Trade induced technical change? The impact of Chinese imports on innovation and Information Technology

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Abstract

There is a popular belief that Chinese imports have devastated US and European manufacturing and contributed to rising inequality. Somewhat paradoxically, the consensus amongst empirical economists is that trade has *not* been a major cause of rising wage inequality (although this is largely based on datasets predating China's rise). We argue that both views have underestimated the positive impact of Chinese trade on technical change. We examine the impact of the growth of Chinese imports innovation and IT diffusion using a panel of over 23,000 European establishments through 2007. We correct for endogeneity using natural experiments such as China's entry into the World Trade Organization. We find that Chinese import competition led to both within firm technology upgrading, and between firm reallocation of employment towards more technologically intensive plants. These effects are growing over time as Chinese trade volumes rise, accounting for about 25% of technology upgrading in the most recent years. These results suggest that trade with low wage countries appear to have potentially large beneficial impacts on technical change as recent theories suggest.

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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, 2008). The growth of China looms large in these discussions, as the China has experienced tremendous export growth over the last two decades, averaging over 20% per year in real terms[1]. In terms of GDP, China now ranks as the world's fourth largest economy at current exchange rates. 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.

Many politicians in Europe and the US have become increasingly vocal in their opposition to increased trade with China. Increasing restrictions on Chinese imports was a major issue in the 2008 US Presidential race and Democratic Primaries. A major benefit of Chinese trade had been lower prices for consumers in the developed world. We argue in this paper that increased Chinese trade has also helped induce faster technical change from both innovation and the adoption of new technologies. Given the well-documented growth enhancing effects of innovation, this could have a large potential upside for the US and Europe. Several detailed case studies such as Bartel, Ichinowski and Shaw (2007) on American valve-makers or Freeman and Kleiner (2005) on footwear suggest this is an important phenomenon (see the collection of case studies surveyed in Wood, 1994). The contribution of our paper is to confirm the importance of low wage country trade for technical change using many thousands of firms.

The rise of China and other emerging economies such as India, Mexico and Brazil has also coincided with an increase in wage inequality in the United States and other developed, "Northern" nations. Many writers have drawn a link between the two trends, not least because basic trade theory would predict that the integration of an economy abundant in less skilled labor with a developed economy abundant in skilled labor would lead to an increase in the relative price of skill in the developed economy. Although this logic is compelling, the consensus among empirical economists was that that

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

trade was not the main culprit[2]. Most authors do find an important role for skill biased technical change (e.g. Machin and Van Reenen, 1998) and/or institutions such as the minimum wage or labor unions (e.g. DiNardo, Fortrin, and Lemieux, 2001). There are at least two major problems with the consensus. First, most of this work used data up only up to the mid 1990s, which largely predates the rise of China (see Figure 1). In the 1980s China only accounted for about 1% of total imports to the US and EU. By 1991 the figure was still only 2%, but by 2007 China accounted for almost 11% of all imports[3]. Secondly, an emerging line of theory has pointed to mechanisms whereby trade can affect the incentives to adopt and develop new technologies[4]. Thus, the finding that measure of technology such as IT are highly correlated with changing skill shares does not mean trade has no role. What may be happening is that trade is affecting technology and this is an intervening variable in changing the demand for skilled labor.

Our paper partially addresses these two criticisms. We use data from the last decade to examine the role of trade in affecting technical change in developed countries. Using the heterogeneous and rapid growth of Chinese imports across different industries, we examine the impact of trade on innovation and technology adoption in over 23,000 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 competition increases innovation and 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

[2] There are many pieces of evidence (see Acemoglu 2002 for an overview). First, the vast majority of the increase in the aggregate share of skilled workers has occurred within industries rather than between industries (e.g. Berman et al, 1994). Basic Heckscher-Ohlin theory suggests the opposite. Secondly, wage inequality does not seem to have systematically fallen in developing countries would predict (e.g. Berman 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 (e.g. Autor et al, 1998). Fourth, although the relative prices of unskilled goods have fallen as Heckscher-Ohlin would predict, the magnitude of these changes is not large (Krueger, 1997)). Fourthly, calibrated general equilibrium models and factor content approaches find only a quantitatively small role of trade (see Krugman, 1995, for a GE approach, Borjas, Katz and Freeman (1997) for factor content analysis and Freeman (1995) for an overview.). Not all trade economists shared the consensus, however. For example, Feenstra and Hanson (1999) do find some role for offshoring as a mechanism to raise the demand for skilled workers.

[3] Figure 1 may overestimate China's importance as the price of the import does not necessarily reflect the value added by China. For example, although I-Pods are produced in China, the key intellectual property is owned by Apple, an American firm (see Koopman et al, 2008).

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

technology for reasons of selection (the low-tech establishments shrink and die) and for reasons of within-establishment change (the surviving establishments innovate more and invest more in IT).

To tackle the issue of endogeneity of Chinese imports we implement several instrumental variable strategies. First, we use China's entry into the WTO and the subsequent elimination of most quotas in the ensuing years under the Agreement on Clothing and Textiles (formerly MFA)[5]. Second, we borrow from the literature on migration which uses "ethnic enclaves" as an instrument by using the fact that Chinese import growth was faster where Chinese firms had already paid the sunk costs of establishing a bridgehead in Europe by the late 1990s. Both these identification strategies strengthen our main finding that trade stimulates technical change.

We offer some back of the envelope quantification of the magnitude of the Chinese import effects. In the 2000-2003 period China accounts for about 5% (under OLS) and 10% (under IV) of the increase in IT intensity and patenting. However, this rises to 20% (under OLS) and almost 40% (for our IV estimates) for the 2004-2007 period. This suggests that trade with emerging nations such as China is now an important factor for technical change and therefore for growth and inequality.

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

Second, there is the literature on the effects of trade on productivity (e.g. Pavnik, 2002; Goldberg and Pavnik, 2006). Many papers have found that trade liberalization increases aggregate industry productivity, but are often unclear over the mechanism[6]. This evidence tends to be indirect as direct

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

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

measures on technical change are generally unavailable at the micro-level[7]. The literature focuses on the reallocation effects (e.g. Melitz, 2003) even though within plant productivity growth is typically as large as this reallocation effect between plants. Using original data on information technology and patenting, we provide evidence that trade not only drives out the low-tech establishments but also affects the incentives of incumbents to speed up technical change and therefore raise aggregate labor productivity.

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

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

II THEORETICAL CONSIDERATIONS

What mechanisms could link integration with low wage countries on technical change in the North? 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. The first relates essentially to composition – lower trade costs with China cause plants and firms to change their product mix from an existing menu of products. The second relates to innovation: firms actually introduce new products and processes (which could increase the use of more sophisticated inputs such as IT). Empirically, we will find that although there is evidence for both sets of theories and we can rule out the idea that all the change we observe is compositional.

[7] Two recent exceptions are Lelarge and Nefussi (2008) on French data and Bustos (2007) on Argentinean data.
[8] On the theory see inter alia Grossman and Helpman (1992), while on the empirics see for example, Trefler (2004), Bustos (2007) and Dunne et al. 2008.

II.A Technology upgrading through compositional change

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

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

Multi-product firms

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

Offshoring

A fall in trade costs with China will mean that producers of goods that intensively use Chinese intermediate inputs will benefit. For example, some firms may slice up the supply chain for their final products and offshore more of the low-skill intensive component to China (see for example Grossman and Rossi-Hansberg, 2007) [9]. This will have a compositional effect if the remaining activities in the home country are more technologically intensive. In addition, the cheaper intermediate inputs from China may have a beneficial effect on technical change which is distinct from the effects of Chinese import competition in the firms' final goods market. To investigate this mechanism we will look explicitly at Chinese imports into the industry from which a firm purchases its intermediate inputs (using a method similar to Feenstra and Hansen, 1999).

II.B Technological upgrading through innovation

In our data we find that in response to Chinese trade firms increase both their use of IT and their rate of innovation. 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 or outsourcing. Trade is creating incentives to generate new products in this case.

Imitation Threats from the South

Grossman and Helpman (1992:11, 12) describe an endogenous innovation model of trade integration between South and North. Northern firms innovate and Southern firms imitate, but both activities are costly. Integration with the South tends to increase innovation in the North in their model. When the South copies Northern products and competes in world markets there is an adverse effect because the innovating firm only enjoys its monopoly rents for a shorter duration (the standard "Schumpeterian" effect). Imitation, however, tends to thin the ranks of Northern innovators which means that while the firm has a monopoly innovation it earns higher per period profits. In their basic model the second

[9] Interestingly, increased IT sophistication may itself be driving this increase in off-shoring, since coordinating international production will require much more extensive communication.

effect dominates so that Southern integration raises innovation incentives in the North. Extensions to the model to that allow Southern firms to also innovate renders the result ambiguous, since these firms may leapfrog the Northern leader. This extension effectively increased product market competition for the Northern firm, so we turn explicitly to consider competition effects next.

Product market competition

Reductions in trade barriers imply that Chinese producers are much more effective competitors because even if their products are lower quality, their lower production costs place a competitive constraint on incumbent Northern producers. It is very likely that the rise of China constitutes a trade-based competitive shock on domestic Northern producers. It is well known that theoretically the impact of competition on innovation is ambiguous. On the one hand, there may be increased managerial innovative effort because of the fear of greater bankruptcy risk (Schmidt, 1997), greater sensitivity of relative profits to effort (Raith, 2003), a stronger "escape competition" effect (Aghion et al, 2005), lower switchover costs (Holmes et al., 2008) and (in equilibrium) larger firm size (see Vives, 2005). On the other hand, lower profits will blunt 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. Our paper is distinctive in three ways; first, we argue that that China's trade growth constitutes the best recent example of a major quasi-experiment increasing competition. Secondly, previous papers have focused on competition in general rather than trade with developing countries in particular. Thirdly, the papers that have looked at trade liberalizations have tended to look at plant productivity (e.g. de Loecker, 2007b) rather than at technology per se. Finally, these papers have focused on developing countries rather than developed countries. Thus, we believe that focusing on the rise of China is novel and interesting extension of this literature.

Market Size

An important feature distinguishing investments in technology from other inputs is the large fixed and sunk cost component that, if successful, reduces marginal costs across all other inputs. Models of endogenous growth where the incentives to invest in new technologies depend on the size of the market have been long discussed since at least Adam Smith (see also Schmookler, 1966) and have had a recent revival (e.g. Acemoglu, 1999, 2008, and Costantini and Melitz, 2007). The essential idea is that greater trade generates a larger market size to spread over the fixed costs for investing in new technology[10].

