in the industry and country of the establishment). In column (4) this enters with a positive sign as expected in the technology equation, but it is not significant. The Chinese import term remains positive and significant. Establishments in industries that had higher growth in human capital also tended to have lower falls in employment (column (8)) and lower probabilities of job losses (column (12)), although again these effects are insignificant.

Although it is reassuring that our results are robust to controls for skills, the insignificance of the skills variable is disappointing. This might be because of the higher level of aggregation of the skills measure (basically two or three digit) as we do not observed skills at the establishment level. An alternative approach is to use information on the average wage as a control for skills. To implement this we matched the HH data into firm level information from the Amadeus accounting database using the name matching technology we developed in the AMAPAT patents data. In the accounting data we can use average wages as a proxy for human capital. A related issue to that of human capital is whether the impact of imports on technical change simply reflects a more general increase in investment in fixed capital. The accounts data also allows us to construct a measure of capital intensity.

Appendix A3 presents these results and is divided into three panels for the equations on information technology (Panel A), employment (Panel B) and plant survival (Panel C). Broadly, our previous results are largely unaffected by these additional covariates. In Panel A column (1) repeats the baseline specification from column (3) in Table 2. Column (2) then includes the long difference of ln(average wages) and the ln(fixed capital to sales ratio). As expected the skills measure is positively associated with the growth of IT intensity (significant at the 10% level). Capital intensity is unrelated to IT growth by contrast. The key coefficient on Chinese imports is unchanged however, and remains positive and significant. These conclusions are unaltered when we include employment growth as an additional control in columns (3) and (4). Our findings of negative effects of Chinese imports on jobs and survival, especially for low-tech firms, are confirmed in Panels B and C after controlling for wages and capital.

Dynamics

Table 8 explores alternative timing assumptions of the way imports affects technical change. Because we only have technology 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 (to 1978 in principle). Here we focus on using patents post 1995. We estimate the long-differenced equation allowing Chinese imports to affect patents at different lag length. Our preferred model allows a five-year lag to reflect the time between a rise in trade competition, investment in R&D and subsequent realizations of patents (innovation outputs). This is the baseline in column (1) of Panel A that has already been presented. Columns (2) to (6) bring the date further forward in time by one year each time, so column (2) for example uses a four year lag, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-4}$ and column (6) the contemporaneous value, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t}$. If our results were spuriously reflecting some other unobservable shock simultaneously increasing patenting and imports we would expect the results to be stronger as the two variables were more closely dated. In fact, the opposite is the case: the coefficient on imports systematically falls as we approach the current day. This is consistent with the view that firms take time to adjust their innovation activities in response to a shock: we would not expect an immediate effect of trade on innovation.

Panel B of Table 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 3. We see almost the mirror image of the earlier panel. The strongest effects on employment are current growth of imports. Growth of imports five or four years earlier are not significantly related to job losses. 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.

VD. Quantification

To get a rough quantification of the magnitudes of the "China effect" we can consider the aggregate changes in our sample combined with the empirical estimates of trade effects in the econometric models. Note that these are only crude "back of the envelope" calculations, as we have no general equilibrium model nor any estimates of the China effect on entry (which is harder to credibly estimate in the Harte-Hanks data). To be conservative, we use the smaller OLS estimates for these calculations. From the descriptive statistics in Table 1 we can see that the average firm increased PC intensity by 19.7 log points over the sample period. Given that there was a 2.7 percentage point increase in Chinese import intensity and the coefficient on this variable in the technology equation was 0.456, this implies we can account for 6.2% of the increase in PC intensity for survivors through the effects of trade [= (0.027*0.456)/0.197]. Therefore, although statistically significant, trade competition with China is a small part of the overall reason for technological upgrading of surviving establishments.

Similar calculations imply that China can account for about 14% of the net employment change in our sample. This is a more economically important fraction than for technology and probably explains the political opposition to greater trade opening. China only accounts for about 2.9% of the exits over this period, however, suggesting a large part of survival is related to other factors (note that there is a lot of exit in the sample: some 11% of the sample has disappeared within 5 years on average). If we put the effects of China on exit and survival growth together then in aggregate trade accounts for 7% of the overall fall in European manufacturing employment[14].

These calculations assume that the effect of China is homogeneous across firms, whereas the analysis of sub-section VA demonstrated that low-tech firms suffer more than high tech firms do. If we focus on firms in the bottom quintile of the IT intensity distribution then Chinese imports account for a much greater proportion of job losses. For these low tech establishments, Chinese import intensity increased by 7.5 percentage points (almost three times more than for the sample as a whole), employment fell by 13.8 log points (double that of the sample as a whole) and the exit rate was 13% (2 percentage points and 18% higher than the sample as a whole). Using the estimates from Table 3 column (6) and Table 4 column (4) implies that Chinese imports can account for 22% of the job losses for the surviving firms in our sample and 19.5% of the aggregate fall in employment for low-tech firms (taking the exits into account).

Therefore, the effects we are obtaining are not trivial, especially for the low-tech firms.

