Trade induced technical change?

The impact of Chinese imports on technology and employment

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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. However, this consensus mainly uses data before the rise of China in the 1990s. In this paper we examine the impact of the growth of Chinese imports on a panel of over 30,000 establishments in 11 European countries. We find that Chinese import competition is associated with a significant increase in the propensity of establishments to adopt information technology. 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 less IT intensive establishments. Despite these effects on the intensive and extensive margins, we calculate that trade with China still only accounts for a small proportion of the increase in IT intensity (around 6%) so does not overturn the conventional wisdom that trade is less important than technical change. We do find, however, that the job effects of Chinese imports are important, accounting for about a fifth of the fall in employment for the low-tech establishments.

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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, these have rarely been spelled out explicitly.

Heckscher-Ohlin

Perhaps the most simple approach is to consider a Heckscher-Ohlin 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 requiting 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 Chennells and Van Reenen, 2002, for a 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, but consider a model whereby there are different production lines within establishments that produce goods with different levels of sophistication and the more sophisticated products require a greater use of IT than the less sophisticated products. In this set-up, trade with China generates a shift within establishments to the more sophisticated products and closing down product lines with less sophisticated products that are less IT intensive.

Endogenous technological change

Moving beyond Heckscher-Ohlin there are several theories suggesting a direct role for trade in endogenous technological change. 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 (e.g. Acemoglu, 1999 and 2007) are examples – trade generates a larger market 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. This is not surprising: if the effect of importing on productivity works through gaining access to better foreign technologies (e.g. Coe and Helpman, 1995), then this will not be a mechanism that helps Western firms, as China is well behind the technological frontier.

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 (cf. Mellitz, 2003). 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 within establishments is more ambiguous. On the one hand, there may be increased managerial effort to adopt leading edge technologies because of the fear of greater bankruptcy risk, greater sensitivity of relative profits to effort, a stronger "escape competition" effect and (in equilibrium) larger firm size (see Vives, 2003). On the other hand, lower profits will blunt the innovation incentives for Schumpeterian reasons.

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 measure of increases in competition is difficult. We argue that China's 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.

In summary, the existing literature has suggested some mechanisms whereby trade will affect technology adoption, 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 at the macro level (nation or industry) rather than at the micro level (establishment).

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 be 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.[4] Because of this HH runs 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. 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, Spain) they had a response rate of 37.2% in 2004 for firms with 100 or more

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

employees[5]. 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.

IIIB. 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.

[5] 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.

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 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[6]. For example, these industries where China has a high export share contrast with more capital and technologically intensive industries

IIIC. 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.

IIID. 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 establishment with at least five years of data on all the key variables and who are alive in 2000 or 20001. 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 (259). In the baseline (generally 2000, but sometimes 2001) PC intensity was 49% (about one PC per two employees), but this rises rapidly over the next 5 years to around 58% in 2005/ 2006. Employment, by contrast, fell during this

[6] 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).

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.

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

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

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

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:

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

Where Δ denotes the long (five-year) difference operator[7]. 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 analogous employment growth equation:

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

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. α^n <0). We are particularly interested in whether trade has

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

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:

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

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 induce exit. Consequently, we also estimate a third equation:

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

which is defined on a cohort of establishments who were alive in 2000. We follow these establishments over the subsequent five years and define $EXIT_{ijk} = 1$ if the establishment has died by 2005 and zero otherwise. If Chinese imports do induce greater exit we expect $\alpha^x > 0$.

Analogously to the employment equation we also estimate:

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

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

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

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. 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)[8]. Nevertheless, there remains a significant and positive association of IT intensity with Chinese imports suggesting that the Chinese import coefficient

[8] 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.

does not simply reflect employment falls. The final 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.

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 where more likely to grow over the next 5 to 6 years.

In column (5) of Table 3 we interact the lagged IT intensity variable with 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 groups based on their lagged IT intensity and we interact these with the Chinese imports growth variable. A clear pattern emerges whereby the imports effect is much less for the more PC intensive firms. In fact, for establishments in the top quintile there is almost no association of Chinese imports with job growth[9]. By contrast, for those in the bottom quintile group a ten percentage point increase in Chinese imports is predicted to reduce employment by 4%. The final two columns show the results are strong even if we look at 2005 alone.