Learning through importing and exporting

Another mechanism through which imports can enhance innovation is through enabling domestic firms to gain access to better technology (e.g. Coe and Helpman, 1995). This may occur directly through the import of new varieties of intermediate inputs and through informal channels as the importing firms build up supply networks (Riviera-Batiz and Romer, 1991; Goldberg et al, 2008a,b). A related literature finds evidence that productivity rises when exporting increases (e.g. de Loecker, 2007a, Verhoogen, 2008). These mechanisms[11] 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). We examine explicitly whether exporting to China may have helped spur technical change, but (unlike imports) we do not empirically identify any significant empirical effect of exports to China on technical change.

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 believe the intuition in Grossman and Helpman (1992, 1991) is a strong one generating a positive effect of Southern integration on Northern innovation. This is likely to be stronger than for North-North trade integration. Nevertheless, the theory is ambiguous, so the effects must be examined empirically.

[10] Recent work by Lelieva and Trefler (2008) has shown some important market size effects on Canadian firms of joining NAFTA.

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

III. DATA

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

IIIA Harte-Hanks IT data (HH CiTDB)

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

Harte Hanks surveys establishments on a rolling yearly basis. This means that at any given time, the data provides a "snapshot" of the stock of a firm's IT. The CiTDB contains detailed hardware, equipment and software information including PCs, many types of software, networking resources, databases, etc. We focus on using PC per worker as our key measure of IT intensity because: (i) this is a physical quantity measure which is recorded in a consistent way across sites, time and countries, and (ii) this avoids the use of IT price deflators which are controversial and are not harmonized across countries. 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 intensity (see, for example, Beaudry, Doms and Lewis, 2006, and Bloom, Sadun and Van Reenen, 2007). In robustness tests we compare econometric results using alternative measures of IT such as Enterprise Resource Planning, Groupware, databases, etc.

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

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

Another valuable feature of the CiDB is its consistency of collection across countries. The data for Europe is collected via a central call centre in Dublin and this ensures that all variables are defined on an identical basis across countries. HH samples all firms with over 100 employees in each country. Thus, we do lose smaller firms, but since we focus on manufacturing the majority of employees are in these larger firms[14].

In terms of survey response rates HH report that large European countries (UK, France, Germany, Italy, and Spain) had a response rate of 37.2% in 2004 for firms with 100 or more employees[15]. As mentioned above, the sampling strategy followed by HH allows us to construct a measure of establishment survival. The company's policy is to continue to conduct follow up surveys with all establishments after they have entered the survey. Since the "first contact" or initial survey of an establishment is arguably the most difficult to achieve it makes sense for HH to capitalise on this sunk cost and conduct regular follow-up interviews. Hence, while the company defines no formal measure of establishment survival in their data we able to infer exit by the disappearance of an establishment from a dataset. Practically, we classify any establishment that has not appeared in the survey for 24 months as an exit. We cross checked these assumptions against matched firms from the Amadeus database and found it to be an accurate rule in almost all cases.

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

[14] It is also worth noting this survey frame is based on *firm* employment - rather than *establishment* employment - so the data contains establishments with less than 100 employees in firms with multiple establishments. In our data we find no systematic differences in results between firms with 100 to 250 employees and those about 250 employees, suggesting the selection on firms with over 100 employees is unlikely to cause a major bias. It is also worth nothing that in the countries we study firms with over 100 employees account for over 80% of total employment in manufacturing.

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

IIIB 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 12 European countries and includes both publicly listed and private firms (in the UK, for example, the data is lodged at Companies House and contains over 2 million firms per year). Because all firms have a four digit company code we were then able to match them to trade data at this level.

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

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

IIIC. 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

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

European countries covered in our establishment data. We aggregate from 6-digit product level to 4-digit US SIC industry level using the Feenstra et al (2005) concordance.

We use the value of imports originating from China as a share of total world imports in a country-industry cell as our key measure of exposure to Chinese trade, following the "value share" approach outlined by Bernard and Jensen (2002)[17]. As two alternative measures we also construct Chinese import penetration by normalizing Chinese imports either on domestic production or on apparent consumption (domestic production less exports plus imports). For domestic production we use Eurostat's Prodcom database. Compared to Comtrade, Prodcom has the disadvantage that there is no data prior to 1996, so this restricts the sample period, especially for the patents equation which requires long lags. It also has the problem that some of the underlying six digit product data is missing (for confidentiality reasons) so some missing values had to be imputed. Although we obtain similar results with all measures we prefer the normalization on world imports which does not have these data restrictions.

In terms of overall trends in China's trade Figure 1 shows the remarkable rise of China's share of all imports to the US and the 12 European countries in our sample. In 2000 only 5.8% of imports originated in China. By 2007 this had doubled to approximately 10.7%. Furthermore, this growth in Chinese imports also appears to be accelerating, rising from an increase of about 0.5 percentage points per annum of imports a year in the 1990s one percentage point a year in the 2000s. Of course, this aggregate disguises considerable heterogeneity by industry. Appendix Table A7 lists the top ten four digit industries in terms of imports from China in 1999, along with the level in 2006. The two things of note here are firstly the heterogeneity in shares that this list reveals – while the aggregate share of 10% could be considered low there are a number of industries where China has a very high share even in 1999. Secondly, these high shares are still associated with high subsequent rates of growth up to 2006. For example, China's share of SIC 3944 (games and toys) was 40% in 1999 and rose to 71% by 2006. It is this feature of high initial presence in particular industries and strong subsequent growth that we exploit for our later instrumental variable strategy. For example, these industries where China has a

[17] See also Bernard et al (2004, 2006).

high export share contrast with more capital and technologically intensive industries where its export share is typically low in both 1999 and 2006.

IIID. Descriptive Statistics

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

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

Figure 3 probes the employment effects more deeply and shows the contrast between establishments who are in the bottom quintile of the increase in Chinese imports ("low exposure industries" in Panel

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

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

IV. EMPIRICAL MODELLING STRATEGY

IVA. Technical progress within establishment and firms

We consider two basic equations to empirically examine the role of Chinese import competition on causing technical progress within incumbents. Consider the basic technology intensity equation:

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

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, but experiment with many other measures of ICT such as ERP, Databases and Groupware. IMP_{jkt}^{CH} 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 IMP_{jkt}^{CH} mainly as the proportion of imports (M) in industry j and country k that originate from China $(M_{jk}^{China} / M_{jk}^{World})$, where we normalize Chinese imports (M^{China}) by total imports from anywhere in the world (M^{World}). Rapid growth in the Chinese import share is therefore used as a proxy for a rapid increase in trade competition from low wage countries in the industry. 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:

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

Where Δ denotes the long (five-year) difference operator[18]. Our interpretation of the trade-induced technical change hypothesis is essentially that $\alpha > 0$.

Consider the analogous equation to (1) for innovation (P) rather than diffusion (as measured by patent counts or cite-weighted patent counts). The first moment of this estimator is:

$$E(P_{ijkt} \mid X_{ijkt}) = \exp(\alpha^{p} IMP_{jkt-m}^{CH} + \beta^{p} x_{ijkt} + \eta_i) \qquad (3)$$

Note that we have lagged the Chinese import measure by m periods to reflect the fact that it will take some time before a firm alters its research behavior in response to trade and again, there will be a lag 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 a five year lag to be consistent with the five year long-differences). Because we have a much longer time series of patents (back to 1978 in principle) 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. We do this, but including the fixed effects in a count data model is much more complicated than a linear model (e.g. Blundell, Griffith and Van Reenen, 1999, for an

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

application to count data models with fixed effects and dynamics). Consequently, our baseline approach is simpler models of the innovation equation specified by including a full set of industry dummies or using long five-year differences[19].

IVB. Endogeneity

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

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

One identification strategy is to use the accession of China to the WTO that generated a fall in trade barriers against China for most OECD economies. We exploit the fact that quotas for textiles and clothing against China were raised very substantially (and abolished in many cases). This is because the Agreement on Textiles and Clothing (the successor to the Multi-Fiber Agreement, the MFA) had very high quotas to begin with. When China joined the WTO in December 2001, it immediately gained access to the first two waves of quota reductions from the MFA and benefited from the planned 2002 liberalization. The next liberalization in 2005 then abolished most of the remaining quotas (see Brambilla, Khandewal and Schott, 2008, for a more detailed description). Thus over the post 2000 period there was a significant relaxation of barriers to Chinese imports into Europe and (as we show) a large increase in Chinese imports in those industries most affected. Since these quotas were largely set in the 1970s under the Uruguay Round, and their phased abolition agreed in 1994, it seems fair to take

[19] In these specifications we use the transformation PATENTS = ln(1 + P) where P is the empirical count of patents. The addition of unity is arbitrary, but close to the sample mean of patents. We compare the results with more complex fixed effect count data models (e.g. Blundell, Griffith and Van Reenen, 1999) which generated qualitatively similar results.

these as exogenous. Note that we use the level of quotas against China in 2000 (prior to WTO accession) as the instrument. We could use the five-year change of these quotas, but some of the quotas remained and were re-introduced in 2006 due to domestic lobbying. Thus, the level of quotas in 2006 and onwards may be endogenous to the increase in Chinese imports (the most effected industries lobbied the most). The initial level of quotas should be robust to this problem.

A disadvantage of the quota-based instrument is that we can only construct the instrument for the affected industries (textiles, clothing, footwear and tableware), so we consider a second identification strategy. The overall increase in Chinese imports is driven fundamentally by the opening up to the global economy because of ongoing liberalization by Chinese policy makers, so is clearly exogenous. The industries where China exported more depended on whether the industry is one in which China has a comparative advantage. For example, if we consider the growth of Chinese imports in Europe between 2005 and 2000, sectors in which China was already exporting strongly in 1999 are likely to be those that China has a comparative advantage in – such as textiles, furniture and toys (see Appendix Table A7) – and so would experience much more rapid increase in import penetration in the subsequent years. Consequently, high exposure to Chinese imports in 1999 can be used (interacted with the overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth. In other words we use ($IMPS_{j99}^{CH} * \Delta M^{China}$) as an instrument for $\Delta IMPS_{jkt}^{CH}$ where $IMPS_{j99}^{CH}$ is the Chinese import share in industry *j* in the world. Note that we do not make $IMPS_{j99}^{CH}$ specific to country *k* to mitigate some of the endogeneity problems with using an initial condition[20].
A priori the instrument has some credibility as Brambilla, Khandewal and Schott (2008) document evidence that Chinese imports grew faster from expansion of existing products (the "intensive margin") rather than the existence from adding new products ("the extensive margin") after 2001. A similar finding also emerged from looking over the period since 1992 in Amiti and Freund (2007). Of course this is not always the case (e.g. after NAFTA Mexico started exporting new goods to the US), which is why the first stage must be carefully examined.