VI. CONCLUSIONS

In this paper we have re-examined the impact of trade on technical change (IT diffusion and innovation), jobs and establishment survival in 14 European countries. Our motivation for this is that the rise of China constitutes perhaps the most important exogenous trade shock to hit OECD economies in the last 30 years. This helps identify the trade-induced technical change hypothesis. We use novel firm and plant-level panel data on diffusion (information technology) and innovation (patents) 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.* The results are easy to summarize. First, IT intensity and the amount of patenting has risen in firms who where more exposed to increases in Chinese imports. Second, Chinese import competition tends to reduce employment in those sectors who were most exposed both through falling

[14] This calculation assumes that the average size of exiters and incumbents is the same. If we take into account that survivors are larger then the China percentage effect will increase.

jobs in surviving establishments, but also through an increasing probability of exit. This finding is consistent with those found in US manufacturing establishments in Bernard, Jensen and Schott (2004, 2006) for the pre-1997 period. Third, the effects of China on jobs and exit are much stronger for establishments that are less IT intensive and the more technologically advanced establishments appear to be somewhat “shielded” from competition. These results appear to be robust to many tests, including treating trade as endogenous using the fact that Chinese import growth was closely related to the level of import penetration prior to our sample period.

Despite this evidence for trade-induced technical change, the magnitude of the effects of Chinese imports (although statistically significant) is relatively small in magnitude, accounting for about 7% of within establishment IT upgrading. China has its largest effects on jobs in the low tech establishments, maybe accounting for a fifth of job losses in the sample. The concentration of employment effects in these establishments is probably why there are such strong political objections to further liberalizations.

Our work is still at a preliminary stage. First, we are investigating other instrumentation strategies using changes in quotas and tariffs. Second, we are refining our measure of innovation by drawing on citations, to examine whether the increase in patenting is more to do with the protection of existing knowledge rather than the generation of new knowledge. Third, we want to complement our European analysis with a similar exercise in the US where we have also recently accessed the HH data. Finally, our work is quite descriptive, so linking the findings more rigorously to a structural general equilibrium trade model would enable us to perform more convincing counterfactual analysis.

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TABLE 1: DESCRIPTIVE STATISTICS

Variable	Description	Means / Median
N_{t-5}	Employment at baseline (mean)	259.9 (611.2)
$(IT/N)_{t-5}$	Employment at baseline (median)	150 -
$(IT/N)_{t-5}$	PCs / Employment (mean at baseline)	0.489 (0.354)
(IT/N)	PCs / Employment (mean at end of period)	0.579 (0.382)
$\Delta \ln N$	Change in ln(Employment)	-0.062 (0.408)
$\Delta \ln(IT/N)$	Change in ln (PC/Employment))	0.197 (0.539)
$\left(M_{jk}^{China} / M_{jk}^{World}\right)$	%China Imports in country k, industry j (baseline))	0.037 (0.070)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	Change in % China Imports in country k, industry j	0.027 (0.051)
Pr (Exit)	Probability of Exit (between 2000-2005) (%)	0.114 (0.318)
Site Types (%)	Standalone Branch	0.708
	Enterprise Branch	0.135
	Divisional HQ	0.151
	Enterprise HQ	0.001
Number of Establishments		20,535
Number of Observations in 2005		14,347
Number of Observations in 2006		13,007
Number of Observations (total)		27,354

Notes: This is for the regression sample using five year differences in Table 2. All changes are given as five-year changes. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. Site type effects are Divisional HQ, Divisional Branch , Enterprise HQ and Standalone Branch. Note that the exit figure is quoted for the baseline sample of 29,008 establishments existing in 2000.

TABLE 2: TECHNOLOGY EQUATIONS

Dependent variable: $\Delta \ln(IT/N)$	Five year change in ln (PCs Per Worker)				
	(1)	(2)	(3)	(4)	(5)
Experiments	No Controls	Include Country Year Effects	Include Site-Type controls	Include control for Employment growth	2005 Only
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.499***	0.497***	0.456***	0.241***	0.211***
Chinese Import Share	(0.088)	(0.087)	(0.086)	(0.078)	(0.082)
$\Delta \ln N$				-0.652***	-0.641***
Growth of firm employment				(0.010)	(0.011)
Site Type Controls	No	No	Yes	Yes	Yes
Country-Year Fixed Effects	No	Yes	Yes	Yes	Yes
Number of Establishments	20,535	20,535	20,535	20,535	14,347
Number of Observations	27,354	27,354	27,354	27,354	14,347

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. There are 2,728 distinct country by industry pairs. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. $\Delta \ln N$ is contemporaneous 5-year change in establishment-level log employment as a control. "Site type controls" are dummies for if the establishments are: a Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch. Sample period is 2000 to 2006.

