

Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity

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- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS

- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS

Overview

- The absolute volume of innovation (not just patents per worker or productivity) increases within the firms more affected by **exogenous reductions in barriers** to Chinese imports.
- We distinguish between the impact of import competition on technology through a *within* firm effect and a *between* firm (reallocation) effect.
- A contribution of our article is to confirm the importance of low-wage country trade for technical change using a larger **more representative sample** of firms and plants.
- A major empirical challenge in determining the causal effect of trade on technical change is the presence of **unobservable technology shocks**.

Overview

Two core results

- ① On the intensive margin, Chinese import competition increases innovation within surviving firms.
- ② Chinese import competition reduces employment and survival probabilities in low-tech firms.

Thus, this article jointly examines the effects of trade on survival/selection and innovation.

Literatures

- The literature focuses on **reallocation effects**, i.e., how trade induces a shift in output from less productive towards more efficient firms (e.g., Melitz, 2003; Melitz and Redding, 2013)
- lowering import barriers increases competitive intensity and such competition could benefit innovation through **reducing agency costs** (e.g., Schmidt, 1997), increasing the incentive to gain market share (Raith, 2003), or lowering cannibalization of existing profits.
- A class of innovation models stresses the importance of **trade in increasing market size and fostering innovation** through this **market expansion effect**. (Schmookler (1966); Krugman (1980); and Grossman and Helpman (1991, 1992))
- Imports could enhance innovation by enabling domestic firms to access overseas' knowledge. (e.g., Coe and Helpman, 1995 or Acharaya and Keller, 2008)

Literatures

The other main strand of the trade and productivity literature is more focused on **compositional effects**.

most of the aggregate changes we observe following trade liberalization have occurred **within rather than between industries**.

This could be explained, however, by firms operating in more finely disaggregated industries and we will show that there are strong reallocation effects whereby **low-tech firms tend to shrink and exit**.

Literatures

We report that China induces faster technical change within firms and plants. In principle, firm TFP increases could be accounted for by two factors not strictly related to innovation: **changes in a firm's product portfolio** or **offshoring**.

- Bernard et al. (2010) investigate the impact of trade liberalization in heterogeneous multi-product firms. In the face of falling trade costs with a low-wage country such as China, Northern firms **shift their product mix** towards more high-tech products (see Bernard et al., 2007).
- A fall in trade costs with China will mean that producers of goods that can use Chinese intermediate inputs will benefit. For example, firms may slice up the production process and **offshore** the low tasks to China (see, e.g., Grossman and Rossi-Hansberg, 2008).

Introduction



FIGURE 1

Share of all imports in the EU and US from China and all low-wage countries

Notes: Calculated using UN Comtrade data. Low-wage countries list taken from Bernard *et al.* (2006) and are defined as countries with less than 5% GDP/capita relative to the US 1972–2001.

- 1 INTRODUCTION
- 2 DATA**
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS

Patents

We combined Amadeus with the population of patent applications to the European Patent Office (EPO) through matching by name. Patent counts have heterogeneous values so we also use future citations to control for patent quality in some specifications. The matching procedure was based on names and location, with details given in Belenzon and Berkovitz (2010).

Productivity and exit

Core method is to use a version of the Olley and Pakes (1996) method applied by De Loecker (2011) to allow for trade and imperfect competition with multi-product firms.

We define exit as a firm being defined as “bankrupt” , “liquidated” ,or “dormant” .

Firms that are taken-over or merged are not counted as exiting since the operations of the firm may still be continuing even though ownership has changed.

Information technology

Harte Hanks (HH) is a multinational company that collects IT data to sell to large IT firms (e.g., IBM, Cisco, and Dell).

We focus on using computers per worker (PCs plus laptops) as our main measure of IT intensity because this:

- is a physical quantity measure which is recorded in a consistent way across sites, time, and countries
- avoids the use of IT price deflators which are not harmonized across countries. In robustness tests, we also use alternative measures of IT such as Enterprise Resource Planning software, Groupware and Database software

UN Comtrade data

We use trade information from the UN Comtrade data system.

We use the value of imports originating from China (M^{China}) as **a share of total world imports** (M^{World}) in a country by four-digit industry cell as our key measure of exposure to Chinese trade, following the “value share” approach outlined by Bernard et al. (2006); i.e., we use

$$IMP^{CH} = M^{China} / M^{World}.$$

As two alternative measures we also construct Chinese import penetration by **normalizing Chinese imports either on domestic production** (M^{China}/D) or **on apparent consumption** (domestic production less exports plus imports), M^{China}/C .