[20] 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 criticism of our use of the quantity flow as 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.

IVC. Increasing technological intensity through reallocation

Equation (2) examines whether Chinese import competition is associated with technological upgrading on the intensive margin – i.e. within surviving plants. We also examine whether trade affects the *extensive* margin by examining employment equations and survival equations. As discussed in the previous section, conventional models would predict that China would cause low-tech plants to shrink and die, as these are the firms competing most closely with Chinese imports.

We estimate employment growth equations of the form:

$$\Delta \ln(N)_{ijkt} = \alpha^n \Delta IMP_{jkt}^{CH} + \beta^n \Delta x_{ijkt}^n + v_{ijkt}^n \tag{4}$$

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 a larger effect on lower tech firms, so to capture this we include the interaction of ΔIMP_{jkt}^{CH} with the (lagged) technology variables (IT or patenting) and estimate specifications of the form:

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

Where *TECH* is the relevant technology variable (IT or patenting). If Chinese trade has a disproportionately negative effect on low-tech firms we would expect $\gamma^n > 0$.

Equations (2), (3) and (5) are estimated on surviving firms. However, one of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate a fourth equation:

$$SURVIVAL_{ijk} = \alpha^s \Delta IMP_{jkt}^{CH} + \beta^s \Delta x_{ijkt}^s + \gamma^s [TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}] + \delta^s TECH_{ijkt-5} + v_{ijkt}^s \qquad (6)$$

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

V. MAIN RESULTS

VA. Technical change within plants and firms

IT Intensity Equations

Table 2 presents the results for the information technology equations. Column (1) has no controls and simply shows that there is a strong and positive association in the data. This confirms the significance of the relationship illustrated in Figure 2: 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 4% increase in IT 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, rather than by increasing IT spending. Consequently, column (4) simply includes the growth of employment as an additional control. This enters with a negative coefficient suggesting that the elasticity of PCs with respect to employment is less than unity. 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.

Innovation Equations

We now turn to the innovation equations (as measured by patent counts) using the European Patent Office data matched with firm accounts. Column (1) of Table 3 presents the results of estimating equation (3) where we regress the number of patents against the level of Chinese imports (lagged five years) and a full set of industry by country pair dummies (as well as the country by year effects). There is a positive and significant relationship between patenting and Chinese imports: 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 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 (0.366) and still significant. In column (4) we include capital intensity and employment in the regression, but this barely shifts the results. The correlation with Chinese trade is not simply an increase in all types of capital, but seems related specifically to technical change. Column (5) includes only lagged sales instead which results in a coefficient of 0.294 on Chinese imports, similar to column (1). Column (6) presents results of a Negative Binomial model where the fixed effects are controlled for using the Blundell, Griffith and Van Reenen (1999) method of conditioning on the long pre-sample history of patenting. The coefficient on Chinese trade is actually higher (0.484), although the standard error is also larger (0.221). In column (6) we estimate in long (five yearly) differences. Although the sample is reduced (to 30,608 observations) the coefficient on Chinese imports remains positive and highly significant and is close to that in column (3). Since this long differenced specification is most comparable to the IT equations (and produces similar marginal effects to other estimation techniques) we use this as our preferred specification. The final column normalizes patents on employment analogously to the IT equation and also reports a positive and significant coefficient on Chinese imports.

VB. Instrumental Variable Results

An obvious concern with the OLS regressions is that Chinese imports are endogenous. *A priori,* the bias is likely to be negative as a positive shock to investment in IT or innovation is likely to reduce Chinese imports.

Table 4 uses identification strategy of China's accession to the WTO that led to a huge fall in quotas against Chinese goods (see Appendix A)[21]. Since this is only relevant for textiles, clothing and tableware we first present the OLS results for the IT equation for these industries in column (1). There is a large positive and significant coefficient on the Chinese trade variable, reflecting the greater importance of low wage country trade in this sector. Column (2) presents the first stage using the height of quotas in the years before China joined the WTO (1999) as the external instrument. Quota reduction appears to be positive and highly significant in predicting future growth of Chinese imports. Column (3) presents the IV results that show a positive and significant effect of Chinese imports with a higher coefficient than under OLS (1.9 compared to 1.3)[22]. A concern is that the height of the quota in 2000 is proxying some other trend correlated with Chinese import growth. To test for this we included Chinese import growth 2000-1995 as an additional control. The coefficient on this control is positive (0.168) but insignificant and the coefficient on Chinese import growth remains positive and significant (1.792 with a standard error of 0.421).

The final three columns implement the same identification strategy but use patents instead of IT. We use Chinese imports growth lagged t-3 (instead of t-5 as in Table 3) because this is the earliest date where the instrument could work. Since the last usable year in the patents data is 2005, a five year lag of Chinese imports for Chinese imports would use the 2000-1995 import growth which is prior to WTO accession, so the instrument would have no power (in the absence of anticipation effects). We discuss the dynamic responses in more detail below and the timing of the trade policy change in Appendix A. Column (4) shows that the OLS results for patents are also strong in this sector and column (5) reports that the instrument has power in the first stage. The IV results in the final column show that the OLS coefficient appeared downward biased, although the standard error is large.

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[21] Note that throughout the IV tables (4 and 5) we cluster by four-digit industry only, instead of four digit by country dummies as in the previous tables. We do this in order to be conservative as the instruments have no country-specific variation.

[22] If we repeat the IV specification of column (3) but also condition on employment growth the coefficient on Chinese imports is 0.687 with a standard error of 0.373. Dropping all the four digit sectors which had a zero quota in 2000 uses only the continuous variation in quotas among the affected industries to identify the Chinese import effect. Although this regression sample has only 766 observations, this produces a coefficient (standard error) under the IV specification of 2.688(1.400) compared to an OLS estimate of 1.238(0.245).

We next consider as an "initial conditions" instrument the growth of total Chinese imports into Europe interacted by the China's lagged share of imports in the (European wide) four-digit industry. Column (1) of Table 5 re-presents the basic OLS results. Column (2) presents the first stage for the instrumental variable regressions. The instrument is strongly correlated with the endogenous variable, the growth of Chinese import intensity. Column (3) then presents the second stage: the coefficient on Chinese imports is 0.727 (and significant at the 5% level). Columns (4) through (6) repeat the experiment for patenting (using the same specification as Table 4). The final column shows the IV results for patenting. The coefficient on Chinese imports is positive and significant at the 10% level and above the OLS estimate[23].

This bias is consistent with our priors as we might expect a technology shock to give some "protection" to an establishment from Chinese imports. Taking the IV tables as a whole, there does not appear to be evidence that we are over-estimating the effects of China on IT diffusion and innovation by treating the growth of Chinese imports as exogenous.

VC. Reallocation effects: jobs and survival

Table 6 examines reallocation effects by analyzing employment growth regressions (still of survivors). First we examine the raw correlations in column (1) suggesting a strong negative association between job growth and exposure to Chinese imports. This suggests a ten-percentage point increase in Chinese imports is associated with a 2.8% fall in employment. Lagged IT intensity enters with a positive and significant coefficient in column (2) suggesting that the more technologically advanced firms in were more likely to grow over the next five years. This reduces the magnitude of the coefficient on trade to 0.203. The interaction of Chinese trade and lagged IT intensity that enters with a positive and significant coefficient in column (3). This suggests that firms that are IT intensive are somewhat "shielded" from the effects of Chinese imports.

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

We divide our firms into five quintiles based on their lagged IT intensity and we interact these with Chinese import growth. A clear pattern emerges whereby the imports effect is much weaker for the more IT intensive firms. In fact, for establishments in the top quintile of the IT intensity distribution there is no association of Chinese imports with job losses. By contrast, for those who were in the bottom quintile of the IT distribution a ten percentage point increase in Chinese imports is predicted to reduce employment by 4%. The final two columns shows similar results using patents[24]. Column (5) continues to condition the sample on firms who took out at least patent since 1978, whereas column (6) uses all firms, even those who never patent.

Table 7 examines models of survival where we consider a cohort of firms alive in 2000 and model the subsequent probability that they survived until 2005 as a function of the growth of industry-wide Chinese imports and their initial characteristics. Column (1) shows that even after conditioning on (lagged) establishment size and 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%, this represents about a 1.4% decrease in survival rates (equivalent to an 11.4% increase in exit rates), which is a non-trivial effect. Larger establishments are more likely to survive as we would expect. Column (2) includes an interaction of lagged IT intensity with Chinese imports. As with the employment equations, the low-tech firms appear most "at risk" from Chinese import competition, as the coefficient on the interaction between Chinese imports and IT intensity is positive (although it is not significant). Column (3) reports the specification where we use the quintiles of the IT intensity. This indicates that the least technologically intensive establishments in the bottom quintile (the omitted base) are significantly *less* likely to survive when Chinese imports grow than the other groups, as the coefficients on all other interactions with the higher quintiles are PC intensity are positive. We show this most clearly in column (4) where we include only the bottom quintile interaction with Chinese imports. This takes a negative and significant coefficient indicating that the effect of Chinese imports on establishment survival is confined to these low-tech

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

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). The final column shows a similar result for patents – firms with a higher patent stock are significantly more likely to survive when faced by a Chinese import shock.

VD. Magnitudes

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

We use the magnitude of our coefficients to perform some "back of the envelope" calculations for how much of the empirical change in technology China could account for. This is explained in detail in Appendix B but summarized here. For IT we estimate this in two steps: first we calculate the growth in aggregate IT intensity in our sample[25], and second we apply the coefficients from our regression results to get a predicted increase in aggregate IT intensity. By comparing the aggregate increase in IT intensity and the "Chinese induced" increase in IT intensity we can crudely attribute a proportion to the impact of Chinese imports. For patents we follow a similar exercise, again calculating overall patents (in this case an estimate from official aggregate data rather than our sample data) and apply our regression coefficients to see what fraction of aggregate patent growth Chinese imports can potentially explain.