TABLE 3: EMPLOYMENT EQUATIONS

Dependent variable: $\Delta \ln N$	Five year change in ln (Employment)							
	(1) No Controls	(2) Include Country-Year Effects	(3) Include Site-Type Controls	(4) Include PC Intensity Control	(5) Include Interaction	(6) Quintiles of IT/N	(7) 2005 Only Interaction	(8) 2005 Only Quintile
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Chinese Import Share	-0.345*** (0.078)	-0.333*** (0.084)	-0.329*** (0.084)	-0.256*** (0.085)	-0.413*** (0.120)	-0.404*** (0.137)	-0.488*** (0.161)	-0.488** (0.212)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$ Chinese Imports*IT intensity					0.352* (0.188)		0.491** (0.228)	
Highest Quintile 5 of (IT/ N)$_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$						0.439** (0.192)		0.535** (0.246)
Quintile4* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$						0.260 (0.159)		0.500 (0.243)**
Quintile 3* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$						0.023 (0.187)		-0.065 (0.332)
Quintile 2* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$						0.106 (0.149)		0.220 (0.217)
(IT/ N) $_{t-5}$ IT Intensity				0.248*** (0.010)	0.239*** (0.011)		0.235*** (0.013)	
Site Type Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Establishments	20,535	20,535	20,535	20,535	20,535	20,535	14,347	14,347
Number of Observations	27,354	27,354	27,354	27,354	27,354	27,354	14,347	14,347

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by 4 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. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. "Site type controls" are dummies for if the establishments is a Divisional HQ, a Divisional Branch , an Enterprise HQ or a Standalone Branch. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline PC intensity, (IT/ N) $_{t-5}$. Note that linear quintile terms are included in columns (6) through (8) but not reported in the table. Sample period is 2000 to 2006.

TABLE 4: ESTABLISHMENT SURVIVAL EQUATIONS

Dependent variable: *SURVIVAL*	**Probability of Firm Survival**			
	(1) Linear	(2) Interaction	(3) Quintiles of IT intensity	(4) Lowest quintile only
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	-0.119***	-0.178**	-0.290***	-0.052
	(0.046)	(0.071)	(0.094)	(0.048)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$		0.128		
		(0.110)		
Highest Quintile 5 of (IT/ N) $_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.209	
			(0.135)	
Quintile4* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.297**	
			(0.118)	
Quintile3* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.153	
			(0.126)	
Quintile2* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.280***	
			(0.104)	
Lowest quintile (IT/ N) $_{t-5}$ * $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				-0.237**
				(0.097)
$\ln N_{t-5}$	0.038***	0.038***	0.039***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
(IT/ N) $_{t-5}$	0.003	-0.001		
	(0.006)	(0.006)		
Lowest Quintile (IT/ N) $_{t-5}$				- 0.019***
				(0.006)
Site Type Controls	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes
Number of Establishments	29,008	29,008	29,008	29,008
Number of Observations	29,008	29,008	29,008	29,008

Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) - four digit industry (j) pair in parentheses. There are 3,007 country-industry clusters. SURVIVAL refers to whether an establishment that was alive in 2000 was still alive in 2005 (mean is 88.5%). $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 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 PC intensity, (IT/ N) $_{t-5}$. Note that linear quintile terms are included in columns (3) and (4) but not reported in the table. There are 3,003 distinct country by industry pairs. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. "Site type controls" are dummies for if the establishments is a Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch.

TABLE 5: INNOVATION EQUATIONS

Dependent variable:	$\ln(1+PAT)$	$\ln(1+PAT)$	$\ln(1+PAT)$	$\ln(1+PAT)$	$\ln(1+PAT)$	$\Delta\ln(1+PAT)$
	(1)	(2)	(3)	(4)	(5)	(6)
Experiment	Baseline	Include Firm fixed effects	Sub-sample with accounting information	Control for lagged ln(capital-sales) ratio and lagged ln(employment)	Control for lagged ln(sales)	Estimate in long-differences
$\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-5}$ Chinese Import Share	0.308*** (0.081)	0.276*** (0.079)	0.349*** (0.095)	0.348*** (0.096)	0.300*** (0.097)	
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-5}$ Growth of Chinese Import Share						0.366*** (0.100)
4 Digit Industry-country fixed effects	Yes	n/a	n/a	n/a	n/a	No
Firm fixed effects	No	Yes	yes	yes	Yes	No
Site Type Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Other controls						
Number of country-industry pairs	2,497	2,497	1,913	1,913	2,244	1925
Number of Observations	96,791	96,791	47,722	47,722	67,145	22,731

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, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. Sample period is 1996 to 2004.

TABLE 6: INSTRUMENTAL VARIABLE ESTIMATES

Dependent variable	Five-year change in log(PCs per Worker) $\Delta(M_{jk}^{China}/M_{jk}^{World})$	$\Delta\ln(IT/N)$	Five year change in log(Employment) $\Delta(M_{jk}^{China}/M_{jk}^{World})$	$\Delta\ln N$	$\Delta\ln N$	Probability of Survival $\Delta(M_{jk}^{China}/M_{jk}^{World})$	Pr(Survival)	Pr(Survival)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First Stage	2SLS	First Stage	2SLS	2SLS		2SLS	2SLS
$\Delta(M_{jk}^{China}/M_{jk}^{World})$		0.343**		-0.479***	-1.255***		-0.313**	-0.264
		(0.165)		(0.182)	(0.200)		(0.139)	(0.143)
$\Delta(M_{jk}^{China}/M_{jk}^{World})$ * (IT/ N) $_{t-5}$					1.724***			
					(0.444)			
$\Delta(M_{jk}^{China}/M_{jk}^{World})$*lowest quintile of (IT/ N) $_{t-5}$								-0.104
								(0.290)
$\Delta\ln N$	0.004***	-0.651***						
	(0.001)	(0.010)						
(IT/ N) $_{t-5}$			-0.004***	0.247***	0.202***	0.003***	0.002	
			(0.001)	(0.010)	(0.017)	(0.001)	(0.006)	
Lowest quintile of (IT/ N) $_{t-5}$								-0.022**
								(0.010)
ln N_{t-5}						0.001***	0.038**	0.039***
						(0.000)	(0.002)	(0.002)
$\Delta M^{China} * (M_j^{China}/M_j^{World})_{1999}$	0.261***		0.261***			0.267***		
	(0.004)		(0.004)			(0.04)		
Site Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Establishments	20,535	20,535	20,535	20,535	20,535	29,008	29,008	29,008
Number of Observations	27,354	27,354	27,354	27,354	27,354	29,008	29,008	29,008

Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. Standard errors are clustered by four digit industry (j) in parentheses. There are 370 industry clusters for the PC intensity and employment regressions and 272 for the exit models. $\Delta(M_{jk}^{China}/M_{jk}^{World})$ 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 $\Delta M^{China} * (M_j^{China}/M_j^{World})_{1999}$ represents the proportion of total Chinese imports in industry *j* as a share of all European imports in industry *j* interacted with the aggregate growth in Chinese imports in the Europe. All regressions include site type controls dummies for establishment type (Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch) and country-year fixed effects. Quintiles represent bands of establishments ordered from highest to the lowest in terms of their baseline PC intensity, (IT/ N) $_{t-5}$. Sample period is 2000 to 2006 in columns (1) through (4) and 2000 to 2005 in column (5) through (7).

TABLE 7: ROBUSTNESS CHECKS ON TOTAL TRADE, EXPORTS TO CHINA AND SKILLS

	Five year change in log (PCs Per Worker)				Five year change in log (Employment)				Probability of Plant survival			
	(1) Sample Comparison	(2) Import Penetration	(3) Exports to China	(4) Skills	(5) Sample Comparison	(6) Import Penetration	(7) Exports to China	(8) Skills	(9) Sample Comparison	(10) Import Penetration	(11) Exports to China	(12) Skills
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.199***	0.198***	0.201***	0.199***	-0.410***	-0.410***	-0.409***	-0.410***	-0.179**	-0.178**	-0.179**	-0.179**
	(0.077)	(0.077)	(0.077)	(0.077)	(0.122)	(0.122)	(0.122)	(0.122)	(0.074)	(0.074)	(0.074)	(0.074)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$					0.327*	0.327*	0.327*	0.325*	0.075	0.075	0.075	0.074
					(0.189)	(0.189)	(0.189)	(0.189)	(0.116)	(0.116)	(0.116)	(0.116)
$\Delta\left(M_{jk}^{World} / Y_{jk}\right)$		0.008				-0.003			-0.017			
		(0.013)				(0.013)			(0.012)			
$\Delta\left(X_{jk}^{China} / X_{jk}^{World}\right)_{t-5}$			0.069				0.007				0.015	
			(0.121)				(0.089)				(0.069)	
$\Delta \ln(SKILL_{jk})$				0.243				-2.951				-0.318
				(3.261)				(2.889)				(1.879)
Site Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Establishments	18,235	18,235	18,235	18,235	18,235	18,235	18,235	18,235	25,633	25,633	25,633	25,633
Number of Observations	23,803	23,803	23,803	23,803	23,803	23,803	23,803	23,803	25,633	25,633	25,633	25,633

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. "Sample comparison" is the baseline specification with all controls estimated in the sub-sample where we have the additional industry data from STAN and EU-KLEMS. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 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. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. $\Delta \ln N$ is the 5-year change in establishment-level log employment as a control. Site type effects are Divisional HQ, Divisional Branch, Enterprise HQ and Standalone Branch. Import penetration ($\Delta\left(M_{jk}^{World} / Y_{jk}\right)$ is the 5-year change industry imports over domestic production. (derived from OECD STAN). $\Delta(SKILL_{jk})$ is the 5-year change in the log share of high skills workers' share of the wage bill (derived from EU KLEMS). $\Delta\left(X_{jk}^{China} / X_{jk}^{World}\right)$ is the 5-year change in Exports to China in country k, industry j as a share of World Exports in the given country-industry pair. Employment growth included in IT equations; linear lagged PC intensity (IT/ N) $_{t-5}$ =included in employment and exit equations and lagged employment N)$_{t-}$ included in exit regressions (these are not reported).