For domestic production we use Eurostat's Prodcom database.

Compared with Comtrade, Prodcom has no data prior to 1996, so this restricts the sample period.

The quota instrument

We examine several threats to the exclusion restriction underlying the quota IV:

- we confirmed that the industries with the toughest quotas in 2000 had no differential trends in observables prior to 2000. The growth of patents, TFP, labour productivity, the capital–labour ratio, the material–labour ratio, average wages, total employment, and total capital were not significantly correlated with the quota instrument.¹⁵
- we show that our results are robust to including firm fixed effects in the differenced equations
- we present an alternative IV strategy exploiting the initial level of Chinese import penetration (an “initial” conditions IV described in Section 5.2).

- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY**
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS

Technical change within surviving plants and firms

Consider a basic firm-level equation for the level of technology (TECH) in firm i in industry j in country k at time t as:

$$\ln TECH_{ijkt} = \alpha IMP_{jkt-1}^{CH} + \eta_i + f_{kt} + \epsilon_{ijkt} \quad (1)$$

IMP_{jkt-1}^{CH} means the proportion of imports(M) in industry j and country k that originate from China($M_{jk}^{China} / M_{jk}^{World}$)

The f_{kt} are a full set of country dummies interacted with time dummies to absorb macro-economic shocks

η_i is a firm fixed effect.

Technical change within surviving plants and firms

To sweep out firm fixed effects we estimate:

$$\Delta \ln TECH_{ijkt} = \alpha \Delta IMP_{jkt}^{CH} + \Delta f_{kt} + \Delta \epsilon_{ijkt} \quad (2)$$

Δ denotes the long (usually five year) difference operator.

We maximize the use of the data by using overlapping five-year differences (e.g., 2005–2000 and 2004–1999) but since we cluster at the country–industry pair level (or sometimes just industry level) this is innocuous.

We report some results using non-overlapping five-year differences and specifications in levels (e.g., **fixed effect Negative Binomial models**).

Technical change within surviving plants and firms

The growth of Chinese imports may still be related to unobserved shocks, $\Delta\epsilon_{ijkt}$ so we consider instrumental variables such as **the removal of quotas when China joined the WTO** to evaluate potential endogeneity biases. The first stage of the model can be written as:

$$\Delta IMP_{jkt}^{CH} = -\varphi \Delta QUOTA_{jkt} + \Delta f_{kt}^Q + \Delta \epsilon_{ijkt}^Q$$

$QUOTA_{jkt}$ is the toughness of the quota as measured by the (value-weighted) proportion of products in the industry that are covered by a quota against China.

Consider the 2005–2000 long difference. we can write the reduced form for innovation as:

$$\Delta \ln TECH_{ijkt} = \pi QUOTA_{jkt,00} + \Delta \zeta_{kt} + \Delta e_{ijkt}$$

Technological upgrading through reallocation between plants and firms

China would cause **low-tech plants** to shrink and die, as they are competing most closely with Chinese imports. Consequently, we estimate firm employment growth equations of the form:

$$\begin{aligned} \Delta \ln N_{ijkt} = & \alpha^N \Delta IMP_{jkt}^{CH} + \gamma^N (TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}) \\ & + \sigma^N TECH_{ijkt-5} + \Delta f_{kt}^N + \Delta \epsilon_{ijkt}^N \end{aligned} \quad (3)$$

N is the employment.

α^N reflects the association of jobs growth with the change in Chinese imports.

$TECH$ is the relevant technology variable (e.g., patenting).

Technological upgrading through reallocation between plants and firms

One of the effects of Chinese trade may be to reduce the probability of plant survival. Consequently, we also estimate:

$$SURVIVAL_{ijkt} = S_{ijkt} = \alpha^S \Delta IMP_{jkt}^{CH} + \gamma^S (TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}) + \sigma^N TECH_{ijkt-5} + \Delta f_{kt}^S + \Delta \epsilon_{ijkt}^S \quad (4)$$

If these establishments (or firms) survived over the subsequent five years we define $S_{ijkt} = 1$ and zero otherwise.

If Chinese imports do reduce survival probabilities, we expect $\alpha^S < 0$ and if high-tech plants are more protected we expect $\gamma^S > 0$.

Technological upgrading through reallocation between plants and firms

There are **two endogenous variables**: ΔIMP_{jkt}^{CH} and $TECH_{ijkt-5} * \Delta IMP_{jkt}^{CH}$ we use $QUOTA_{jk,00}$ and $QUOTA_{jk,00} * TECH_{ijkt-5}$ as **two instruments** in each first stage.

