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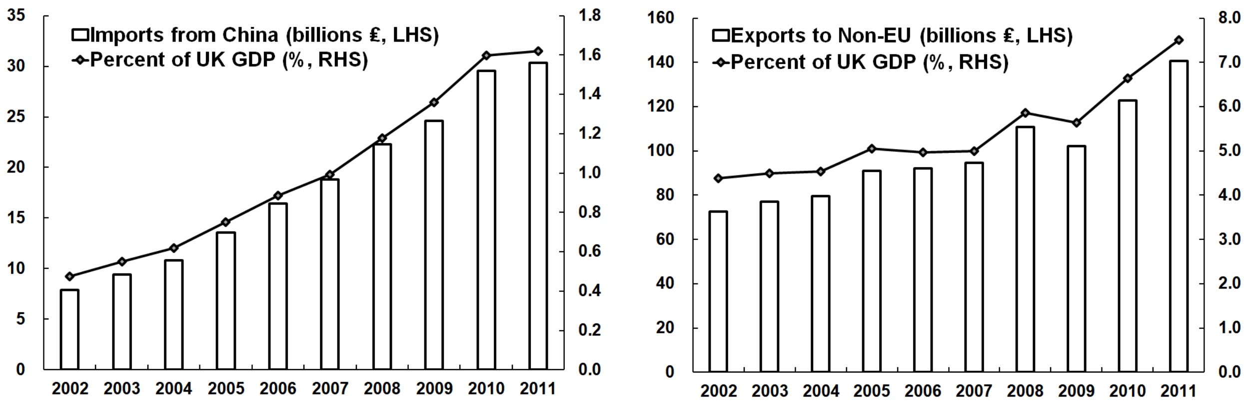
1 Introduction

How trade affects innovation is a central question for academics and policy makers as it determines the fundamental gains from a trade liberalization. The recent literature emphasizes the importance of dynamic gains from trade: Trade may induce an endogenous change in firm innovation and productivity. A large body of literature exploring this question highlights three main channels: (1) export market access (Lileeva and Trefler (2010) and Bustos (2011)), (2) import competition (Bloom, Draca and Van Reenen (2015) and Autor et al. (2020)) and (3) access to imported inputs (Amiti and Konings (2007) and Goldberg, Khandelwal, Pavcnik and Topalova (2010)). Several of these papers find that improved access to export markets and imported inputs following trade liberalizations raises firm productivity, primarily in developing countries. For import competition, however, empirical evidence is mixed: Autor et al. (2020) find a negative impact of Chinese competition on innovation for US firms while Bloom, Draca and Van Reenen (2015) document increased patenting and technological upgrading by European firms facing Chinese import competition. Theories on how product-market competition affects innovation also suggest conflicting predictions (Shu and Steinwender (2019)). On the one hand, competition reduces the potential rents that firms can enjoy from innovating in a given market and thus their incentive to invest in innovation (the so called "Schumpeterian effect"). On the other hand, tougher competition may stimulate firms to develop entirely new types of products or to introduce more efficient processes to shield themselves from the competition (the "escape-competition effect").

Using UK administrative data, this paper empirically investigates how trade affects R&D investment of UK manufacturers over 2002-2011. The data used in this analysis are drawn from three datasets – (1) firm R&D expenditures from UK corporate tax return data, (2) UK firms' trade transactions with extra-EU countries, and (3) the Business Structure Database (BSD) which contains key firm characteristics for a near population of UK enterprises. To explore the long-debated impact of import competition, I follow the leading literature that focuses on the Chinese expansion in global trade following China's accession to the World Trade Organization (WTO) in 2001. Relative to the existing literature such as Bloom, Draca and Van Reenen (2015) and Autor et al. (2020) which focuses on import competition, I evaluate two channels - import competition and export demand - jointly using firm-level trade data. The last decades witnessed a rapid trade integration around the globe, in which firms in one country not only confronted increasing foreign competition but also gained better access to export markets. For the UK, its merchandise imports from China as a ratio of the UK's gross domestic product (GDP) soared from 0.48 percent to 1.62 percent between 2002 and 2011 (left-hand side of figure 1). During the same period, the UK's merchandise exports to non-EU destinations as a share of the UK's GDP almost doubled from 4.38 percent to 7.51 percent (right-hand side of figure 1).[1] In these circumstances, a joint investigation into both channels will help us gain a better insight into the overall impact of globalization and allow us to assess their relative importance.

Figure 1: UK merchandise trades



Note: 'Non-EU' indicates all destinations excluding 27 EU membership countries. Source: Office for National Statistics (ONS).