TABLE 8: EXPLORATION OF DYNAMICS USING THE AMAPAT SAMPLE

PANEL A: PATENT GROWTH EQUATIONS

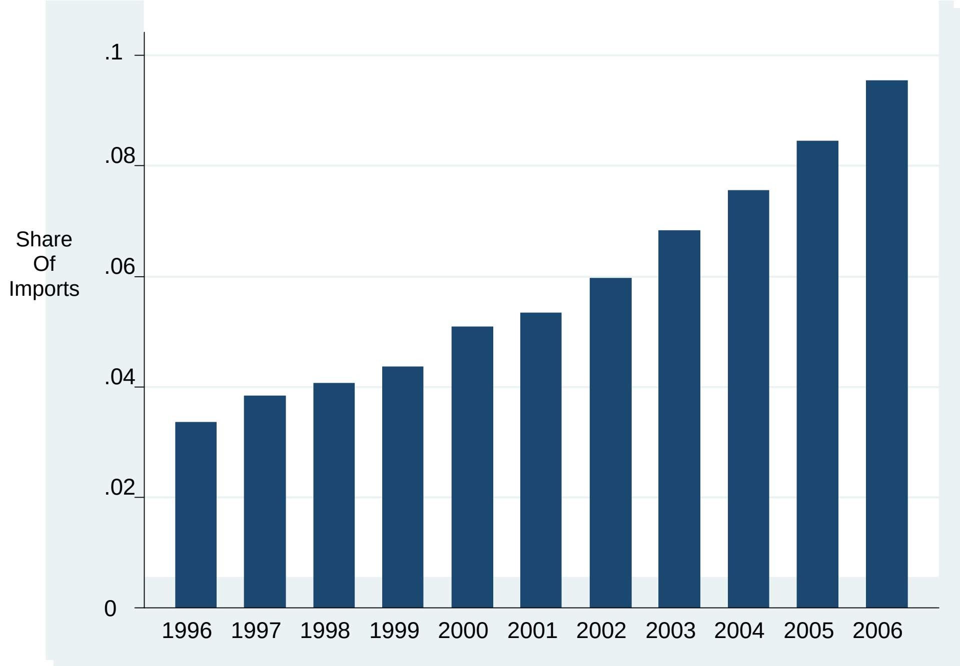
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$\Delta \ln(1+PAT)$					
5 year growth in imports						
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_t$ current						0.088 (0.076)
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-1}$ One year lagged					0.159*** (0.061)	
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-2}$ Two years lag				0.231*** (0.071)		
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$ Three years lag			0.326*** (0.081)			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-4}$ Four years lag		0.346*** (0.093)				
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$ Five years lag	0.366*** (0.100)					
Number of Observations	22,731	27,995	31,914	33,391	33,527	33,678

PANEL B: EMPLOYMENT GROWTH EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$\Delta \ln N$					
5 year growth in imports						
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_t$ current						-0.206** (0.097)
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-1}$ One year lagged					-0.228** (0.098)	
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-2}$ Two years lag				-0.255** (0.116)		
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$ Three years lag			-0.182 (0.120)			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-4}$ Four years lag		-0.028 (0.113)				
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$ Five years lag	0.098 (0.138)					
Number of Observations	14,528	18,155	21,082	22,157	22,259	22,413

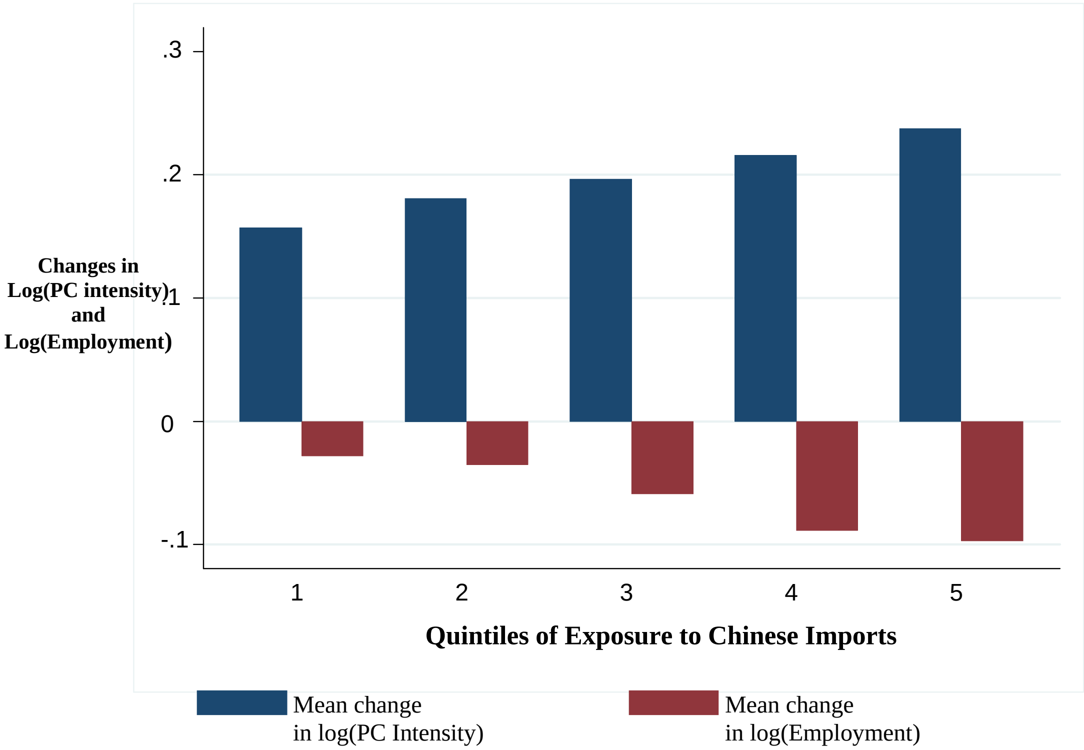
Notes: These are based on the AMAPAT database. All regressions include country-year fixed effects. Standard errors are clustered by four digit industry by country pair. Estimation by OLS.