In Table 8 we see that over our entire period Chinese imports appear to have accounted for about 15% of the increase in IT intensity and 23% of the increase in patents. For TFP (which we will discuss later), China appears to account for 18% of the aggregate growth. Beyond the aggregate numbers two other results stand out. First, the impact of Chinese imports appears to be rapidly increasing over this

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

period. For example, we estimate that Chinese imports accounted for 18% (12%) of the increase in patents (IT) over the 2000-04 period but 28% (19%) over the 2004-2007 period. One reason for this acceleration is clear in Figure 1, where we see that Chinese import growth has rapidly increased over this period, with the annualized percentage point increase in China's share growth rate increasing from 1.35 between 1997-2000 to 2.51 between 2004-2007. A similar pattern is evident for TFP. Second, for patents and TFP the contributions of the within and between components are roughly equal which is consistent with the literature on trade liberalization (e.g. Pavcnik, 2002). For IT, the within component is much larger. This may be because the adjustment costs of adopting IT are less than those for increasing innovative activity or TFP more broadly (e.g. if this requires extensive re-organization of managerial practices).

VI EXTENSIONS

VIA Alternative Normalizations of Chinese imports

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

VIB. Imports from low wage countries vs. imports from high wage countries

We focus on China as a canonical example of import competition from low wage countries. Over the last decade the increase in low wage imports is overwhelmingly dominated by China. We use the definition of a low wage country from Bernard et al (2006) as those countries with GDP per capita less than 5% of that in the US between 1972 and 2001. On this definition, the increase in non-Chinese low wage imports (as a proportion of all imports) between 1996 and 2007 was close to zero (0.005) whereas China's growth was substantial (See Figure 1). Furthermore, analysis of the imports shares reveals that 91% of the variance of industry by country growth of low wage imports is accounted for by China.

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

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

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

VIC Offshoring and outsourcing

We have focused on China's effect through competition in the final goods market. However, an alternative way in which China could affect technical progress is through allowing Western firms to buy cheaper intermediate inputs from China and allow the offshoring of low value added parts of the production chain[26]. We investigate this by building an adapting the offshoring measure of Feenstra and Hansen (1999) for China, so we have a measure of the proportion of intermediate inputs that are offshored to China.

Column (1) of Table 11 includes this offshoring measure in the IT equation. It enters with a positive coefficient indicating that there may be some effect here (since the mean of the offshoring variable is smaller than that of Chinese imports, the implied effect is of a similar order of magnitude). However, when we control for employment in column (2) the coefficient on offshoring becomes zero. One interpretation of this is that offshoring is associated with reductions in employment in low-tech tasks and this can raise IT intensity through a compositional change. Despite all this, the Chinese import variable remains positive and highly significant in all specifications, suggesting the effects we identify are not purely from offshoring of inputs.

VID Do Chinese imports induce greater protection of Intellectual Property?

An alternative interpretation of the patents equation could be that the increased threat of China causes firms to take out more patent protection. Rather than increasing innovation, firms could simply be employing more patent lawyers more to keep out Chinese imports. Although an interesting phenomenon, this would clearly be different from an increase in innovation. To test for the "lawyer" effect we used information on patent citations.

We constructed a measure of future citations per patent and regressed this on Chinese imports in Table A1. We would expect to see the number of cites per patent falling if China was inducing firms to take out more patents to protect marginal innovations. Inspection of Table A1, however, shows that the coefficient on China is actually positive rather than negative (although insignificant) in all columns.

Another piece of evidence against the legal story is an examination of the dynamic effects of Chinese imports. Table A2 explores alternative timing assumptions of the way imports affect technical change.

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

Because we only have IT data post 1999 in Harte Hanks, we are rather limited in our ability to investigate this. For patents, by contrast, we have a much longer time series so we can estimate the long-differenced equation allowing Chinese imports to affect patents at different lag lengths. 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 of Chinese imports, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-4}$ and column (6) the contemporaneous value, $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t}$. If our results spuriously reflected legal inducement or more generally some unobservable shock simultaneously increasing patenting and imports we would expect the contemporaneous effect to be stronger. In fact, the opposite is the case: the coefficient on imports systematically falls as we approach the current year. This is consistent with the view that firms take time to adjust their innovation activities in response to a shock.

Panel B of Table A2 shows the same results for employment. To keep the sample similar to Panel A we use the Amadeus firm-level employment numbers rather than the plant-level employment numbers presented already in Table 6. We see a quite different pattern to patents. Growth of imports five or four years earlier are not significantly related to job losses whereas there is a significant relationship in years that are more recent. This is exactly what we would expect as adjustment costs for labor are much lower than they are for innovation. Overall, the dynamic patterns look economically sensible.

VIE Product and Industry Switching

The leading "compositional" theory we discussed in the theory section was the hypothesis that in the face of Chinese import competition, European firms change their product mix. To investigate this idea we can examine whether a plant changes its primary four digit industrial sector in the CiTDB data. On average 11% of plants switch industries over a five year period, a substantial number that is consistent with some evidence from recent papers[27]. We examine first whether trade with low wage countries like

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

China is associated with switching and second, whether this switching can account for much of the faster technical change induced by trade.

Table 12 begins by regressing a dummy for switching on Chinese imports and the usual controls. Industries more exposed to China where significantly more likely to switch industries. This is consistent with the evidence from US plants in Bernard et al (2006). In column (2) we include a control for lagged IT intensity which reduces the probability of switching, but only slightly reduces the coefficient on Chinese imports. Column (3) includes employment growth that has little impact. The second half of the Table uses IT intensity growth as the dependent variable. Column (4) shows that switching is indeed associated with greater use of IT, but the magnitude of the effect is small: plants who switched industries had a 2.5% faster growth in IT intensity than those who did not. Column (5) displays the standard regression for this sample showing the positive relationship between IT intensity and Chinese imports for the sub-sample where we have switching data. Column (6) includes the switching dummy. This reduces the coefficient on imports by only a small amount. A similar story is evident when we include employment growth in the final two columns.

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

VIF Total Factor Productivity (TFP)

The literature has tended to focus on TFP as direct measures of technology are rarely available. It is possible to construct reliable TFP measures in four of the countries in BVD where reporting of materials (as well as employment, capital and sales) is available – France, Italy, Spain and Sweden. To do this we implement a version of the Olley Pakes (1996) estimator suggested by de Loecker (2007) which allows for imperfect competition and multi-product firms. We estimate production functions across 1.4 million firm-year observations to estimate the technology coefficients in each two-digit industry and then use these to construct firm-year specific TFP. This is an index relative to a base year-country-industry. We then estimate our three main equations: the growth of TFP (as a new measure of technical change), the growth of employment and firm survival. The results are contained in Table 13.

Column (1) has the TFP growth equation. Consistently with the direct measures of IT we find that a 10 percentage point increase in Chinese imports is associated with a 2.8% increase in TFP. Column (2) presents the employment growth regressions. As before, Chinese import competition reduces employment in firms at the mean level of productivity, but the more productive firms are significantly less likely to suffer employment losses than the less productive firms (as indicated by the positive interaction between lagged productivity and trade growth). The final column shows a similar result for survival rates – high TFP gives firms some protection against exit from the effect of China[28].

VIG Alternative measures of IT diffusion

We use PCs per employees as our main measure of IT diffusion as this is a good indicator of a general-purpose technology used widely across industries. We also investigated the introduction of three other types of IT software available in CiTDB in Table A3. Although, none of these has the same continuous metric as PCs they are important parts of corporate computing. Enterprise Resource Planning (ERP) provided by companies such as SAP is a major way in which firms use software to systematize their data. Chinese imports are positively associated with the introduction of ERP in column (1) and the difference is particularly marked between the lowest decile of Chinese important growth and the higher deciles (see columns (2) and (3)). A similar finding emerges in the next three columns when we examine the introduction of major database software. Finally, the last three columns look at groupware tools (which enable workers to use networking to organize meetings and projects). Here the main difference is between the top quintile of import growth and the others.

VIH Human capital and fixed capital

[28] There is a small but negative linear coefficient on lagged TFP. TFP has a positive effect at the mean and further investigation shows that all the action of low TFP is in the bottom quintile: moving through higher quintiles of the productivity distribution has no effect on exit. This is exactly the same picture as we saw for exit rates in the IT sample.

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

In Table A4 we include the growth of industry wages as a proxy for skills changes in column (2). The variable enters with a positive and significant coefficient, but it does not change the coefficient on Chinese imports very much (see column (1)). When we control for employment the coefficient on the skills proxy is insignificant. We also obtained a direct measure of skills – the proportion of college educated workers in the three-digit industry from EU KLEMS. The coefficient was also positive, but had little effect on the Chinese imports term. A second issue is whether technical change simply reflects a more general upgrading of the capital stock. To check on this we included the growth of the industry level capital-worker ratio in columns (3) and (4). As with human capital, the variable does enter positively but is insignificant and barely affects the Chinese trade coefficient.

VII Exports to China

We have focused on imports from China as driving changes in technology, but as discussed earlier exports may also have an effect. COMTRADE allows us to construct variable reflecting exports to China (as a proportion of total exports in the industry-country pair) in an analogous way to imports. Table 5 presents the results. In the IT equation the exports variable has a positive coefficient as we might expect, but it is insignificant. The coefficient is also negative and insignificant in the other three equations. This is unsurprising as most of the theories of export-led productivity growth focus on exporting to *developed* countries rather than emerging economies, like China. It is unclear what benefit there is to learning, for example, from China that is behind the European technology frontier.

VII. CONCLUSIONS

In this paper we have re-examined the impact of trade on technical change in 12 European countries. Our motivation for this is that the rise of China constitutes perhaps the most important exogenous trade shock from low wage countries to hit the "Northern" economies. This helps identify the trade-induced technical change hypothesis. We use novel firm and plant-level panel data on 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 and firms. 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 jobs in surviving establishments, but also through a decreased probability of survival. 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 survival are much stronger for establishments that are "low-tech" (i.e. less IT and patent 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 China's accession to the WTO in 2001. In terms of magnitudes, China could account for as much as two fifths of the overall rise in technical change (IT or innovation) in Europe after 2004. Its affect appears to be increasing over time.