An important feature of this paper is in its focus on firms' R&D expenditure – a key innovation input - as an outcome of interest. Most previous work uses patenting or total factor productivity (TFP) to measure firm innovation. However, changes in TFP could reflect other forces like markup changes rather than productivity changes due to innovation (Shu and Steinwender (2019)). Patenting, a recently popularized measure of innovation output, is not without limitations: Not all innovations are patented, nor does patenting necessarily represent new innovation as firms may patent to protect their existing knowledge from threats of imitation by competitors (Aghion et al. (2018)). The information on firms' R&D expenditure in this paper is based on UK corporate tax returns from the UK tax authority - Her Majesty's Revenue and Customs (HMRC). And, relative to previous studies, there are two advantages in using the R&D expenditure from administrative data: a more precise definition of R&D and a broader coverage of firms. First, the UK tax return dataset allows us to infer the actual amount of R&D expenditures of individual firms. In 2000, the UK government introduced an R&D tax incentive to financially support innovation activities of small and medium firms (SMEs), which was extended to large firms in 2002.[2] The reported

[1]The non-EU countries indicate all other countries except for 27 EU membership countries as of 2021. In fact, there were two major changes in the number of EU membership countries between 2002 and 2011. In 2004, 10 countries joined EU as new members; Cyprus, Malta, Czech Republic, Slovak Republic, Estonia, Latvia, Lithuania, Hungary, Poland and Slovenia. In 2007, Bulgaria and Romania gained the EU membership as well.

[2]The UK R&D tax credit allows firms to deduct their qualified R&D spending with an enhanced rate from

R&D is validated and corrected by HMRC to the extent that the expenditure complies with the HMRC's definition of innovation activity.[3] The majority of prior work using firm R&D relies on survey data or financial statements of listed firms which may omit some data as R&D is not a compulsory item to report.[4] Second, this paper covers a large number of SMEs. Analysing these SMEs together with larger firms not only sheds light on the behaviours of firms across the firm-size distribution, but also has more relevance for policies to promote the growth of these firms.

To summarize key results, I find strong evidence of an adverse impact of import competition on firms' innovation efforts. UK firms in industries that are more exposed to rising Chinese imports experienced a larger fall in their R&D investment. To account for the increased availability of Chinese inputs, I also examine firms' own imports from China. I find no evidence of the impact of firms' use of Chinese imports on their R&D. The negative R&D response to import competition is in line with the Schumpeterian hypothesis, which is also supported by Autor et al. (2020). As another trade channel, I verify a significant and positive effect of export demand on firm R&D. The economic magnitudes of both channels are substantial. A one standard deviation rise in Chinese import penetration is associated with a decline in firms' R&D spending of 26 percent. Interestingly, a positive export demand shock could more than compensate for the adverse impact of tougher competition: A one standard deviation rise in a firm-level measure of export demand boosts firms' R&D spending by about 55 percent. These large magnitudes suggest that changes in the trade environment surrounding firms are a key driver for their investment in innovation.

I further examine heterogeneous effects of foreign competition and export demand shocks depending on firms' initial conditions. For Chinese competition, there is no significant difference in R&D responses across the firms' productivity distribution. Instead, I find some

their taxable profits. Firms initially claim a tax credit for a given amount of enhanced R&D expenditure based on the enhancement rate set by HMRC. The tax authority derives the value of the actual R&D spending of the firm from this enhanced expenditure. For details on the UK's R&D tax relief scheme, see Dechezleprêtre et al. (2016) and Guceri and Liu (2019).

[3]HMRC Corporate Intangibles and R&D Manual sets three main categories of qualifying R&D expenditures for tax relief claims - staffing costs, consumables (water, electricity etc.) and software that are directly used for R&D. The R&D expenditure in the HMRC dataset is different from the UK business R&D statistics in the Business Enterprise Research and Development (BERD) data published by the ONS. It is estimated that the R&D expenditure which qualified for tax relief reported to HMRC amounts to approximately 70% of the R&D in BERD for 2011. The difference may be because HMRC adopts a narrower definition of R&D for tax purposes. For instance, BERD admits R&D spending on capital investment while HMRC R&D only covers current expenses (Dechezleprêtre et al. (2016)).

[4]For instance, among the papers using R&D data in part of their analysis, Bloom, Draca and Van Reenen (2015) use European listed firms from Amadeus. Xu and Gong (2017), Hombert and Matray (2018) and Autor et al. (2020) study US firms from Compustat. Iacovone (2012) uses survey data on Mexican manufacturers that are more representative of large firms. Bøler, Moxnes and Ulltveit-Moe (2015) also use survey data for a subset of Norwegian firms with 50 or more employees.

evidence that firms that initially engaged in exporting were less hurt by rising import competition. It is possibly because these firms that had already entered into exporting could more easily reallocate their sales abroad away from the shrinking domestic market. In contrast to my findings on the competition channel, I observe strong heterogeneity in the effects of export demand across firms' productivity: Firms whose productivity is higher in the initial periods raise their R&D by much more in response to a foreign demand shock. These findings together imply that the innovation efforts by purely domestic and less profitable firms were most adversely affected by globalization, leading to a widening productivity gap across firms.