FIGURE 1: SHARE OF CHINESE IMPORTS IN TOTAL IMPORTS IN EUROPE, 1996-2006.



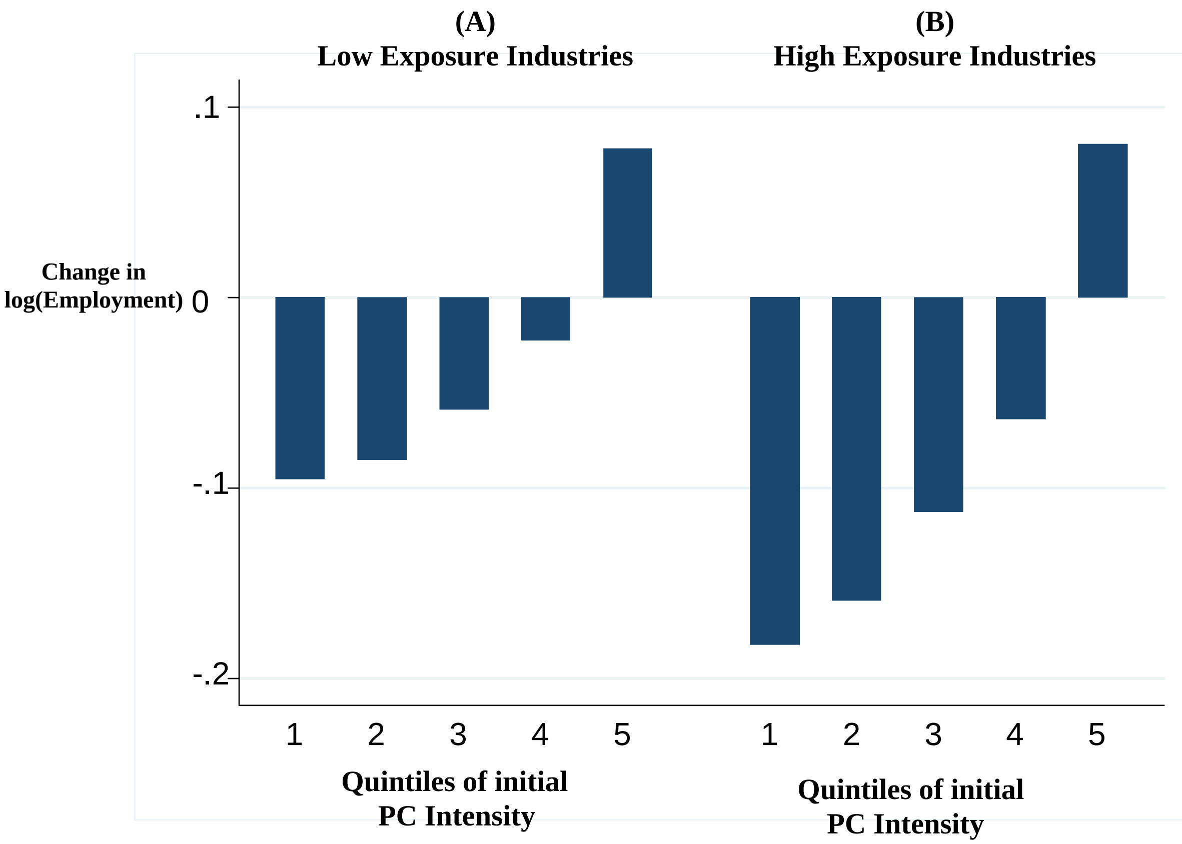
Notes: Calculated using product-level UN Comtrade data aggregated to 4-digit US SIC codes. There are 430 4-digit industries in our dataset. The vertical axis measures $\left(M_j^{China} / M_j^{World}\right)$, the proportion of total imports from China in industry j as a share of all world imports (excluding imports into China). All available countries in the UN COMTRADE dataset are used to calculate world exports.