Tables 2 and 3 conditioned on establishments who survived at least five years. Table 4 examines models of exit where we consider a cohort of firms alive in 2000 and model the subsequent probability that they exited by 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 more likely to exit than those less exposed. A ten percentage point increase in Chinese imports increases the exit probability by 1.2

[9] For this group the effect of Chinese imports is -0.065 (= 0.439 - 0.404). This implies that a ten percentage point increase in Chinese imports are associated with two-thirds of a percentage point fewer jobs.

percentage points. Since the average exit rate in our sample period is 11.4%, this represents about a 10.4% increase in exit rates which is a sizeable effect. Larger and more IT intensive establishments are less likely to exit. 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 is negative (although it is not significant). Column (3) reports the specification where we use the quintiles of the PC intensity instead of the linear PC intensity. This indicates that the least technologically intensive establishments in the bottom quintile (the omitted base) are significantly *more* likely to exit when Chinese imports grow than the other groups, as the coefficients on all other quintiles are negative. We show this most clearly in the final column where we include only the bottom quintile interaction with Chinese imports. Essentially the effect of Chinese imports on establishment exit is confined to these low-tech firms (outside the bottom quintile of the IT intensity distribution the effect on exit is small and insignificant).

Taking Tables 2 through 4 together, we have a clear empirical picture of the role of Chinese imports. Competition with China tends to be associated with increased IT intensity in an industry for 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.

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 (worldwide) 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 5 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[10]). 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 5 presents the 2SLS results for employment growth (note that the first stage is identical to column (1)). 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 5 report the exit 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

[10] 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).

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.

With the exception of the final column, the instrumental variable results in Table 5 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.

VC. Robustness Tests

We report some further robustness tests in Table 6 looking at total imports, exports to China and skills. 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 2003 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, $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$[11]. 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.

The overall 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.

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

[11] 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.

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. This is perhaps unsurprising as most of the theories of export-led productivity growth focus on exporting to *developed* countries rather than emerging economies, like China.

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 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). This enters with a positive sign as expect 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 and lower probabilities of job losses, 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. In future work we will use the match with Amadeus and other datasources that have more disaggregated proxies for skill.

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[12].

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.

[12] 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.

VI. CONCLUSIONS

In this paper we have re-examined the impact of trade on technology, jobs and establishment survival in 11 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 establishment-level panel data on technology combined with detailed industry-level data on trade. Our results suggest that increased import competition with China has been associated with a significant increase in technological upgrading within and between establishments. First, IT intensity has risen in establishments who where more exposed to Chinese imports. Second, Chinese import competition tends to reduce employment in those sectors who were most exposed both through falling 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. Although statistically significant, the magnitude of the effects of Chinese imports is 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. We are currently matching our data to company level accounting information so we can examine the impact of trade and IT on productivity and other forms of capital investment. We are also investigating the effect of trade on innovation (rather than the diffusion of IT as is the focus here) by examining the China effect on cite-weighted patents using matched data from the European and US patent offices.

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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 log(Employment)	-0.062
		(0.408)
$\Delta \ln(IT/N)$	Change in log (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 log (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
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ Chinese Import Share	0.499***	0.497***	0.456***	0.241***	0.211***
	(0.088)	(0.087)	(0.086)	(0.078)	(0.082)
$\Delta\ln N$ Growth of firm employment				-0.652***	-0.641***
				(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 is 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 log (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 EXIT EQUATIONS

Dependent variable: EXIT	Probability of Firm Exit			
	(1) Linear	(2) Interaction	(3) Quintiles of IT intensity	(4) Lowest quintile only
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.119*** (0.046)	0.178** (0.071)	0.290*** (0.094)	0.052 (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) $_{t-5}$ * $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				0.238** (0.097)
$\ln N_{t-5}$	-0.038*** (0.002)	-0.038*** (0.002)	-0.039*** (0.002)	-0.039*** (0.002)
(IT/ N) $_{t-5}$	-0.003 (0.006)	0.001 (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. EXIT refers to whether an establishment that was alive in 2000 exited by 2005. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline 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: INSTRUMENTAL VARIABLE ESTIMATES