There are several directions we are taking this work. First, we want to complement our European analysis with a similar exercise in the US where we have also recently accessed the Harte Hanks IT data. We have a longer time span for the US, so we can do more analysis of pre-sample trends. Second, we find a larger role for within plant changes in than between plant changes. This is somewhat at odds with the recent literature on productivity decompositions which finds a larger role for reallocation effects following liberalizations. One way to reconcile these results is to recognise that we focus on technology which is only one part of TFP differences. If TFP differences are largely driven by managerial practices that are much harder to change than say introducing IT, a trade shock will have a large effect on allocating employment away from badly managed plants. We plan to investigate this in future working using our data matched with firm-level productivity measures.

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APPENDIX A: THE TEXTILE AND CLOTHING QUOTA RELAXATION

In 2005 restrictions on the fourth (and final) set of products regulated by the Agreement on Tariffs and Clothing (ATC) were removed. The ATC was the successor to the Multi-Fiber Agreement (MFA). The removal of quotas under the ATC came in four stages (1995, 1998, 2002 and 2005) but because China only joined the WTO in December 2001, it did not benefit initially from the first two stages. China enjoyed a substantial fall in these quotas between the end of 2001 (when it joined the WTO) and 2005 (when the ATC quotas were essentially all removed). Brambilla et al (2007) describe how there was a huge jump in Chinese exports into textiles and clothing to the US during this period (e.g. 7 percentage points increase in China's share of all US imports in 2005-2006 alone). China's increase was substantially larger than other countries not just because it joined the WTO but also because the existing quotas seemed to bite more heavily on China as indicated by the higher "fill rates" of Chinese quotas. This seemed to be because under the ATC/MFA Chinese quotas were increased more slowly over time than those in other countries.

Although formally quotas fell to zero in 2005, for 22 product groups domestic industries successfully lobbied for some "safeguards". Nevertheless, these were much lower than the pre-existing quotas. The quota policy is EU wide. It is reported in the form of the SIGL (System for the Management of Licenses for Textile Imports) database that is available online at http://trade.ec.europa.eu/sigl/choice.html. This database is classified according to 172 grouped quota categories defined by the EU. However, these categories are closely based on HS6 products so we are able to map them into the US four digit industry classification. In addition, we added in quotas on footwear and tableware products as described in the WTO's articles of accession

For each four-digit industry we calculated the proportion of product categories that were covered by a quota in each year (data on the amount produced in each industry is not available so we use a simple mean proportion of products). For the five-year change in imports 2005 to 2000 in the IT equation we use the quota variable in 2000 immediately prior to China's WTO entry. Specifically, this proportion represents the share of all quota-affected HS6 products in all world imports per SIC4 industry. The idea is that the market expected at this point all the quotas to be lifted. Using the actual change renders similar results, but there is a concern that the quotas still remaining in 2006 are endogenous as they were the result of lobbying by the effected sectors. The fill rates for most quotas were high for China implying that these constraints were binding. This also limits anticipation effects, although to the extent that they exist this will make it harder for us to identify a first stage. The products upon which the quotas were set were determined in the 1970s under the Uruguay Round which makes them likely to be exogenous to any post 2000 actual (or anticipated) shocks. To be specific, in the regression sample of Table 4 we use US SIC4 two digit industries 22, 23, 28, 30 and three digit industries 314 and 326. We show that the results are robust to dropping all four digit industries within this group with zero quotas against China in 2000 and dropping the tableware and footwear quotas.

APPENDIX B: CALCULATING MAGNITUDES

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

To undertake this quantification for IT requires 2 steps:

1) Calculating the employment weighted growth in IT intensity in our sample. This was done by comparing the employment weighted IT intensity at the end period with the beginning period. The employment weighted IT intensity is calculated as the sum of all PCs dived by the sum of all employees in our regression sample at each point of time.
2) Calculating the Chinese import "contribution" to this increase in IT intensity. This is calculated using the coefficients from Tables 2, 6 and 7 (for IV) and Table A6 for IV multiplied by the actual Chinese import growth rates and IT intensity rates (for interactions) to generate a predicted change in IT intensity arising from changing Chinese imports.

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

To undertake this quantification for patents also requires 2 steps:

1) Calculating the total increase in patenting over our sample period. The natural analogue to IT would be to look at the increase in patents in our dataset over this period. However, our firms in total do not have a rising number of patents because of: (i) delays in the provision of firms accounts (we match to firm accounts and some of these are not available yet for 2005/06 due to reporting delays) and (ii) processing delays at the European Patent Office since we only use granted patents (dated by their year of application). As a result instead we use the aggregate growth rate of the US Patent Office (which provides long-run total patent numbers) over the proceeding 10 years (1996-2005), which is 2.2%. This growth rates of total patents is stable over long-run periods, for example being 2.4% over the proceeding 20 years period of 1986 to 2005.[29]
2) Calculating the Chinese contribution to this increase in Patenting. Again, this is calculated using the coefficients from Tables 3, 6 and 7 (for IV) and Table 5 for IV multiplied by the actual Chinese import growth rates to generate a predicted change in Patenting intensity arising from changing Chinese imports.

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

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

TABLE 1: DESCRIPTIVE STATISTICS

Variable	Mean (standard deviation)
Number of Employees	248.3
	(566.1)
Number of Employees at Median	140.0
	-
5-year Change in log Employment	-0.058
	(0.409)
PCs Per Employee at (t-5)	0.494
	(0.355)
PCs Per Employee	0.580
	(0.385)
5-year Change in log(PCs/Employment)	0.183
	(0.544)
Number of Patents (per firm-year)	0.698
	(5.07)
Level of Chinese Import Share at *t*	0.066
	(0.102)
Plant Survival (% firms surviving from 2000-2005)	0.879
	(0.326)
Industry switchers (% plants switching four digit sector in five year period)	0.112
	(0.316)
Number of establishments	22,957
Number of observations	37,500

Notes: Standard deviations in parentheses. Data is from HH/CiTDB except patents that are from Amapat (European Patent Office data matched to BVD company accounts data).

TABLE 2: INFORMATION TECHNOLOGY EQUATIONS, 5 YEAR DIFFERENCES

Dependent Variable:	$\Delta \ln(IT / N)$			
	(1)	**(2)**	**(3)**	**(4)**
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Change in Chinese Imports	0.429*** (0.080)	0.396*** (0.077)	0.361*** (0.076)	0.195*** (0.068)
$\Delta \ln N$ Change in employment				-0.617*** (0.010)
Country Year Effects	No	Yes	Yes	Yes
Site-Type Controls	No	No	Yes	Yes
Number of Establishments	22,957	22,957	22,957	22,957
Observations	37,500	37,500	37,500	37,500

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2007-2000 (so first 5-year difference is 2005-2000). Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. There are 2,816 distinct country by industry pairs. All changes are in five-year differences, e.g. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls are dummies for establishment type; these are Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch.

TABLE 3: INNOVATION EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Approach	**OLS levels with industry or firm dummies**				**Negative Binomial**	**OLS Long Differences**	
Dependent Variable	*PATENTS*	*PATENTS*	*PATENTS*	*PATENTS*	PATENTS	ΔPATENTS	$\Delta(PATENTS/N)$
Sample	All	All	No missing values on accounts	Include capital and employment		All	All
$\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$ Level Chinese Imports at (t-5)	0.303*** (0.105)	0.273*** (0.097)	0.365*** (0.129)	0.364*** (0.129)	0.484** (0.221)		
Level ln(Employment) at (t-1)				-0.002 (0.008)			
Level ln(Capital/Sales) at (t-1)				0.005 (0.004)			
Level ln(Sales) at (t-1)							
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-5}$ Change in Chinese Imports at (t-5)						0.354*** (0.098)	0.484*** (0.199)
Industry*Country Fixed Effects	Yes	-	-	-	-	No	No
Firm Fixed Effects	No	Yes	Yes	Yes	Yes	No	No
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	15,119	15,119	8,897	8,897	15,119	8,991	6,758
Observations	92,910	92,910	46,227	46,227	92,910	30,608	20,238

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country (k) by four digit industry (j) pair in parentheses. There are 2,225 distinct four digit industry by country clusters. Columns (2)-(5) include a full set of firm dummies, column (6) controls for fixed effects using the Blundell et al (1999) pre-sample mean scaling estimator for count data models, and column (7) is estimated using 5-year differences. $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents Chinese imports as a fraction of total imports in a four-digit industry by country pair, this calculated as a five-year difference in column(6). Column (3) re-estimates column (2) on the sub-sample with non-missing employment and capital-sales data. Capital is defined as tangible fixed assets, Sales as operating revenue, Employment as number of employees (all from AMADEUS company database). Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the UK. Sample period is 1996 to 2005.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$\Delta \ln(IT/N)$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta \ln(IT/N)$	$\Delta PATENTS$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta PATENTS$
	OLS	**First Stage**	**IV**	**OLS**	**First Stage**	**IV**
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ Change in Chinese Imports	1.284*** (0.172)		1.851*** (0.400)			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$ Change Chinese Imports (t-3)				1.294*** (0.478)		3.933 (2.382)
Quotas removal		0.088*** (0.004)			0.034*** (0.005)	
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Site Type Controls	Yes	Yes	Yes	n/a	n/a	n/a
Number of units	2,891	2,891	2,891	1,810	1,810	1,810
Observations	2,891	2,891	2,891	3,339	3,339	3,339

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Standard errors for all regressions are clustered by four digit industry in parentheses. Five-year differences 2000- 2005 for IT and 2005 for patents. There are 83 distinct industry clusters for columns (1)-(3) and 81 for (4)-(6). $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quota reduction is based on EU SIGL data and defined as the (value weighted) proportion of HS6 products in the 4 digit industry that were covered by a quota restriction on China in 1999 (prior to China's WTO accession) that were planned to be removed by 2005 (see the Appendix A for details). Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls are dummies for establishment type: Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch.