There is no **“initial” technology level** for entering firms.
Estimating an industry-level version of Equation (2):

$$\Delta \ln TECH_{jkt} = \alpha^{IND} \Delta IMP_{jkt}^{CH} + \Delta f_{kt}^{IND} + \Delta \epsilon_{jkt}^{IND} \quad (5)$$

The coefficient on Chinese imports, α^{IND} , in Equation (5) reflects the combination of **within firm effects**, **the reallocation effects**, and **the unmodelled entry effects**.

Sample size across regressions

- Sample sizes differ between columns within a table primarily because of different samples for the three technology variables due to missing data.
- Samples also change when we move from pooling across all industries (e.g., Table 1) to focusing on just the clothing and textile sector (e.g., Table 2).

- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS**
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS

Within firm results

TABLE 1
Technical change within incumbent firms and plants

| Panel A: Baseline results | | | |
|--|-------------------------------------|----------------------------------|----------------------------|
| Dependent variable | (1) $\Delta \ln(\text{PATENTS})$ | (2) $\Delta \ln(\text{IT}/N)$ | (3) ΔTFP |
| Estimation method | Five-year differences | Five-year differences | Five-year differences |
| Change in Chinese imports | 0.321*** | 0.361** | 0.257*** |
| $\Delta \text{IMP}_{jk}^{\text{CH}}$ | (0.102) | (0.076) | (0.072) |
| Sample period | 2005–1996 | 2007–2000 | 2005–1995 |
| Number of units | 8,480 | 22,957 | 89,369 |
| Number of country by industry clusters | 1,578 | 2,816 | 1,210 |
| Observations | 30,277 | 37,500 | 292,167 |
| Panel B: Include industry trends | | | |
| Dependent variable | $\Delta \ln(\text{PATENTS})$ | $\Delta \ln(\text{IT}/N)$ | ΔTFP |
| Change in Chinese imports | 0.191* | 0.170** | 0.128** |
| $\Delta \text{IMP}_{jk}^{\text{CH}}$ | (0.102) | (0.082) | (0.053) |
| Number of units | 8,480 | 22,957 | 89,369 |
| Number of country by industry clusters | 1,578 | 2,816 | 1,210 |
| Observations | 30,277 | 37,500 | 292,167 |

Within firm results

Panel C: Normalize imports by domestic production

| Dependent variable | $\Delta \ln(\text{PATENTS})$ | $\Delta \ln(\text{IT}/N)$ | ΔTFP |
|---|------------------------------|---------------------------|---------------------|
| Change in Chinese imports $\Delta \text{IMP}_{jk}^{\text{CH}}$ | 0.142** (0.048) | 0.129*** (0.028) | 0.065*** (0.020) |
| Number of units | 8,474 | 20,106 | 89,369 |
| Number of country by industry clusters | 1,575 | 2,480 | 1,210 |
| Observations | 30,221 | 31,820 | 292,167 |

Panel D: Offshoring

| Dependent variable | $\Delta \ln(\text{PATENTS})$ | $\Delta \ln(\text{IT}/N)$ | ΔTFP |
|---|------------------------------|---------------------------|---------------------|
| Change in Chinese imports $\Delta \text{IMP}_{jk}^{\text{CH}}$ | 0.313*** (0.100) | 0.279*** (0.080) | 0.188*** (0.082) |
| Change Chinese imports in source industries $\Delta \text{OFFSHORE}$ | 0.174 (0.822) | 1.685*** (0.517) | 1.396*** (0.504) |
| Number of units | 8,480 | 22,957 | 89,369 |
| Number of country by industry clusters | 1,578 | 2,816 | 1,210 |
| Observations | 30,277 | 37,500 | 292,167 |

Within firm results

A concern with patenting as an innovation indicator is that firms may simply be **taking out more patents to protect their existing knowledge** in the face of greater Chinese competition.

To test this **“lawyer effect”** we also look at citations per patent—if firms are now patenting more incremental knowledge for fear of being copied by the Chinese, the average quality of their patents should fall, so citations per patent should drop.

Within firm results

We subjected the baseline results to a number of robustness checks.

- we were concerned that unobserved productivity shocks could be driving the positive correlation so in Panel B we include a full set of three-digit industry dummies in the growth specifications
- we normalized Chinese imports by a measure of domestic activity such as production or apparent consumption instead of total imports in Panel C.
- the opening up of China could have affected technical progress by allowing Western firms to buy cheaper intermediate inputs and offshore low value-added parts of the production chain.