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



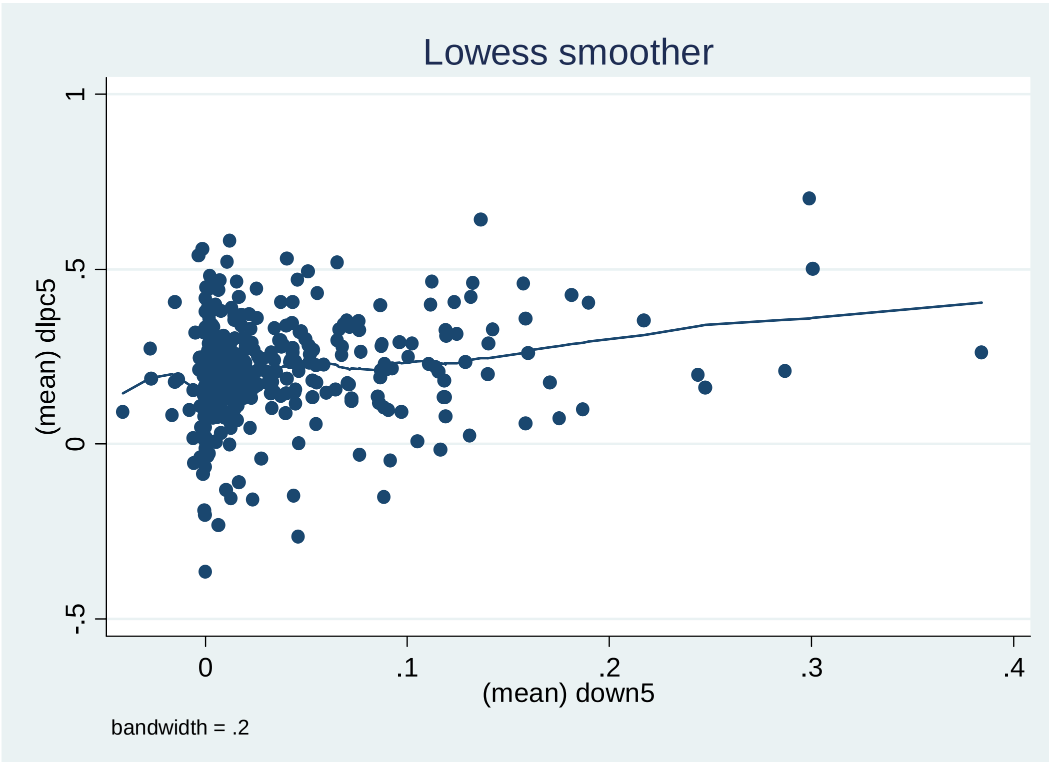
Notes: Calculated using regression sample of 27,354 observations for two waves of 5-year differences occurring in 2005 and 2006. The "Quintiles of Exposure to Chinese Imports" along the horizontal axis are classified according to the distribution of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$, 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 log (PCs per worker) and $\Delta \ln(N)$, the 5 year change in log (Employment).

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



Notes: Calculated using regression sample of 27,354 observations for 2005 and 2006. "Low Exposure" industries in panel (A) defined as observations falling in the lowest quintile (1) of 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. "High exposure" industries in panel (B) defined as observations classified in the highest quintile (5) 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 PC intensity, going from lowest (1) to highest (5).

FIGURE 4: NONPARAMETRIC REGRESSION OF THE PLANT-LEVEL IT INTENSITY AND THE GROWTH OF CHINESE IMPORTS



Notes: This is the results of a local linear regression of the growth in plant-level ln(IT/N) over a five year period and the growth of Chinese import intensity over the same five year period.

APPENDIX TABLE A1

GENERAL COMPANY INFORMATION

Rolls Royce Power Engineering

Employees: 350
Survey Date: 24/08/04
Site Type: Enterprise Branch

Postcode: L30 4UZ

DETAILED EQUIPMENT INFORMATION

Class Description	Class	Manufacturer	Series	Group	Model	Quantity
PCs	CPC	DELL	PC	P3-DESK	P3-DESK	150
PCs	CPC	COMPAQ	PC	P3-DESK	P3-DESK	110
PCs	CPC	DELL	PC	P3-PORT	P3-PORT	30
SERVERS	CPU	IBM	RS/6000	RS/6000-5XX	RS/6000-5XX	1
SERVERS	CPU	COMPAQ	SERVER	SERVER	SERVER	1
SERVERS	CPU	COMPAQ	WORKSTATION	WORKSTATION	ALPHASTATION	8
NETWORKING	NET	CABLE&WIRE	FRAME-RELAY	FRAME-RELAY	FRAME-RELAY	1
NETWORKING	NET	WAN-CONNECT	WAN	WAN	INTERNATIONA	4
NETWORKING	NET	WAN-CONNECT	WAN	WAN	TOTAL	6
OPERATING SYSTEMS	OPR	COMPAQ	UNIX	UNIX	UNIX	1
OPERATING SYSTEMS	OPR	MICROSOFT	WINDOWS	WINDOWS	WIN2000	1
OPERATING SYSTEMS	OPR	IBM	UNIX	AIX	AIX6000	1
OPERATING SYSTEMS	OPR	COMPAQ	UNIX	UNIX	UNIX	1
OPERATING SYSTEMS	OPR	MICROSOFT	WINDOWS	WINDOWS	WIN/NT	1
PROGRAMMES	PRG	MICROSOFT	BROWSER	BROWSER	EXPLORER	3
PROGRAMMES	PRG	SAP	ERP	ERP	ERP	1
PROGRAMMES	PRG	MCAFEE	SYS-UTILITY	ANTI-VIRUS	TVD	1
PROGRAMMES	PRG	MICROSOFT	OFFICE	SUITES	OFFICE-97	1
PROGRAMMES	PRG	MACROMEDIA	APPL-DEVELOP	WEB-DESIGN	DREAMWEAVER	1
PROGRAMMES	PRG	ORACLE	DATA-MGMT	DBMS	ORACLE	1
PROGRAMMES	PRG	MICROSOFT	OFFICE	E-MAIL	OUTLOOK	1
PROGRAMMES	PRG	MICROSOFT	GEN-BUSINESS	PROJECT-MGMT	PROJECT	1
PROGRAMMES	PRG	MICROSOFT	DATA-MGMT	DBMS	ACCESS	1
PROGRAMMES	PRG	MICROSOFT	APPL-DEVELOP	INTG-APP/DEV	VISUALBASIC	1
PROGRAMMES	PRG	MICROSOFT	DATA-MGMT	DBMS	SQL-SERVER	1