This research relates to a broad empirical literature on trade and innovation. First, this paper revisits the long-standing debate on the relationship between import competition and innovation. While empirical evidence on this relationship is inconclusive (in line with the theoretical ambiguity), Shu and Steinwender (2019) point out that studies on developing countries such as Pavcnik (2002), Fernandes (2007), Amiti and Konings (2007), Topalova and Khandelwal (2011) and Iacovone (2012) provide supportive evidence of the positive impact of foreign competition on productivity and innovation. More recent work on advanced economies presents more conflicting evidence in the context of a drastic rise in Chinese imports as seen in Bloom, Draca and Van Reenen (2015) and Autor et al. (2020). This paper adds another case-study for an advanced economy, the UK, but concentrates on the response of firm R&D rather than a measure of innovation outputs such as patenting. This paper also adds to literature on the interaction between export market access and technology upgrading of individual firms including Lileeva and Trefler (2010), Bustos (2011), Coelli, Moxnes and Ulltveit-Moe (forthcoming) and Aghion, Bergeaud, Lequien and Melitz (2018). Several studies argue that an increased export market size raises the profitability of firms' investment in technology and thus encourages firm innovation. By constructing a firm-level measure of the export demand shock, I examine the role of exporting opportunities in determining firm R&D and assess its quantitative importance in comparison to import competition.[5]

The remainder of the paper proceeds as follows. Section 2 describes the data source and section 3 details the empirical strategy. Section 4 presents the empirical results. Section 5 concludes.

[5]For some recent works studying the two channels together, Berthou, Chung, Manova and Sandoz (2020) use sector-level data for 14 European countries to investigate the impact of exogenous shocks to export demand and import competition on aggregate productivity. Lim, Trefler and Yu (2018) conduct a comprehensive study on the impact of export market size and foreign competition using Chinese firm data.

2 Data

The empirical analysis builds on three datasets: (1) UK firms' R&D expenditure derived from the HMRC corporate tax returns; (2) the HMRC overseas trade dataset; (3) the UK's Business Structure Database (BSD) from the Office of National Statistics (ONS) that contains firm characteristics such as employment and industry affiliation of a near population of UK enterprises.[6]

R&D expenditure data: The key variable in my analysis is the amount of R&D expenditure of each firm in each year that is reported for R&D tax relief claims to Her Majesty's Revenue and Customs (HMRC) - the UK tax authority. This information is from the Research and Development Tax Credits (RDTC) dataset which is an extension of the UK corporate tax return dataset (CT600).[7] The amount of R&D expenditure is initially reported by the firm and is further validated and corrected by the tax authority using other information on the firm's tax returns.[8]

Business Structure Database: For key firm characteristics, I use the UK's Business Structure Database (BSD) which is a snapshot of the Inter Departmental Business Register (IDBR) – a live register of UK enterprises maintained by the Office for National Statistics (ONS). The BSD contains details on the near universe of active UK firms covering nearly 99% of UK economic activity. The BSD used in this paper contains information such as enterprise reference number (Entref), employment, turnover, country of ownership, industry affiliation based on the UK Standard Industrial Classification (UK SIC) 2003 revision, year of birth (company start-up date) as well as location of company by UK postcode over the period between 1998 and 2012.

Firm-level trade data: Another data source for my analysis is the firm-level overseas trade dataset from HMRC. The trade dataset contains information on UK firms' import and export declarations with extra-EU countries. These include monthly information on the

[6] The HMRC administrative datasets can be accessed only within a designated HMRC facility - HMRC Datalab. The HMRC Datalab is an Research Data Centre (RDC) that allows approved researchers to use HMRC data in a secure environment. Merging these data with other datasets like the BSD in this paper is also subject to permission from HMRC.

[7] The CT600 dataset is a confidential panel dataset constructed by the UK tax authority (HMRC) which contains corporate tax returns or assessments made from the returns for the universe of companies in the UK. See Dechezleprêtre et al. (2016) for more details on the CT600 dataset.

[8] Note that the qualifying R&D expenditures are available only for the R&D-tax-relief-claiming firms for the years in which they make the claims. Therefore, as in Dechezleprêtre et al. (2016) and Guceri and Liu (2019), I assume that non-claiming firms did not spend on R&D.

value of exports and imports at the 8-digit Combined Nomenclature (CN) product-level and countries of destination or origin. The dataset covers the period from 1996 to 2011.[9]

In addition to these datasets, I use the UN Comtrade database for bilateral trade flows at the HS 6-digit level to construct some trade variables detailed later.