Within firm results

An obvious problem with estimating these equations is the **potential endogeneity** of Chinese imports due to **unobserved technology shocks** correlated with the growth of Chinese imports.

This is most likely to cause a **downward bias** on the OLS estimates of the effects of China on technology, as more exogenous innovation will lead to fewer Chinese imports.

There could be **demand side shocks** working in the opposite direction, so ultimately the direction of the OLS bias is an **empirical question**.

Within firm results

| | (1) | (2) | (3) |
|--------------------------|------------------------------|---------------------------------|------------------------------|
| | Patenting activity | | |
| Dependent variable | $\Delta \ln(\text{PATENTS})$ | $\Delta \text{IMP}^{\text{CH}}$ | $\Delta \ln(\text{PATENTS})$ |
| Method | OLS | First stage | IV |
| Change Chinese imports | 1.160*** (0.377) | | 1.864* (1.001) |
| Quotas removal | | 0.108*** (0.022) | |
| QUOTA | | | |
| <i>F</i> -statistic | | 24.1 | |
| Sample period | 2005–1999 | 2005–1999 | 2005–1999 |
| Number of units | 1,866 | 1,866 | 1,866 |
| Number industry clusters | 149 | 149 | 149 |
| Observations | 3,443 | 3,443 | 3,443 |

Within firm results

| (4) | (5) | (6) | (7) | (8) | (9) |
|----------------------------------|--|---------------------------------|----------------------------|--|---------------------------|
| Information technology | | | Total factor productivity | | |
| $\Delta \ln(\text{IT}/N)$ OLS | $\Delta \text{IMP}^{\text{CH}}$ First stage | $\Delta \ln(\text{IT}/N)$ IV | ΔTFP OLS | $\Delta \text{IMP}^{\text{CH}}$ First stage | ΔTFP IV |
| 1.284*** (0.172) | 0.088*** (0.019) | 1.851*** (0.397) | 0.902*** (0.118) | 0.107*** (0.032) | 1.629** (0.326) |
| 2005–2000 | 2005–2000 | 2005–2000 | 2005–1999 | 2005–1999 | 2005–1999 |
| 2,891 | 2,891 | 2,891 | 12,247 | 12,247 | 12,247 |
| 83 | 83 | 83 | 177 | 177 | 177 |
| 2,891 | 2,891 | 2,891 | 20,625 | 20,625 | 20,625 |

Within firm results

The major concern with the IV strategy is that there could be **some unobserved trend** in the sectors that had the highest quotas that meant they would have had faster technical change even in the absence of China joining the WTO.

We use the reduced forms for a longer time period covering pre- and post-WTO accession to capture the trend. Hence, we estimate:

$$\Delta \ln TECH_{ijkt} = \pi \Delta Z_{jkt} + \eta_{ijk} + \Delta \zeta_{kt} + \Delta e_{ijkt}$$

$\Delta Z_{jkt} = QUOTA_{jk,00} * I(YEAR \geq 2001)$ remains the “toughness” of the quotas in 2000.

Within firm results

| Dependent variable | Patenting | | | |
|--|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
| | (1) $\Delta \ln(\text{PATENTS})$ | (2) $\Delta \ln(\text{PATENTS})$ | (3) $\Delta \ln(\text{PATENTS})$ | (4) $\Delta \ln(\text{PATENTS})$ |
| Quotas removal * I(year > 2000) | 0.197** (0.095) | 0.216** (0.105) | | |
| Quotas removal * # years after 2000 | | | 0.066** (0.029) | 0.075** (0.033) |
| Firm-specific trends? | No | Yes | No | Yes |
| Sample period | 2005–1992 | 2005–1992 | 2005–1992 | 2005–1995 |
| Number of firms | 2,435 | 2,435 | 2,435 | 2,435 |
| Number industry clusters | 159 | 159 | 159 | 159 |
| Observations | 14,768 | 14,768 | 14,768 | 14,768 |

Within firm results

| Total factor productivity | | | |
|---------------------------|---------------------|---------------------|---------------------|
| (5) Δ TFP | (6) Δ TFP | (7) Δ TFP | (8) Δ TFP |
| 0.152*** (0.037) | 0.178*** (0.037) | | |
| | | 0.028** (0.014) | 0.033* (0.017) |
| No | Yes | No | Yes |
| 2005–1995 | 2005–1995 | 2005–1995 | 2005–1995 |
| 16,495 | 16,495 | 16,495 | 16,495 |
| 187 | 187 | 187 | 187 |
| 55,791 | 55,791 | 55,791 | 55,791 |