TABLE 5: INSTRUMENTAL VARIABLE ESTIMATES USING INITIAL CONDITIONS

Dependent Variable	$\Delta \ln(IT/N)$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta \ln(IT/N)$	$\Delta PATENTS$	$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	$\Delta PATENTS$
	(1) OLS	**(2) First Stage**	**(3) IV**	**(4) OLS**	**(5) First Stage**	**(6) IV**
$\Delta M^{China} * \left(M_j^{China}/M_j^{World}\right)_{t-6}$		0.254***			0.230***	
Growth of total Chinese imports in Europe* level of Chinese imports in four digit European industry (at t-6)		(0.003)			(0.003)	
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$	0.361***		0.727**			
Change in Chinese Imports	(0.106)		(0.220)			
$\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)_{t-3}$				0.342***		0.455*
Change in Chinese Import at (t-3)				(0.095)		(0.251)
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Site-Type Controls	Yes	Yes	Yes	n/a	n/a	n/a
Number of Units	22,957	22,957	22,957	8,713	8,713	8,713
Observations	37,500	37,500	37,500	15,847	15,847	15,847

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Standard errors are clustered by four-digit industry in parentheses. There are 370 industry clusters for columns (1)-(3) and 354 for (4)-(6). $\Delta\left(M_{jk}^{China}/M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The instrumental variable is the share of Chinese imports in all imports in an industry across the whole of the Europe and the US (in a base year) interacted with the aggregate growth in Chinese imports in Europe and the US. The base share is (t-6). The IT equations cover data between 2007-2000 and the patents data cover 1999-2005. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls are dummies for establishment type: Divisional HQ, Divisional Branch, Enterprise HQ or a Standalone Branch.

TABLE 6: EMPLOYMENT EQUATIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Sample		Harte-Hanks IT data set			Patenting firms	All firms
Dependent Variable	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$	$\Delta \ln N$
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Change in Chinese Imports	-0.277*** (0.074)	-0.203*** (0.072)	-0.379*** (0.105)	-0.396*** (0.120)	-0.336*** (0.111)	-0.286*** (0.069)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right) * (IT/N)_{t-5}$ Change Chinese Imports*PCs per worker at (t-5)			0.385** (0.157)			
$(IT/N)_{t-5}$ PCs per worker (t-5)		0.241*** (0.009)	0.230*** (0.010)			
Quintile2* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				0.165 (0.126)		
Quintile3* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				0.009 (0.174)		
Quintile4* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				0.362*** (0.139)		
Highest Quintile 5 of $(IT/N)_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$				0.514*** (0.159)		
$PATSTOCK_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ (ln(pat stock per worker at t-5))*Change in Chinese imports					2.240*** (0.854)	2.142*** (0.824)
$PATSTOCK_{t-5}$ ln(patent stock/employees) at (t-5)					0.408*** (0.059)	0.336*** (0.060)
Country Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Site-Type Controls	Yes	Yes	Yes	Yes	n/a	n/a
Number of Units	22,957	22,957	22,957	22,957	6,795	116,191
Observations	37,500	37,500	37,500	37,500	21,315	336,028

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four digit industry pair) in parentheses. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. $PATSTOCK$ is (1+ the log of) firm's patent stock normalized on employment. There are 2,816 distinct country by industry pairs for columns (1)-(4), 1,532 for column (5) and 2,833 for column (6). Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. In column (5) only patenting firms (defined as a firm which had at least one European patent since 1978) are included, while in column (6) all firms from these countries are included. Site type controls include dummies Divisional HQ, a Divisional Branch, Enterprise HQ or a Standalone Branch. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline PC intensity, $(IT/N)_{t-5}$. Note that linear quintile terms are included in column (4) but not reported in the table. Sample period is 2000 to 2007 for columns (1)-(4) and 1996-2005 for columns (5) and (6). "Number of units" is defined as number of plants in columns (1)-(4) and number of firms in columns (5) and (6).

TABLE 7: SURVIVAL EQUATIONS

Sample	Harte-Hanks IT data set				Patenting firms	All firms
Dependent Variable	**SURVIVAL**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Change in Chinese Imports	-0.118** (0.047)	-0.182** (0.072)	-0.274*** (0.098)	-0.060 (0.049)	-0.053 (0.044)	-0.113*** (0.025)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$ Change Chinese Imports*PCs per worker at (t-5)		0.137 (0.112)				
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * Quintile1 Change Chinese Imports*Lowest PC Quintile (t-5)				-0.214** (0.102)		
PATSTOCK$_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ patent stock * Change in Chinese Imports					0.171** (0.081)	0.194* (0.111)
Quintile2* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.238** (0.104)			
Quintile3* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.135 (0.137)			
Quintile4* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.272** (0.124)			
Highest Quint. 5 of (IT/ N)$_{t-5}$* $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$			0.201 (0.138)			
(IT/ N)$_{t-5}$ PCs per worker at (t-5)	0.001 (0.006)	-0.002 (0.006)				
ln(N)$_{t-5}$ Ln(Employment) at (t-5)	0.038*** (0.002)	0.038*** (0.002)	0.038*** (0.002)	0.039*** (0.002)	0.001 (0.001)	0.001 (0.001)
Quintile 1 Lowest Quintile of PCs per worker at (t-5)				-0.018** (0.006)		
PATSTOCK$_{t-5}$ ln(patent stock/employees) at (t-5)					-0.007 (0.009)	0.034*** (0.009)
Country Year effects	Yes	Yes	Yes	Yes	Yes	Yes
SiteType Controls	Yes	Yes	Yes	Yes	n/a	n/a
Number of Units	28,624	28,624	28,624	28,624	6,848	122,336
Observations	28,624	28,624	28,624	28,624	6,848	122,336

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four digit industry in parentheses. There are 2,863 country-industry clusters for columns (1)-(4), 1434 for column (5) and 2896 for column (6). SURVIVAL refers to whether an establishment that was alive in 2000 was still alive in 2005 for the HH-Amatech sample. SURVIVAL is based on AMADEUS company status for the AmaPat data (see Data Appendix for definitions of survival) and is based on whether firms alive in 1999 or 2000 where dead by 2005. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their baseline PC intensity, (IT/ N) t-5. Note that linear quintile terms are included in the column (3) regression but not reported in the table. *PATSTOCK* is (1+ the log of) firm's patent stock normalized on employment. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. Site type controls are dummies for establishment type and include Divisional HQ, a Divisional Branch, an Enterprise HQ or a Standalone Branch. "Number of units" is defined as number of establishments in columns (1)-(4) and firms in columns (5) and (6).

TABLE 8: "BACK OF THE ENVELOPE" MAGNITUDES

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

Period	Within	Between	Exit	Total
2000-07	11.1	3.1	1.2	15.4
2000-04	9.2	2.3	0.9	12.4
2004-07	13.7	4.0	1.6	19.3

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

Period	Within	Between	Exit	Total
2000-07	10.8	10.0	1.8	22.6
2000-04	8.3	8.4	1.4	18.1
2004-07	14.3	11.2	2.2	27.6

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

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

Notes: The top panel reports the share of employment weighted growth in PCs per employee that China accounts for, the middle panel the increase in patents/employee that China accounts for and the bottom panel the increase in productivity growth China accounts for. This is calculated by multiplying the regression coefficients from by the actual observed Chinese import share to generate a predicted changes in IT/Employee, Patents/Employee and TFP applied to the panel average samples of IT, Patents and TFP from 2000 to 2005 inclusive. This aggregate predicted growth in IT/Employee is then divided by the average change in PCs per employee over the span of our data (1999 to 2007) which is 2.5%. This aggregate predicted change in Patents/Employee is then divided by 3.5% (the aggregate growth rate of patents from 1986 to 2006 in the USPTO). And the aggregate predicted growth in TFP is divided by 2.0% (the average TFP growth in manufacturing**)** . The coefficients that are used are as follows: Table 2 Column (1) for IT within, Table 6 column (3) for IT between OLS and Table 7 column (2) for IT exit; Table 3 Column (7) for patents within, Table 6 Column (6) for patents between, and Table 7 column (6) for patents exit. TFP numbers are from Table 13.

TABLE 9: ALTERNATIVE MEASURES OF THE CHANGE IN IMPORTS

Panel A: Chinese Imports Normalized by Domestic Production

Dependent Variable:	**(1)** $\Delta\ln(IT/N)$	**(2)** $\Delta PATENTS$	**(2)** $\Delta\ln N$	**(3)** Survival
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$ Change in Chinese Imports (over production)	0.053** (0.024)		-0.192*** (0.043)	-0.060*** (0.022)
$\Delta\ln N$ Change in firm employment	-0.625*** (0.011)			
$\Delta\left(M_{jk}^{China}/D_{jk}\right)_{t-4}$ Change in Chinese Imports (t-4)		0.364*** (0.114)		
$\Delta\left(M_{jk}^{China}/D_{jk}\right)_{t-4}$ * $(IT/N)_{t-5}$ Change Chinese Imports*PCs Per Worker at (t-5)			0.138** (0.057)	
$\Delta\left(M_{jk}^{China}/D_{jk}\right)_{t-4}$ * Quintile 1 Change Chinese Imports*Lowest Quintile IT (t-5)				-0.128** (0.051)
$(IT/N)_{t-5}$ PCs Per Worker (t-5)			0.248*** (0.011)	
Quintile 1 Lowest quintile of PCs per worker at (t-5)				-0.014** (0.006)
Number of Units	20,106	7,130	20,106	25,130
Observations	31,820	7,130	31,820	25,130

Panel B Chinese Imports Normalized by Apparent Consumption

Dependent Variable	**(1)** $\Delta\ln(IT/N)$	**(2)** $\Delta PATENTS$	**(3)** $\Delta\ln N$	**(4)** Survival
$\Delta\left(M_{jk}^{China}/C_{jk}\right)$ Change in Chinese Imports (over apparent consumption)	0.169* (0.089)		-0.759*** (0.124)	-0.191*** (0.063)
$\Delta\ln N$ Change in firm employment	-0.623*** (0.011)			
$\Delta\left(M_{jk}^{China}/C_{jk}\right)_{t-4}$ Change in Chinese Imports(t-4)		0.555*** (0.168)		
$\Delta\left(M_{jk}^{China}/C_{jk}\right)_{t-4}$ * $(IT/N)_{t-5}$ Change Chinese Imports*PCs Per Worker at (t-5)			0.631*** (0.198)	
$\Delta\left(M_{jk}^{China}/C_{jk}\right)_{t-4}$ * Quintile 1 Change Chinese Imports*Lowest Quintile IT (t-5)				-0.333** (0.140)
$(IT/N)_{t-5}$ PCs Per Worker (t-5)			0.241*** (0.011)	
Quintile 1 Lowest quintile of PCs per worker at (t-5)				-0.013** (0.006)
Number of Units	19,793	7,130	19,793	24,495
Observations	31,225	7,130	31,225	24,495