APPENDIX TABLE A2: 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 share 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 A3: CONTROLLING FOR FIXED CAPITAL AND SKILLS

Panel A: Technology Adoption Equation

	(1)	(2)	(3)	(4)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.456***	0.456***	0.241***	0.240***
	(0.086)	(0.086)	(0.078)	(0.078)
$\Delta \ln N$			-0.652***	-0.653***
			(0.010)	(0.010)
Δ ln(Wage)		0.039*		-0.018
		(0.024)		(0.020)
Δ ln(Capital/Sales)		-0.004		-0.009
		(0.008)		(0.007)

Panel B: Employment Equation

Dependent variable: $\Delta \ln N$	(1)	(2)	(3)	(4)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	-0.413***	-0.116	-0.404***	-0.260
	(0.120)	(0.263)	(0.137)	(0.338)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$* $(IT/N)_{t-5}$	0.352*	0.391**		
	(0.188)	(0.190)		
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$*$\ln(Wage)_{t-5}$		-0.020		
		(0.033)		
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$*ln(Capital/Sales)		0.081		
		(0.070)		
$\ln(Wage)_{t-5}$		-0.006***		
		(0.002)		
$\ln(Cap/Sales)_{t-5}$		0.005		
		(0.005)		
Highest quintile of $(IT/N)_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.439**	0.490***
			(0.192)	(0.190)
Quintile4* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.260	0.290*
			(0.159)	(0.158)
Quintile3* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.023	0.053
			(0.187)	(0.184)
Quintile2* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.106	0.129
			(0.149)	(0.153)
F-Tests of joint significance				
$(IT/N)_{t-5}$ quintiles - linear terms			105.30***	105.92***
$(IT/N)_{t-5}$ quintiles - interactions			2.01*	2.37**
$\ln(Wage)_{t-5}$ quintiles – linear terms				3.77***
$\ln(Wage)_{t-5}$ quintile interactions				2.64**
$\ln(Cap/Sales)_{t-5}$ quintiles - linear terms				1.29
$\ln(Cap/Sales)_{t-5}$ quintiles - interactions				1.59

Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. 27,354 observations over 20,535 plants. Estimation is by OLS with standard errors clustered by country (k) – four digit industry (j) pair in parentheses. All specifications include Site Type Controls and Country-Year fixed effects. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Δ ln(Wage) is the change in the log of the wage bill divided by the number of employees over the same 5-year period as the dependent variable. Δ ln(Capital/Sales) is the change in the log of tangible fixed assets divided by employment also over the same five-year period as the dependent variable. There are 2,728 distinct country by industry pairs. $\Delta \ln N$ is 5-year change in establishment-level log employment. Site type effects are Divisional HQ, Divisional Branch , Enterprise HQ and Standalone Branch. 20,535 establishments and 27,354 observations.

TABLE A3 Panel C: Survival Equation

	(1) Baseline	(2) Interactions	(3) Linear	(4) Lowest Quintile interactions
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	-0.052	0.116	-0.127***	0.014
	(0.048)	(0.141)	(0.045)	(0.070)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$*Lowest Quintile $(IT/N)_{t-5}$	-0.052	0.152		-0.257***
	(0.048)	(0.112)		(0.100)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$*Lowest Quintile of $\ln(Wage)_{t-5}$		-0.015		0.121
		(0.18)		(0.104)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$*Lowest Quintile of		0.073*		-0.117
$\ln(Capital/Sales)_{t-5}$		(0.043)		(0.124)
$\ln (IT/N)_{t-5}$	-0.025***	-0.001	0.003	
	0.006	(0.006)	(0.006)	
$\ln N_{t-5}$	-0.039***	0.037***	0.038***	
	(0.002)	(0.002)	(0.002)	
$\ln(Wage)_{t-5}$		0.006***	0.005***	
		(0.001)	(0.001)	
$\ln(Cap/Sales)_{t-5}$		-0.002	-0.003	
		(0.002)	(0.002)	
Lowest Quintile of $\ln(Wage)_{t-5}$				-0.018**
				(0.008)
Lowest Quintile of $\ln(Capital/Sales)_{t-5}$				0.001
				(0.008)

Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) – four digit industry (j) pair in parentheses. All specifications include Site Type Controls and Country-Year fixed effects. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. $\ln(Wage)_{t-5}$ is calculated as the log of the wage bill divided by the number of employees at t-5. $\ln(Capital/Sales)_{t-5}$ is calculated as the log of tangible fixed assets divided by sales at t-5. The $\ln(Wage)_{t-5}$ and $\ln(Capital/Sales)_{t-5}$ terms are divided into quintiles and interacted with $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ in columns (6)-(8). There are 3,003 distinct country by industry pairs. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK.. $\Delta \ln N$ is contemporaneous 5-year change in establishment-level log employment as a control. Site type effects are Divisional HQ, Divisional Branch , Enterprise HQ and Standalone Branch.29,007 observations.