Between firm results

TABLE 4
Between firm effects—employment and survival

| Panel A: Employment $\Delta \ln N$ | | | | | | |
|--|----------------------|----------------------|---------------------|----------------------|----------------------|----------------------|
| Dependent variable: Employment growth, $\Delta \ln N$ | (1) | (2) | (3) | (4) | (5) | (6) |
| Technology variable (TECH) | PATENTS | PATENTS | IT | IT | TFP | TFP |
| Change in Chinese imports ΔIMP_{jk}^{CH} | -0.361*** (0.134) | -0.434*** (0.136) | -0.203** (0.086) | -0.379*** (0.105) | -0.377*** (0.094) | -0.377*** (0.096) |
| Change in Chinese imports * technology at $t-5$ $\Delta IMP_{jk}^{CH} * TECH_{t-5}$ | | 1.435** (0.649) | | 0.385** (0.157) | | 0.795** (0.307) |
| Technology at $t-5$ $TECH_{t-5}$ | 0.389*** (0.043) | 0.348*** (0.049) | 0.241*** (0.010) | 0.230*** (0.010) | 0.152*** (0.012) | 0.136*** (0.012) |
| Number of units | 6,335 | 6,335 | 22,957 | 22,957 | 89,369 | 89,369 |
| Countries by industry clusters | 1,376 | 1,376 | 2,816 | 2,816 | 1,210 | 1,210 |
| Observations | 19,844 | 19,844 | 37,500 | 37,500 | 292,167 | 292,167 |
| Panel B: Survival | | | | | | |
| Dependent Variable: SURVIVAL | (1) | (2) | (3) | (4) | (5) | (6) |
| Technology variable (TECH) | PATENTS | PATENTS | IT | IT | TFP | TFP |
| Change in Chinese imports ΔIMP_{jk}^{CH} | -0.057 (0.046) | -0.078 (0.049) | -0.118** (0.047) | -0.182** (0.072) | -0.207*** (0.051) | -0.208*** (0.050) |
| Change in Chinese imports * technology at $t-5$ $\Delta IMP_{jk}^{CH} * TECH_{t-5}$ | | 0.260** (0.122) | | 0.137 (0.112) | | 0.110* (0.059) |
| Technology at $t-5$ $TECH_{t-5}$ | 0.003 (0.007) | -0.005 (0.009) | 0.001 (0.005) | -0.002 (0.006) | -0.001 (0.003) | -0.004 (0.003) |
| Survival rate for sample (mean) | 0.977 | 0.977 | 0.886 | 0.886 | 0.927 | 0.927 |
| Number of country by industry clusters | 1,647 | 1,647 | 2,863 | 2,863 | 1,242 | 1,242 |
| Observations (and number of units) | 7,928 | 7,928 | 28,624 | 28,624 | 60,883 | 60,883 |

Between firm results

We also examined the dynamic effects of Chinese imports on employment and technology.

- Chinese imports appear to have the largest impact on patents after three years whereas for jobs the largest impact for Chinese imports is contemporaneously.
- This is consistent with the idea that firms respond to Chinese imports by cutting employment and starting innovation projects, but it takes around three years for these projects to create patentable innovations.