I combine the three datasets using the look-up tables provided internally by HMRC that match the different firm identifiers in each dataset. The constructed dataset, labelled as 'BSD-R&D-Trade', is an unbalanced panel of 4,107 firms between 2002 and 2011; the total number of firm-year observation is 28,966.[10] These firms are R&D performing firms in manufacturing sectors that reported a positive R&D spending to HMRC at least once between 2002 and 2011. Appendix table B1 presents some descriptive statistics. In this dataset, the mean turnover and employment are £7.6 million and 52.1 persons with standard deviations of 68.3 and 239.9, respectively. These firms are smaller in size compared to major European firms that were studied in Bloom, Draca and Van Reenen (2015) with a mean employment of 739.5.[11] In order to assess the robustness of the results, I also use an alternative dataset that combines the BSD and the R&D data but is not merged with firm-level trade data (labelled as 'BSD-R&D'). This alternative sample includes more firms - 4,798 in total - and, using this dataset, I test the robustness of my findings on an industry-level import competition measure which does not require firm-level trade information. By the number of firms, this sample is estimated to cover more than 70% of UK manufacturing firms that report R&D tax credit claims for 2011.[12] In terms of R&D amount, firms in this sample are representative of SMEs in UK manufacturing, accounting for approximately 62 percent of the total qualifying R&D expenditures under the SME tax credit scheme. It further covers around 14 percent of the total R&D expenditures reported under the large company tax credit scheme.[13]

[9] My analysis covers UK firms' trade with non-EU countries only because data on within-EU transactions are available from 2005, while the non-EU transactions are available from 1996.

[10] For the detailed process of combining the datasets, see appendix A.

[11] An interesting aspect of the firms in our dataset is that, albeit small in size, more than half of them engaged in extra-EU trade. This is somewhat inconsistent with the Melitz model that only large (and more productive) firms import and/or export. Exporting by many small firms is also found in Lileeva and Trefler (2010) that use Canadian plant-level data.

[12] This is based on Fowkes, Sousa and Duncan (2015) - a technical report published by HMRC which provides the number of R&D tax credit claims by each 2-digit UK SIC industry in 2012.

[13] Until 2012, HMRC operated two distinct R&D tax credit schemes based on the firm size - "Large Company" and "SME". And our R&D dataset over the sample period (2002-2011) contains information on the specific scheme to which a firm's R&D tax claim is classified. After 2012, the UK government introduced another R&D support scheme - Research and Development Expenditure Credit (RDEC) - in April 2013 and gradually replaced the Large Company tax credit scheme which was abolished in the financial year 2016-17.

3 Empirical strategy

In this section, I set up an estimating equation for UK firms' R&D that includes the measures of Chinese import competition and firm-specific export demand as key determinants. I then detail how these measures are constructed. The baseline estimating equation is

$$\begin{aligned}\text{RnD}_{f(k),t} = \beta_1 \text{IMP}^{CN}_{k,t-1} + \beta_2 \text{EXD}^{nEU}_{f,t-1} + \gamma \log(\text{Import}_{f,t-1}) \\ + \text{Controls}_{f,t-1} + \alpha_f + \delta_{s,t} + \nu_{r,t} + \epsilon_{f,t}\end{aligned}$$

where subscripts f, k, s, r and t denote firm, UK SIC 4-digit industry, UK SIC 2-digit sector, geographic region defined by the first one or two letters of the outward code in the UK postcode and year, respectively. The outcome variable $\text{RnD}_{f(k),t}$ is either the logarithm of firm R&D expenditure or an R&D dummy. In the case of the log R&D, I add one to the original R&D amounts before the log transformation due to many zeros reported for R&D expenditures.[14] I use an R&D dummy as an alternative outcome because I hypothesize that, at least for some firms, R&D is a binary decision.

The above equation relates firm R&D expenditure to trade exposures, as the main focus of this paper, together with other firm characteristics. The first term $\text{IMP}^{CN}_{k,t-1}$ aims to test the two conflicting hypotheses as to whether foreign competition hinders ("Schumpeterian effect") or spurs ("escape competition effect") firm innovation. As in the previous literature, I focus on the rise of Chinese imports for its salience and enormous scale over the last two decades. As the second determinant, $\text{EXD}^{nEU}_{f,t-1}$ evaluates the importance of export market size in firms' R&D decisions. Intuitively, the larger the product market is, the more profitable it would be for firms to invest in new inventions.[15]

(Chinese competition) Following the prior literature, I measure the exposure of UK firms to Chinese competition using UK imports from China at the SIC 4-digit industry level normalized by the UK industry's output:

$$\text{IMP}^{CN}_{k,t} = \frac{\text{Import}^{CN}_{k,t}}{\text{Turnover}_{k,2000}}$$

[14]This transformation is ad-hoc but is still less problematic as R&D expenditures in this paper are 6-digit numbers (hundreds of thousands pounds sterling) on average and adding one to the original value does not seriously distort the overall distribution of R&D.