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

TABLE 10: LOW WAGE COUNTRY AND HIGH WAGE COUNTRY IMPORTS

(A) HH-Amatech **Dependent Variable**	$\Delta \ln(IT/N)$						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$	0.053**	0.048*			0.050*		0.047*
Change in Chinese Imports	(0.024)	(0.026)			(0.026)		(0.027)
$\Delta\left(M_{jk}^{Low}/D_{jk}\right)$		0.028					
Change in Non-China Low Wage Imports		(0.042)					
$\Delta\left(M_{jk}^{Low}/D_{jk}\right)$			0.051**				
Change in All Low Wage Imports			(0.023)				
$\Delta\left(M_{jk}^{High}/D_{jk}\right)$				0.009	0.004		
Change in High Wage Imports				(0.008)	(0.009)		
$\Delta\left(M_{jk}/D_{jk}\right)$						0.012	0.005
Change in World Imports						(0.008)	(0.009)
$\Delta \ln N$	-0.625***	-0.625***	-0.625***	- 0.625***	-0.625***	-0.625**	-0.625***
Change in employment	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Country Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Site Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of plants	20,106	20,106	20,106	20,106	20,106	20,106	20,106
Number of Observations	31,820	31,820	31,820	31,820	31,820	31,820	31,820

(B) Amapat Dependent Variable	$\Delta PATENTS$						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
$\Delta\left(M_{jk}^{China}/D_{jk}\right)$	0.365***	0.361***					0.405***
Change in Chinese Imports	(0.114)	(0.126)					(0.129)
$\Delta\left(M_{jk}^{Low}/D_{jk}\right)$		0.002					
Change in Non-China Low Wage Imports		(0.025)					
$\Delta\left(M_{jk}^{Low}/D_{jk}\right)$			0.181***		0.179***		
Change in All Low Wage Imports			(0.055)		(0.059)		
$\Delta\left(M_{jk}^{High}/D_{jk}\right)$				-0.024	-0.023		
Change in High Wage Imports				(0.016)	(0.016)		
$\Delta\left(M_{jk}/D_{jk}\right)$						-0.012	-0.021
Change in World Imports						(0.016)	(0.017)
Country Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Site Type Controls	na	na	na	na	na	Na	na
Number of Firms	7,130	7,130	7,130	7,130	7,130	7,130	7,130
Number of Observations	7,130	7,130	7,130	7,130	7,130	7,130	7,130

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. $\Delta\left(M_{jk}^{China}/D_{jk}\right)$ represents the 5-year difference Chinese Imports normalized by domestic production (D). $\Delta\left(M_{jk}^{Low}/D_{jk}\right)$ is the 5-year difference in All Low Wage Country imports normalized by production (D). $\Delta\left(M_{jk}^{High}/D_{jk}\right)$ is the 5-year difference in total World Imports normalized by production (D). These variables are lagged by four years in Panel (B). Production data sourced from Eurostat's Prodcom database with details of construction given in the Data Appendix. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, and the UK. Note that Switzerland is not included because it does not report production data to Eurostat's Prodcom database. "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 2007 for panel (A) and 1996-2005 for panel (B).

TABLE 11: OFFSHORING, IT AND INNOVATION

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

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

TABLE 12 INDUSTRY/PRODUCT SWITCHING AND TECHNICAL CHANGE

Dependent Variable:	**Switched Industry**	**Switched Industry**	**Switched Industry**	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$	$\Delta \ln(IT/N)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Chinese Imports	0.138***	0.132***	0.131***		0.469***	0.466***	0.247***	0.244***
	(0.050)	(0.050)	(0.050)		(0.083)	(0.083)	(0.081)	(0.081)
IT intensity (t-5)		-0.018**	-0.018**					
		(0.007)	(0.008)					
Industry Switching				0.025***		0.023*		0.018*
				(0.012)		(0.012)		(0.011)
Employment growth			-0.002				-0.619***	-0.619***
			(0.006)				(0.011)	(0.011)
Observations	32,917	32,917	32,917	32,917	32,917	32,917	32,917	32,917

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. “Switched Industry” is a dummy variable equal to unity if a plant switched four digit industry classification over the 5 year period. Estimation is by OLS standard errors clustered by four digit industry and country. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK. All regressions include country-year effects and site-type controls. Sample period is 2000 to 2007.

TABLE 13: TOTAL FACTOR PRODUCTIVITY EQUATIONS

	(1)	(2)	(3)
Dependent Variable	$\Delta(\ln TFP)$	$\Delta \ln N$	SURVIVAL
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.280***	-0.485***	-0.243***
Change in Chinese Imports	(0.096)	(0.131)	(0.065)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * ln(TFP) $_{t-5}$		1.697***	0.309***
Change in Chinese Imports*ln(TFP) at (t-5)		(0.644)	(0.085)
ln(TFP) $_{t-5}$		0.232***	-0.012**
		(0.023)	(0.005)
Country Year Effects	Yes	Yes	n/a
Number of firms	89,869	89,869	246,815
Observations	293,447	293,447	246,815

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by country and four digit industry pair in parentheses. Size as measured by ln(employment) is included as an additional control in the SURVIVAL equations. There are 405 distinct country by industry pairs. $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. Countries include France, Italy, Spain and Sweden (the countries with mandatory reporting requirement for materials as well as labor and capital). TFP is calculated for all 1.41 million observations in these countries where we have data on sales, labor, capital and materials for any year between 1996 and 2006. We estimate TFP by implementing the de Loecker (2007) version of the Olley-Pakes (1996) method where we allow for imperfect competition, firm specific prices, trade and multi-product firms (see Appendix for details). The production functions are estimated separately for each two-digit sector and then normalized so the TFP index is always relate to an industry-time-country mean.

TABLE A1: CITES PER PATENT

Dependent Variable	(1) CITES/PATENT	(2) CITES/PATENT	(3) CITES/PATENT	(4) ln(1+ CITES/PATENT)
$\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-5}$	0.090	0.023	0.082	0.025
Level Chinese Imports at (t-5)	(0.242)	(0.842)	(0.242)	(0.115)
ln(PAT)			0.021***	
Log of patents			(0.007)	
Country Year effects	Yes	Yes	Yes	Yes
Site-Type Controls	n/a	n/a	n/a	n/a
SIC4 Industry Fixed Effects	Yes	n/a	Yes	Yes
Firm Fixed Effects	No	Yes	No	No
Number of Firms	10,010	10,010	10,010	10,010
Observations	21,273	21,273	21,273	21,273

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. All columns are estimated by within-groups (WG) $\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-5}$ represents Chinese imports as a fraction of total imports in a four-digit industry by country pair, this calculated as a five-year lag in all columns. All specification include country-year fixed effects. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and the UK. Sample period is 1996 to 2005.

TABLE A2: DYNAMICS OF THE EFEFCT OF CHINA ON PATENTS AND EMPLOYMENT

(A) PATENTS

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

(B) EMPLOYMENT

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

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

TABLE A3: ALTERNATIVE IT ADOPTION AND CHANGES IN CHINESE IMPORTS, 2000-2006.

	(A) *ΔEnterprise Resource Planning*			(B) *ΔDatabase*			(C) *ΔGroupware*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$	0.040 (0.034)			0.002 (0.070)			0.249*** (0.083)		
Quintile5 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Highest Quintile for Change in Chinese Imports		0.013*** (0.005)			0.020** (0.010)			0.034** (0.014)	
Quintile4 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 4th Quintile for Change in Chinese Imports		0.006 (0.005)			0.030*** (0.010)			0.021 (0.013)	
Quintile3 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 3rd Quintile for Change in Chinese Imports		0.014*** (0.005)			0.043*** (0.010)			-0.008 (0.013)	
Quintile2 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 2nd Quintile for Change in Chinese Imports		0.010** (0.005)			0.024*** (0.011)			-0.018 (0.013)	
Quintile1 $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ 1st Quintile for Change in Chinese Imports			-0.011*** (0.004)			-0.028** (0.009)			-0.000 (0.001)
$\Delta \ln N$	0.005 (0.004)	0.005 (0.004)		0.021*** (0.008)	0.021*** (0.008)	0.023*** (0.001)	0.001 (0.009)	0.002 (0.009)	0.000 (0.009)
Site-Type Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	24,741	24,741	24,741	24,741	24,741	24,741	24,741	24,741	24,741

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation by OLS with standard errors (clustered by country by four digit industry pair) in parentheses $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. There are 2,728 distinct country by industry pairs. . Quintiles represent bands of establishments ordered from highest (5) to the lowest (1) in terms of their change in Chinese Imports, that is, quintiles of $\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$. Countries include Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland and the UK

TABLE A4: ROBUSTNESS TO WAGE AND CAPITAL CONTROLS

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

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

TABLE A5: EXPORTS TO CHINA

Dependent Variable	$\Delta \ln(IT/N)$ (1)	$\Delta PATENTS$ (2)	$\Delta \ln N$ (3)	Survival (4)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ Change in Chinese Imports	0.196*** (0.068)		-0.380*** (0.105)	-0.179** (0.074)
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)_{t-5}$ Change in Chinese Imports (t-5)		0.349*** (0.100)		
$\Delta\left(M_{jk}^{China} / M_{jk}^{World}\right)$ * (IT/ N) $_{t-5}$ Change Chinese Imports*PCs per worker at (t-5)			0.385** (0.157)	0.075 (0.116)
$\Delta\left(X_{jk}^{China} / X_{jk}^{World}\right)_{t-5}$ Change in Exports to China	0.028 (0.098)		-0.059 (0.096)	0.015 (0.069)
$\Delta\left(X_{jk}^{China} / X_{jk}^{World}\right)_{t-5}$ Change in Exports to China (t-5)		-0.085 (0.158)		
$\Delta \ln N$ 5-year change in ln(Employment)	-0.617*** (0.010)			
Number of Units	22,957	8,814	22,957	28,624
Number of Observations	37,500	21,560	37,500	28,624