Between firm results

TABLE 5
Between firm effects—using quota removal as an IV for Chinese imports

| Panel A: Employment | | | | | | |
|---|----------|-----------|-----------|-----------|-----------|----------|
| Dependent variable: Employment growth | (1) | (2) | (3) | (4) | (5) | (6) |
| Technology variable (TECH) | PATENTS | PATENTS | IT | IT | TFP | TFP |
| Estimation technique | OLS | IV | OLS | IV | OLS | IV |
| Change in Chinese imports | -1.068** | -3.266*** | -1.119*** | -2.746*** | -0.376** | -2.041** |
| ΔIMP_{jk}^{CH} | (0.453) | (1.148) | (0.227) | (0.735) | (0.168) | (0.930) |
| Change in Chinese imports * technology at $t-5$ | 3.670* | 3.256 | 1.341** | 3.481** | 0.110 | 1.058 |
| $\Delta IMP_{jk}^{CH} * TECH_{t-5}$ | (2.162) | (4.609) | (0.509) | (1.584) | (0.441) | (0.763) |
| Technology at $t-5$ | 0.445*** | 0.453*** | 0.239*** | 0.189*** | 0.113*** | 0.076** |
| $TECH_{t-5}$ | (0.120) | (0.152) | (0.027) | (0.031) | (0.019) | (0.031) |
| First stage F -Stat (ΔIMP_{jk}^{CH}) | | 11.7 | | 11.6 | | 10.45 |
| First stage F -Stat ($\Delta IMP_{jk}^{CH} * TECH_{t-5}$) | | 2.8 | | 11.7 | | 7.66 |
| Number of units | 1,388 | 1,388 | 2,891 | 2,891 | 12,247 | 12,247 |
| Number of country by industry clusters | 140 | 140 | 83 | 83 | 177 | 177 |
| Observations | 2,377 | 2,377 | 2,891 | 2,891 | 20,625 | 20,625 |
| Panel B: Survival | | | | | | |
| Dependent variable: SURVIVAL | (1) | (2) | (3) | (4) | (5) | (6) |
| Method | OLS | IV | OLS | IV | OLS | IV |
| Sample | PATENTS | PATENTS | IT | IT | TFP | TFP |
| Change in Chinese imports | -0.182 | -0.271 | -0.483** | -1.162*** | -0.220*** | -0.308* |
| ΔIMP_{jk}^{CH} | (0.171) | (0.247) | (0.200) | (0.383) | (0.083) | (0.142) |
| Change in Chinese imports * Technology at $t-5$ | 0.432** | 0.617* | 0.175 | 0.163 | 0.209* | 0.243 |
| | (0.211) | (0.347) | (0.359) | (0.637) | (0.110) | (0.159) |
| Technology at $t-5$ | -0.024 | -0.030 | 0.002 | -0.015 | -0.017 | -0.018 |
| $TECH_{t-5}$ | (0.027) | (0.032) | (0.014) | (0.018) | (0.009) | (0.012) |
| First stage F -Stat (ΔIMP_{jk}^{CH}) | | 18.4 | | 13.2 | | 8.68 |
| First stage F -Stat ($\Delta IMP_{jk}^{CH} * TECH_{t-5}$) | | 17.9 | | 10.7 | | 7.04 |
| Number of industry clusters | 113 | 113 | 84 | 84 | 202 | 202 |
| Observations (and number of units) | 1,624 | 1,624 | 5,980 | 5,980 | 11,794 | 11,794 |

Between firm results

- Column (1) of Panel A shows that the higher tech firms appear to be somewhat protected from Chinese imports, just as we found in the larger sample.
- In Column (2) the standard error rises on the interaction, but the coefficient is largely unchanged (3.3 compared with 3.7 in Column (1)).
- Panel B of Table 5 repeats the specifications using survival as the outcome. The pattern is broadly similar with the coefficients on the key interaction term all being positive (except Column (4)).

Magnitudes

To run our magnitude calculations we use a standard productivity decomposition following papers such as Foster et al. (2000), to decompose aggregate increases in productivity into a within firm term and between firm reallocation term.

$$\Delta P_t = \sum_{i=1}^N s_{i0}(p_{ijt} - p_{ij0}) + \sum_{i=1}^N (s_{it} - s_{i0})p_{ij0} + \sum_{i=1}^N (s_{it} - s_{i0})(p_{ijt} - p_{ij0}) - \sum_{i \in \text{exit}} s_{it}^{\text{exit}}(p_{ij0}^{\text{exit}} - \bar{p}_{j0}) + \sum_{i \in \text{entrant}} s_{it}^{\text{entrant}}(p_{ijt}^{\text{entrant}} - \bar{p}_{jt})$$

s_{it} is the firm share of total employment

p_{ijt} is the firm technology level

\bar{p}_{jt} is the average technology level of all firms

p_{ij0}^{exit} and p_{ijt}^{entrant} are the technology levels of exiters and entrants

Magnitudes

- The first term is the *within* effect (the increase in technology holding firm size constant).
- The second term is the *between* component (the increase in aggregate technology from shifting employment from low-tech firms towards high-tech firms).
- The third term is the cross effect (the correlation of the increase in technology within firms and their change in employment share)
- The fourth term is the exit component (the impact of the relative technology level of exiting firms versus incumbent firms).
- The final term is the entry component (the impact of technology level of entering firms versus incumbent firms).