[15]This is particularly so when the investment in innovation incurs an upfront fixed cost.

where $\text{Import}_{k,t}^{CN}$ denotes Chinese imports into the UK in industry k in year t and $\text{Output}_{k,2000}$ is the output of industry k which is fixed at the pre-sample year 2000. This import penetration measure can be arguably considered as exogenous from the perspective of an individual firm as any firm's individual decision is unlikely to induce changes in aggregate industry imports. But still, an omitted variable bias cannot be ruled out: The surge in Chinese imports could be correlated with unobserved factors that are also related to both the UK's import demand and a firm's investment in innovation. To isolate the component of the growth of Chinese imports that is due to China's supply shocks, I adopt the IV strategy by Autor et al. (2020). Specifically, I exploit China's exports to 20 other developed economies ('$D20$') in the same year as an instrument for the UK's imports from China:[16]

$$\text{IV for IMP}_{k,t}^{CN} = \frac{\text{Export}_{k,t}^{CN \to D20}}{\text{Output}_{k,2000}}$$

where $\text{Export}_{k,t}^{CN \to D20}$ denotes China's exports to 20 advanced countries of industry k in year t. The underlying assumption in this identification strategy is that the high-income countries are similarly exposed to China's export supply shocks such as falling trade costs and expanding product variety.[17] Along with this IV strategy, I control for any unobserved sector-specific demand and/or technology shocks with 2-digit SIC sector by year dummies.

(Export demand) Next, to assess the export demand channel, I construct an exogenous firm-level measure of the export market size following Bombardini, Li and Wang (2018) and Aghion, Bergeaud, Lequien and Melitz (2018):

$$\text{EXD}_{f,t}^{nEU} = \sum_p \sum_d \omega_{f,p,d} \log(\text{World Export}_{p,d,t})$$

where $\text{World Export}_{p,d,t}$ denotes the world's total exports (excluding the UK) of HS 6-digit product p into non-EU destination d in year t. $\omega_{f,p,d} = \frac{\text{Export}_{f,p,d,2000}}{\sum_p \sum_d \text{Export}_{f,p,d,2000}}$ and $\text{Export}_{f,p,d,2000}$

[16] The countries used here are Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland and the USA.

[17] As a potential threat to this IV strategy, there is a possibility that unobserved technology shocks that are common to high-income economies including the UK may generate similar changes in demand for Chinese imports across these countries. As Hombert and Matray (2018) point out, however, the fast-growing Chinese exports observed in the 2000's are mainly driven by supply-side factors in China such as regulatory reforms and its entry into the WTO in 2001. Thus, what is captured by this instrument should be primarily the supply shock to China.

is a UK firm f's average exports of product p to non-EU destination d over 1998-2000 (pre-sample period).

The key assumption in this identification is that the global trade flows (excluding the UK) into a given product-destination market (p, d) (World Export$_{p,d,t}$) reflects the overall demand changes in that market which are exogenous to an individual UK firm f. This measure then sums over the logarithm of the world exports across all the product-destination pairs weighted by the relative importance of each market in the firm f's total non-EU exports. The HMRC trade dataset enables us to construct this firm-specific exposure to demand changes in each product-destination market. Note that this firm-level weight is based on the average exports over the pre-sample period between 1998 and 2000 to circumvent endogenous changes in the firm's exports due to innovation. Therefore, time variation in this measure stems only from World Export$_{p,d,t}$. This export demand measure is highly correlated with the logarithm of firm exports (correlation of 0.602) and the export dummy (0.579), suggesting that it predicts the firm's current engagement in exporting very well.[18]

(Other controls) Apart from Chinese import penetration and firm-level export demand, the equation also includes firm-level imports (Import$_{f,t}$) as an additional trade variable. Its inclusion is is based on Bøler, Moxnes and Ulltveit-Moe (2015) who find that R&D and importing are complementary activities.[19] Related to the firm's own importing, it is also important to note that increasing availability of cheaper inputs from China may affect firms' innovation independently of the competition channel. I will further check this alternative channel explicitly by including firms' imports from China, together with Chinese competition. I add firm characteristics (Controls$_{f,t}$) such as firm size measured by the logarithm of employment, turnover growth and a dummy equal to one if the firm is foreign-owned in a

[18] I also test two variants of the export demand measure. First, I modify the benchmark measure above by scaling it by the firm's initial export intensity – the ratio of the firms' total non-EU exports to its turnover. And then, I run a regression that includes both unscaled and scaled export demand measures. The coefficient of the unscaled measure is highly significant while that of the scaled measure is not different from zero. Second, I construct a new measure of export demand at the SIC 4-digit industry level. In this case, the firm-level exposure weight is replaced by the industry-specific weight for each market. This industry-level measure has an advantage of accounting for export entry by firms that did not initially engage in exporting. But still, the response to an industry-level demand shock would be different between initially exporting and non-exporting firms. Thus, I add an interaction term between the industry-level export demand measure and a dummy for firms' initial export statuses as well. The results of estimating the specification with the industry-level export demand are reported in appendix table B3.

[19] Under imperfect substitutability between domestic and imported inputs, firms may gain from input variety. Firms may also find the quality-adjusted prices of imported inputs from more productive foreign suppliers are lower than the domestic ones. Therefore, increasing use of imported inputs could raise the overall profitability which in turn encourages firm investment in productivity. R&D may also encourage importing. Assuming that importing incurs a fixed cost, R&D raises future profits, thereby making it more profitable to engage in importing to cut input costs.

given year. All the variables on the right-hand side of the equation are lagged by one year to alleviate simultaneity concerns.