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

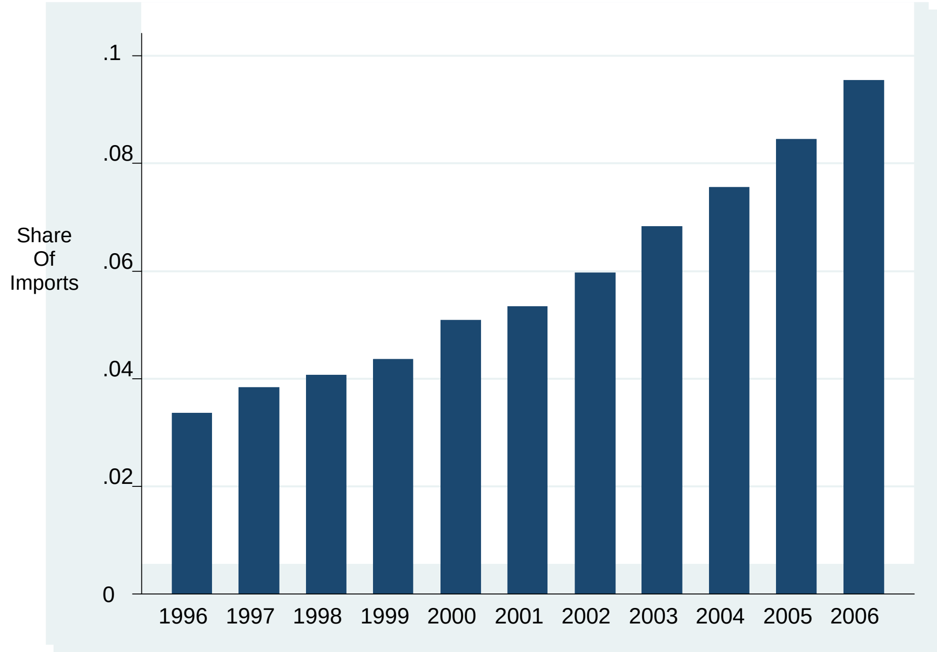
Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. Standard errors are clustered by four digit industry (j) in parentheses. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The instrumental variable $\Delta M^{China} * \left(M_{j}^{China} / M_{j}^{World}\right)_{1999}$ represents the proportion of total Chinese imports in industry *j* as a share of all world imports in industry *j* interacted with the aggregate growth in Chinese imports in the world include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. 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 6: 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 Firm Exit			
	(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

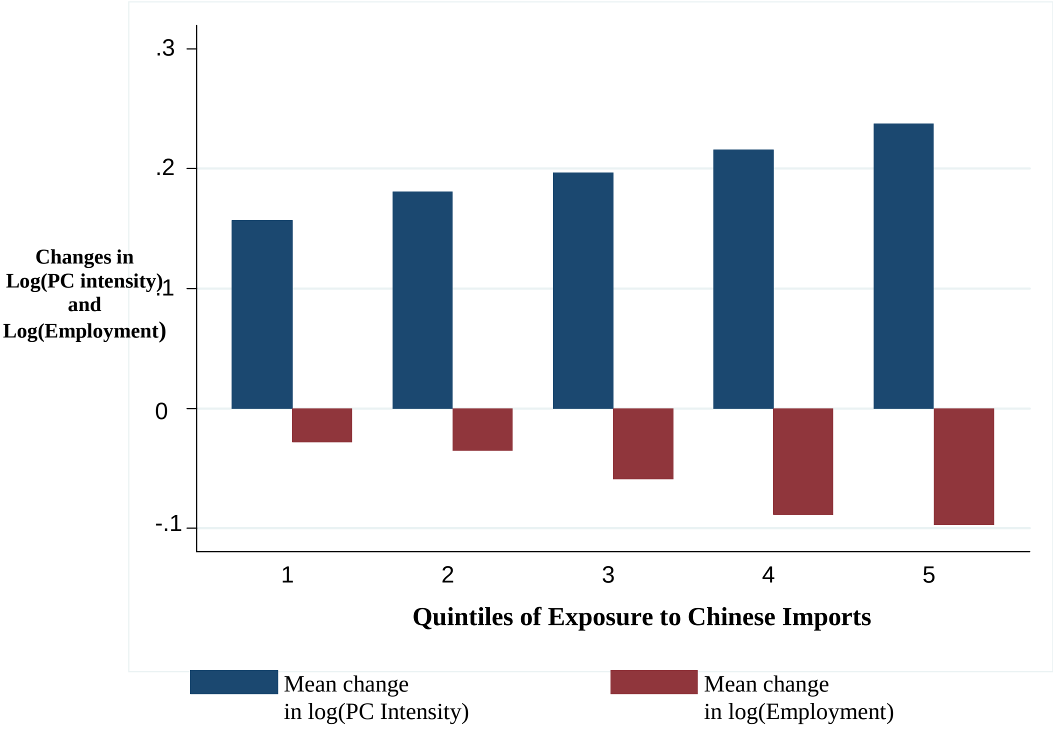
Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. "Sample comparison" is the baseline specification with all controls estimated in the sub-sample 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).