Magnitudes

TABLE 6
Magnitudes

Panel A: Increase in patents per employee attributable to Chinese imports

| Period | Within | Between | Exit | Total |
|-----------------------------|--------|---------|------|-------|
| Product market | 5.1 | 6.7 | 2.1 | 13.9 |
| Product market + offshoring | 5.8 | 8.6 | 2.7 | 17.1 |

Panel B: Increase in IT per employee attributable to Chinese imports

| Period | Within | Between | Exit | Total |
|-----------------------------|--------|---------|------|-------|
| Product market | 9.8 | 3.0 | 0.6 | 13.5 |
| Product market + offshoring | 23.2 | 5.4 | 3.2 | 31.8 |

Panel C: Increase in total factor productivity attributable to Chinese imports

| Period | Within | Between | Exit | Total |
|-----------------------------|--------|---------|------|-------|
| Product market | 9.9 | 2.4 | 0.2 | 13.5 |
| Product market + offshoring | 25.0 | 7.6 | 1.1 | 33.7 |

- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS**
- 6 CONCLUSIONS

Dynamic selection bias

A concern with our finding of positive effects of Chinese imports competition on within firm technical change is that it reflects dynamic selection bias.

Dynamic selection bias would mean, however, that we attribute **too much of this aggregate industry effect to the within firm component** and **too little to the reallocation component** in the magnitude calculations.

We create **pseudo observations** for firms who exit and give them a value of zero patents for all post-exit periods until the end of the sample in 2005. This is a **“worst case bounds”** bounds approach (see Manski and Pepper, 2000 or Blundell et al., 2007) as the effect of trade could never be less than this lower bound.

Dynamic selection bias

TABLE 7
Assessing dynamic selection bias in the patents equation

| Estimator Method | (1) Five-year long differences Baseline | (2) Five-year long differences Worst-case Lower Bound | (3) Fixed effects Negative Binomial Baseline | (4) Fixed effects Negative Binomial Worst-case Lower Bound |
|--|--|---|---|--|
| Change in Chinese imports $\Delta \left(M_{jk}^{\text{China}} / M_{jk}^{\text{World}} \right)$ | 0.321*** (0.102) | 0.271*** (0.098) | | |
| Level of Chinese imports $\left(M_{jk}^{\text{China}} / M_{jk}^{\text{World}} \right)$ | | | 0.398*** (0.168) | 0.395*** (0.166) |
| Number of clusters | 1,578 | 1,662 | 1,578 | 1,620 |
| Number of firms | 8,480 | 8,732 | 8,480 | 8,732 |
| Number of observations | 30,277 | 31,272 | 74,038 | 74,486 |

Initial conditions as instrumental variables

A disadvantage of the quota-based instrument is that we can only construct the instrument for the affected industries (textiles and clothing), so we consider **a second identification strategy**.

The industries where China exports grew more depended on whether the industry is one in which China had a **comparative advantage**.

Consequently, high exposure to Chinese imports in 1999 can potentially be used (interacted with the exogenous overall growth of Chinese imports, ΔM^{China}) as a potential instrument for subsequent Chinese import growth.

In other words, we use $(IMP_{jt-6}^{CH} * \Delta M_t^{China})$ as an instrument for ΔIMP_{jkt}^{CH} , where IMP_{jt-6}^{CH} is the Chinese import share in industry j in the EU and US.