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

TABLE A6: ADDITIONAL IV ESTIMATES USING INITIAL CONDITIONS

	$\Delta(\ln N)$ (1) First Stage	$\Delta(\ln N)$ (2) IV	Survival (3) First Stage	Survival (4) IV
$\Delta(M_{jk}^{China}/M_{jk}^{World})$ Change in Chinese Imports		-1.069*** (0.254)		-0.266** (0.127)
$\Delta(M_{jk}^{China}/M_{jk}^{World})$ * $(IT/N)_{t-5}$ Change Chinese Imports*PCs per person at (t-5)		1.387*** (0.458)		
$\Delta(M_{jk}^{China}/M_{jk}^{World})$ * Quintile1 Change Chinese Imports*Lowest PC Quintile				-0.032 (0.253)
$\Delta(M_{jk}^{China}/M_{jk}^{World})_{t-3}$ Change in Chinese Import at (t-3)				
$(\ln N)_{t-1}$ log Employment at (t-1)				
$(IT/N)_{t-5}$ PCs per person at (t-5)		0.201*** (0.016)		
Quintile 1 Lowest Quintile of PCs per person at (t-5)				-0.022** (0.010)
$\Delta M^{China} * (M_j^{China}/M_j^{World})_{t-6}$ Level*growth t-6	0.254*** (0.003)		0.270*** (0.005)	
Country Year effects	Yes	Yes	Yes	Yes
Site-Type Controls	Yes	Yes	Yes	Yes
Observations	37,500	37,500	28,624	28,624

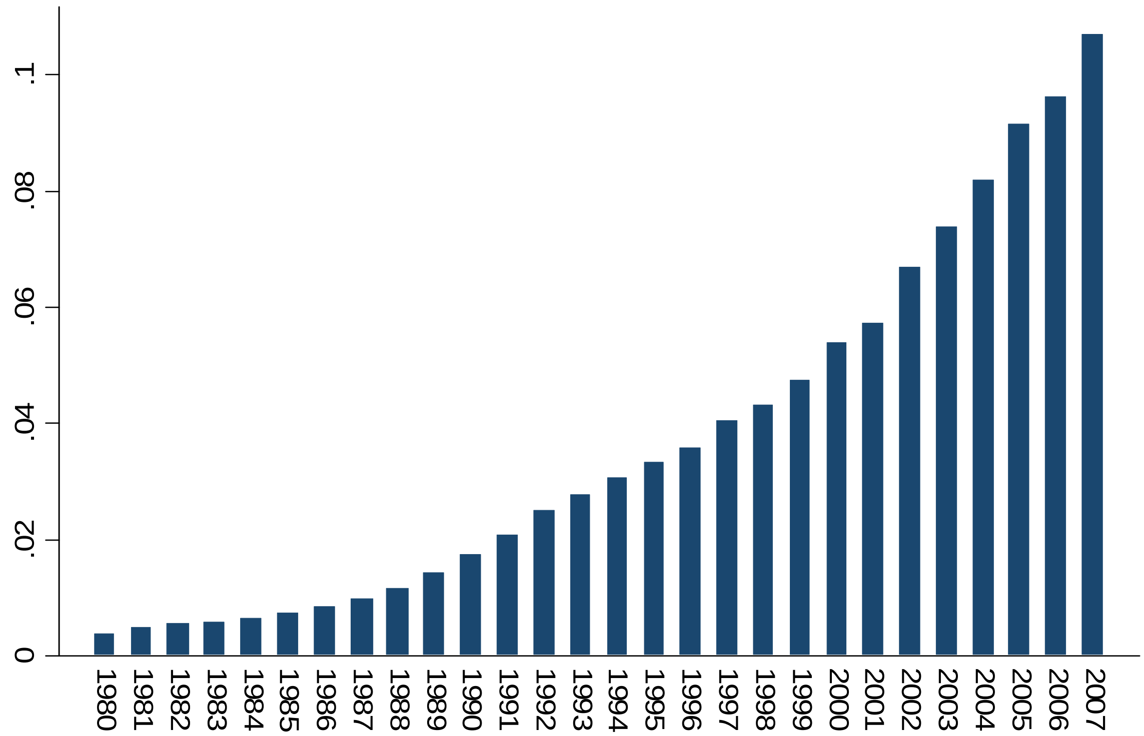
Notes: *** denotes 1% significance ; ** denotes 5% significance; * denotes 10% significance. Standard errors are clustered by four digit industry in parentheses. There are 370 industry clusters for columns (1)-(2) and 272 for columns (3)-(4). $\Delta(M_{jk}^{China}/M_{jk}^{World})$ represents the 5-year difference in Chinese imports as a fraction of total imports in a four-digit industry by country pair. The IV is the proportion of total Chinese imports in an industry j as a share of all European imports in industry j interacted with the aggregate growth in Chinese imports in Europe. IT sample is estimated for 2005-2007, patents sample covers 1996-2005.

TABLE A7: 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)

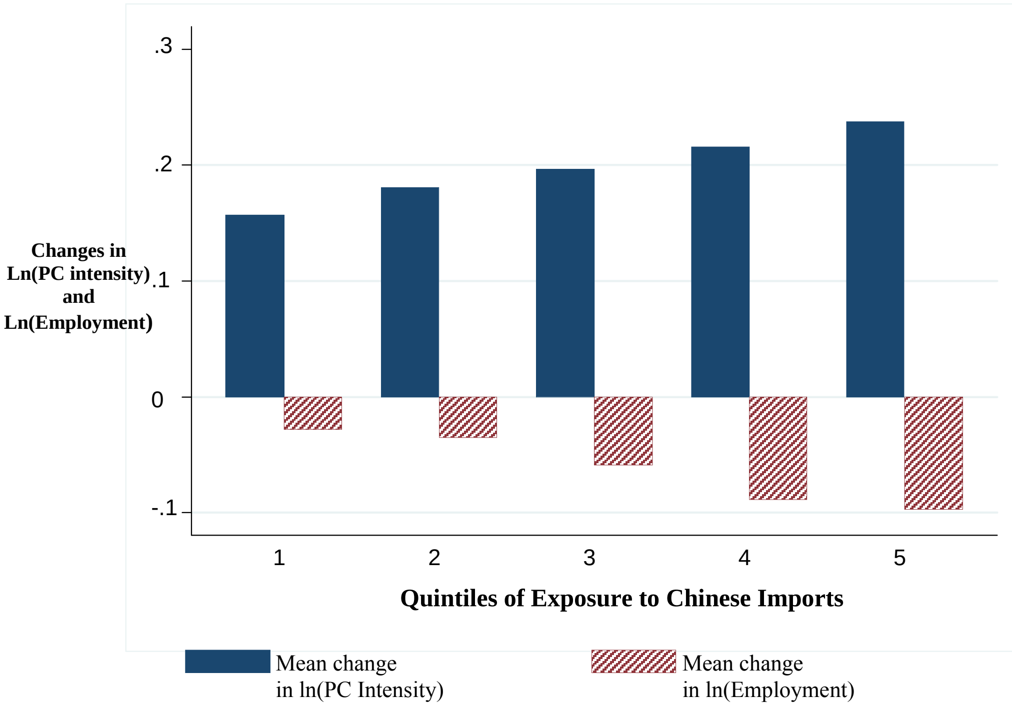
Notes: Calculated using product-level UN Comtrade data aggregated to 4-digit US SIC codes. There are 430 4-digit industries in our dataset. China's global share of all imports $\left(M_j^{China} / M_j^{World}\right)_{1999}$ is the proportion of imports from China in industry *j* as a share of imports 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.

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



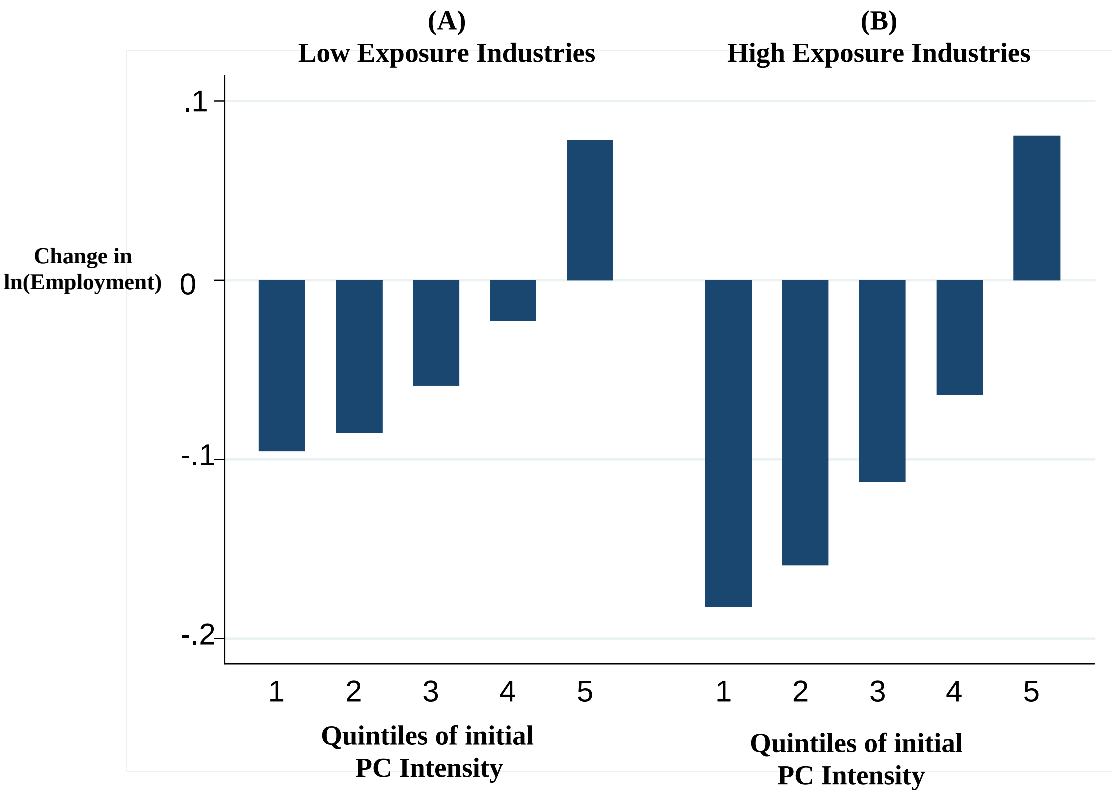
Notes: Calculated using UN Comtrade data.

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 LN(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).