By adding firm fixed effects (α_f), the analysis examines within-firm changes in R&D in response to trade shocks. As noted by Autor et al. (2020) and Lim, Trefler and Yu (2018), there is a possibility of pre-trends that cannot be explicitly controlled for since our R&D data does not allow us to trace as far back as the early 1990s - before China's rapid growth.[20] Moreover, there could be various unobservable shocks not directly related to the trade shocks investigated in this paper. To tackle these issues, the equation includes a comprehensive set of fixed effects, beyond firm fixed effects. The sector by year fixed effects ($\delta_{s,t}$) are aimed at absorbing any unobserved technology shocks at the sector level as mentioned before. I further test region by year fixed effects ($\nu_{r,t}$). It is to account for the effect of, for instance, immigration of low-wage workers to specific UK regions that may affect firms' R&D decisions as a labor cost shock (Gray, Montresor and Wright (2020)).[21] In all estimations, I cluster standard errors by 4-digit SIC industry.[22]

4 Estimation results

This section presents estimation results. To summarize, I find robust evidence of the detrimental effect of Chinese import competition on UK firms' R&D investment. Export demand, by contrast, is found to significantly stimulate their R&D.

4.1 Baseline

Table 1 presents the baseline results. The coefficient for Chinese competition in column 1 is negative and statistically significant, suggesting that firms in industries more exposed to Chinese import competition reduced their R&D expenditures. This specification, and all following columns, control for firm fixed effects and time-varying firm controls including log employment, sales growth and a dummy for foreign ownership. Column 2 controls for sector by year fixed effects that absorb unobserved demand and/or technological shocks at

[20]The R&D tax credit scheme was introduced for SMEs in 2000. My analysis covers the period from 2002 because it was only in 2002 when the scheme was extended to large corporations and the applications among SMEs increased for the sample size to be sufficient for analysis.

[21]Gray, Montresor and Wright (2020) find that the increased supply of low-skill foreign workers from eight Central and Eastern European countries, driven by these countries' accession to EU in 2004, led to an increase in innovation by UK firms - primarily process innovation. The extent of immigration by these workers was largely different across UK regions and, interestingly, the paper finds a tendency of the immigrants to settle in areas where their compatriots were already settled.

[22]I also test two-way clustering by industry and year and find the results are almost the same.

the sector level. The coefficient becomes smaller in absolute terms (-6.142 → -4.305) but is still highly significant.[23] Column 3 introduces *firm-specific* export demand as another determinant for R&D and column 4 tests the most stringent specification, adding region by year fixed effects. The estimate for Chinese competition becomes slightly smaller but remains significant.

Column 5 implements an IV estimation exploiting China's exports to other advanced countries in the same industry to purge the supply-driven component of the rising Chinese imports. The first-stage F-statistic is 21, suggesting that the instrument is a strong predictor of Chinese imports into the UK.[24] The 2SLS estimate for Chinese competition is very similar to the OLS counterpart in column 4 (-3.989 vs -3.925). To interpret, a one percentage point rise in Chinese import penetration is associated with a decline in UK firms' R&D spending by 3.9 percent on average. Finally, column 6 reports the IV estimation for a linear probability model using the R&D dummy as an outcome variable and shows that Chinese competition leads to a lower R&D participation.[25] All together, these results support the hypothesis of the negative Schumpeterian effect on UK firms facing the onslaught of low-cost Chinese imports.

As another important channel of trade impacts, I verify a stimulating role of export demand in firms' technology investment, in line with the prior literature including Lileeva and Trefler (2010), Bustos (2011) and Aghion, Bergeaud, Lequien and Melitz (2018). This indicates that an increase in the size of export markets raises the potential profits that firms could earn from investing in innovation. The statistically significant estimate of 0.064 means that a one percent increase in the measure of export demand is associated with a 6.4 percent increase in firm R&D. Recall that our measure of export demand uses global trade flows into each destination that are plausibly exogenous to individual firms, weighted by their initial exports. Therefore, it does not simply pick up a correlation but can be interpreted as a casual impact running from export demand towards R&D.[26]

I also find a positive association between firms' importing and their R&D spending, which

[23] Changes in the size of coefficient for Chinese competition shows the quantitative importance of controlling for sectoral trends as emphasized by Autor et al. (2020).

[24] All the first-stage F-statistics reported herein are Kleibergen-Paap Wald statistic which is robust to non-i.i.d errors. For the first-stage regression, see column 1 of appendix table B2.

[25] Specifically, a one percentage point rise in import competition from China reduces the probability for a firm to undertake R&D by 0.34 percentage points. This impact of Chinese competition on the extensive margin of R&D appears to be rather small compared to the effect on the level of R&D. I also find a smaller estimate for Chinese competition from the Poisson Pseudo-Maximum Likelihood estimation (PPML) which is known to be more robust to outcome variables with many zeros such as R&D in log-linear specifications. For the PPML result, see the section 4.5 as well as appendix table B5.

[26] The results using an industry-level measure of export demand are reported in appendix table B3. I find that, while the industry-specific export demand measure is not significant, firms that are initially exporting positively respond to the export demand shock.