Initial conditions as instrumental variables

TABLE 8
Using “initial conditions” as an instrumental variable

| Panel A: Within firm technology equations | | | | | | |
|---|--|---|---|--|-----------------------------------|----------------------------------|
| Dependent variable Method | (1) $\Delta \ln(\text{PATENTS})$ OLS | (2) $\Delta \ln(\text{PATENTS})$ IV | (3) $\Delta \ln(\text{IT}/N)$ OLS | (4) $\Delta \ln(\text{IT}/N)$ IV | (5) ΔTFP OLS | (6) ΔTFP IV |
| Change in Chinese imports | 0.321*** (0.117) | 0.494** (0.224) | 0.361*** (0.076) | 0.593*** (0.252) | 0.257*** (0.087) | 0.507* (0.283) |
| Initial condition IV | | | | | | |
| First-stage F -statistic | | 95.1 | | 38.7 | | 14.5 |
| Sample period | 2005–1996 | 2005–1996 | 2007–2000 | 2007–2000 | 2005–1996 | 2005–1996 |
| Number of units | 8,480 | 8,480 | 22,957 | 22,957 | 89,369 | 89,369 |
| Number of industry clusters | 304 | 304 | 371 | 371 | 354 | 354 |
| Observations | 30,277 | 30,277 | 37,500 | 37,500 | 292,167 | 292,167 |
| Panel B: Employment | | | | | | |
| Dependent variable: Employment growth Technology variable (TECH) Method | (1) PATENTS OLS | (2) PATENTS IV | (3) IT OLS | (4) IT IV | (5) TFP OLS | (6) TFP IV |
| Change in Chinese imports | −0.434*** (0.137) | −0.734*** (0.313) | −0.379*** (0.130) | −1.070*** (0.258) | −0.377*** (0.108) | −2.039*** (0.761) |
| $\Delta \text{IMP}_{jk}^{\text{CH}}$ | | | | | | |
| Change in Chinese imports * technology at $t-5$ | 1.434** (0.560) | 0.876 (1.634) | 0.385** (0.180) | 1.473*** (0.587) | 0.795** (0.347) | 2.443*** (0.732) |
| $\Delta \text{IMP}_{jk}^{\text{CH}} * \text{TECH}_{t-5}$ | | | | | | |
| Technology at $t-5$ | 0.348*** (0.049) | 0.365*** (0.071) | 0.230*** (0.01) | 0.199*** (0.020) | 0.136*** (0.013) | 0.103*** (0.021) |
| TECH_{t-5} | | | | | | |
| First stage for $(\Delta \text{IMP}_{jk}^{\text{CH}})$, F -stat | | 39.3 | | 22.6 | | 15.6 |
| First stage for $(\Delta \text{IMP}_{jk}^{\text{CH}} * \text{TECH}_{t-5})$, F -Stat | | 31.8 | | 24.2 | | 13.3 |
| Number of units | 6,335 | 6,335 | 22,957 | 22,957 | 89,369 | 89,369 |
| Industry clusters | 300 | 300 | 371 | 371 | 354 | 354 |
| Observations | 19,844 | 19,844 | 37,500 | 37,500 | 292,167 | 292,167 |

Other robustness tests

- ***Low-wage versus high-wage country trade***

Using the normalization by domestic production (Table 1 Panel C) we found that in the technology equations the coefficient on all low-wage countries **was essentially the same as the coefficient** on China. By contrast, the coefficient on the growth of imports from high-wage countries is always insignificant either by itself or when Chinese imports are included in the technology equations.

- ***Heterogeneity of the China effect on innovation***

We examined the extent to which the China effect was heterogeneous across countries and industries. The coefficients were surprisingly stable across countries and we **cannot statistically reject homogeneity of the coefficients across countries.**

Other robustness tests

- ***China's effect on skill demand***

We estimated industry-level skill demand equations and found evidence to suggest **Chinese imports are associated with a significant increase in the wage-bill share of college-educated workers**, consistent with the idea of trade integration with low-wage countries **reducing the relative demand for less-skilled workers**.

- ***Product and industry switching***

A leading compositional theory was that in the face of Chinese import competition European firms change their product mix, However, this only **accounts for a small fraction** of the correlation of Chinese imports and technological upgrading.

Other robustness tests

- ***Exports to China***

Our main results are all robust to including **controls for exports to China** in the regressions. Imports from China appear to be the dominant force on innovation, at least in the micro-data.

- 1 INTRODUCTION
- 2 DATA
- 3 EMPIRICAL MODELLING STRATEGY
- 4 RESULTS
- 5 EXTENSIONS AND ROBUSTNESS
- 6 CONCLUSIONS**

Conclusions

We have examined the impact of trade on technical change in twelve European countries.

- 1 The absolute volume of innovation as measured by patenting rose within firms who were more exposed to increases in Chinese imports.
- 2 In sectors more exposed to Chinese imports, jobs and survival rate fell in low-tech firms (e.g., lower patenting intensity), but high-tech firms are relatively sheltered (the between firm effect).

Conclusions

- In terms of magnitudes, China could account for around 14% of the overall technical change in Europe between 2000 and 2007. These are likely to be underestimates as we also identify a similar sized role for offshoring to China in increasing TFP and IT adoption (although not for innovation) and obtain much larger effects under IV.
- In terms of policy, our results imply that reducing import barriers against low-wage countries such as China may bring important welfare gains through technical change.

Conclusions

There are **several directions** this work could be taken.

- We would like to investigate more deeply the **impact of low-wage countries on the labour market**, using worker-level data on the non-employment spells and subsequent wages of individuals most affected by Chinese trade.
- It would be valuable to complement our European analysis with a similar exercise in other countries.
- We would like to **further develop our trapped factor model**, to see how important it is in explaining trade effects compared with the more conventional market size and competition effects.
- It would be helpful to structurally extend the analysis to take into account **general equilibrium effects**.

Thanks For Listening!