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



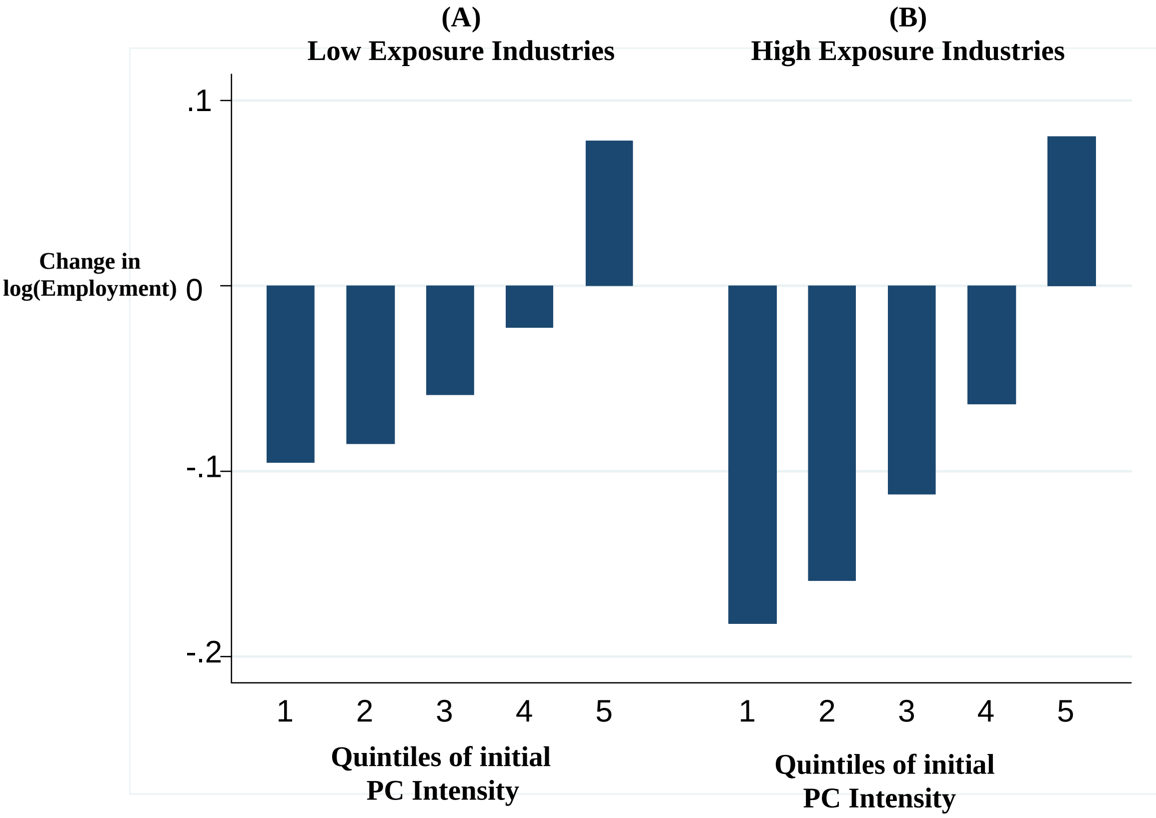
Notes: Calculated using product-level UN Comtrade data aggregated to 4-digit US SIC codes. There are 430 4-digit industries in our dataset. The vertical axis measures $\left(M_j^{China} / M_j^{World}\right)$, the proportion of total imports from China in industry *j* as a share of all world imports in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

APPENDIX TABLE A1

GENERAL COMPANY INFORMATION

Rolls Royce Power Engineering | Employees: 350 | Postcode: L30 4UZ

Survey Date: 24/08/04

Site Type: Enterprise Branch

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 (standard-deviation)	-	0.054 (0.098)	0.108 (0.154)	0.054 (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.