Table 1: Impact of Chinese import competition on firm R&D

	log(R&D)					I(R&D)
	OLS	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{IMP}^{CN}_{k,t-1}$	-6.142***	-4.305***	-4.235***	-3.989***	-3.925**	-0.343**
	(1.623)	(1.088)	(1.094)	(1.069)	(1.568)	(0.14)
$\text{EXD}^{nEU}_{f,t-1}$			0.067***	0.064***	0.064***	0.005***
			(0.013)	(0.013)	(0.013)	(11663)
$\log(\text{Import}_{f,t-1})$	0.074***	0.075***	0.071***	0.070***	0.070***	0.006***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.001)
$\log(\text{Employment}_{f,t-1})$	0.245***	0.251***	0.236***	0.218***	0.218***	0.016***
	(0.089)	(0.082)	(0.080)	(0.078)	(0.077)	(0.007)
$\Delta \log(\text{Turnover}_{f,t-1})$	0.030	0.030	0.027	0.032	0.032	0.002
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.162	-0.153	-0.149	-0.166	-0.166	-0.015
	(0.149)	(0.151)	(0.150)	(0.149)	(0.149)	(0.013)
N Obs	28,966	28,966	28,966	28,966	28,966	28,966
Adj R2	0.412	0.414	0.415	0.416	-	-
First-stage F-stat	-	-	-	-	21.0	21.0
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓					
Sector-year FE		✓	✓	✓	✓	✓
Region-year FE				✓	✓	✓

Note: The dependent variable is either log R&D or an R&D dummy (I(R&D)). Columns 5 and 6 run 2SLS instrumenting for $\text{IMP}^{CN}_{k,t-1}$ only. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

is supportive of the complementarity hypothesis between imported inputs and R&D of Bøler, Moxnes and Ulltveit-Moe (2015).

At this stage, one may be interested in the relative importance of the two trade channels - import competition and export demand. I implement a simple quantification exercise of comparing the impacts of a one standard deviation increase of each trade shock. Based on the estimates from column 5, a one standard deviation increase in the exposure to Chinese competition is estimated to reduce UK firms' R&D expenditures by around 26 percent (=-3.925*0.067). Interestingly, a positive export demand shock of the same magnitude could more than compensate for the adverse impact of tougher competition: A one standard deviation rise in export demand boosts firms' R&D spending by about 55 percent (=0.064*8.609). Then, how large are these effects of trade-related shocks when compared to, for instance, firm size which is a key R&D determinant as documented in the literature? Note that a one standard deviation increase in firm size, measured by log employment, is associated with an increase in the R&D expenditure by about 31 percent (=0.218*1.402). It suggests that a change in the trade environment surrounding firms may exert an influence that is as large or even larger in absolute magnitudes than the firm size. And by comparison, when determining their R&D investment, firms are more responsive to the expansion of foreign markets than the shrinking share in their domestic market due to foreign competition.

Turning to other firm controls, sales growth and foreign ownership were not significant.

4.2 Chinese vs non-Chinese import competition

Is the rise of Chinese imports a unique competitive shock or does it simply reflect that overall foreign competition intensified over the last decades? To check this, I include a measure of import penetration from all other non-EU countries ($\text{IMP}_{k,t-1}^{non-CN}$) in combination with Chinese competition and compare their effects. Column 1 of table 2 reports an OLS result. Even after controlling for the contemporaneous changes in other non-Chinese imports, Chinese competition is found to significantly reduce firms' R&D investment. The estimate for non-Chinese import penetration, by contrast, is not different from zero. Column 2 runs 2SLS instrumenting for Chinese competition and the result is essentially the same. These imply that the drastic rise in Chinese imports, accelerated by its accession into the WTO in 2001, posed an unparalleled competitive threat to UK manufacturing firms, discouraging their innovation efforts. Further regressions with the R&D dummy as an outcome variable in columns 3 and 4 provide qualitatively similar results.

4.3 Accounting for firm's own imports from China

As previously noted, firms' own importing from China could separately affect the firms' innovations. For instance, a greater supply of cheaper Chinese intermediate inputs may improve profitability of firms, which in turn leads to investment in innovation. Alternatively, firms may choose to offshore labor-intensive parts of their production to China and put more resources into inventions of new high-tech products. Considering these possibilities, I check more explicitly whether the increased availability of Chinese imports by firms affected their R&D, independently of the import competition channel. To establish a casual impact, I build an instrument for firms' imports from China, again exploiting China's exports to other developed countries:

Table 2: Chinese vs non-Chinese competition

	log(R&D)		I(R&D)	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.271***	-4.326**	-0.385***	-0.365**
	(1.076)	(1.986)	(0.089)	(0.180)
$\text{IMP}^{non-CN}_{k,t-1}$	0.361	0.371	0.024	0.020
	(0.649)	(0.824)	(0.059)	(0.076)
$\text{EXD}^{nEU}_{f,t-1}$	0.064***	0.064***	0.005***	0.005***
	(0.013)	(0.013)	(0.001)	(0.001)
$\log(\text{Import}_{f,t-1})$	0.070***	0.070***	0.006***	0.006***
	(0.010)	(0.010)	(0.001)	(0.001)
N Obs	28,966	28,966	28,966	28,966
Adj R2	0.416	-	0.4677	-
First-stage F-stat	-	17.7	-	17.7
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: Columns 2 and 4 run 2SLS instrumenting for Chinese competition. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

$$\text{IV for } \log(\text{Import}^{CN}_{f,t}) = \textstyle\sum_p \psi^{CN}_{f,p} \log(\text{Export}^{CN\to D20}_{p,t})$$

where $\text{import}^{CN}_{f,t}$ denotes either firms' total import values from China or the number of HS 6-digit products imported from China (import variety). $\text{Export}^{CN\to D20}_{p,t}$ denotes China's exports of HS 6-digit product p to 20 advanced countries in year t. $\psi^{CN}_{f,p} = \frac{\text{Import}^{CN}_{f,p,2000}}{\sum_p \text{Import}^{CN}_{f,p,2000}}$ and $\text{Import}_{f,p,2000}$ is a UK firm f's average imports of product p from China over 1998-2000 (pre-sample period). Analogous to the instrument for Chinese competition, this firm-level instrument exploits the time variation in China's exports to 20 other advanced countries at the product level that are weighted by the share of product p in the UK firms' initial imports from China. I further include a binary indicator for firms' importing from other non-EU countries ($I(\text{Import}^{non-CN}_{f,t-1})$) to control for firms' importing statuses regardless of their imports from China.[27]

Column 1 in table 3 uses firms' import variety from China while column 2 uses firm's import values from China, each of which is instrumented for by the above-mentioned IV. For both measures, the firms' own importing from China does not have a significant impact on firms' R&D. By contrast, the Chinese competition – which is not instrumented for - remains negative and highly significant. Column 3 instruments for both Chinese competition and the firm's import values from China using the respective instruments. The impact of Chinese competition is essentially the same in magnitude and is significant at the 10% level while the coefficient for firms' own imports from China is again not different from zero.[28] These suggest that increased access to Chinese inputs, despite a possible cost-saving effect, did not lead firms to increase their R&D expenditure to offset the adverse impact of the competition channel.[29]

4.4 Firm heterogeneity

We thus far document that import competition from China significantly hinders R&D while export demand encourages it for average UK firms. One interesting pattern emerging from the prior literature is that the innovation response to trade shocks varies across firms according to their initial productivity. This section explores the potential heterogeneity in R&D responses to both import competition and export demand shocks. Similarly to Bustos (2011) and Bombardini, Li and Wang (2018), I split firms into four groups based on the two-year lagged labor productivity within the 2-digit sector by year cells. Labor productivity herein is measured by turnover per employee.[30] $\mathrm{H}_{f,t-2}$ or $\mathrm{L}_{f,t-2}$ is defined as a dummy equal to one if the firm is above the 75th percentile or below the 25th percentile according to its two-year lagged productivity, respectively. I add the interaction terms between the two trade shocks with these dummies as follows:

[27] Looking at the first-stage regressions in columns 2 and 3 of appendix table B2, the proposed instrument has a strong positive correlation with both firm's import variety and import values from China.

[28] One needs a caution that the instrument is not strong for the firm's import values from China according to the first-stage F-statistic. The problem gets even worse when instrumenting for both firm-level import values from China and Chinese competition. This would be partly because the two instruments rely on similar sources of time variation - China's exports to other advanced countries.

[29] The offshoring hypothesis would not be pertinent to the firms in this analysis as many of these firms are small and medium-sized and thus would not engage in a multi-stage production process, any part of which is to be delegated to foreign affiliates. Bloom, Draca and Van Reenen (2015) also show mixed evidence on the impact of a Chinese input supply shock such that it did not increase firm patenting while positively affecting firm TFP and IT adoption.

[30] It would be ideal to use value-added instead of turnover in measuring labor productivity. But since information on individual firms' value-added is not available, I use turnover as a proxy.

Table 3: IV estimation for firm-level imports from China

	log(R&D)			I(R&D)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{IMP}^{CN}_{k,t-1}$	-4.266***	-4.142***	-4.480*	-0.377***	-0.372***	-0.365*
	(1.380)	(1.310)	(2.427)	(0.113)	(0.103)	(0.208)
$\text{EXD}^{nEU}_{f,t-1}$	0.065***	0.060***	0.060***	0.005***	0.005***	0.005***
	(0.014)	(0.019)	(0.019)	(0.001)	(0.002)	(0.002)
$\log(\text{Import variety}^{CN}_{f,t-1})$	0.741			0.032		
	(1.848)			(0.159)		
$\log(\text{Import value}^{CN}_{f,t-1})$		0.227	0.225		0.010	0.010
		(0.558)	(0.553)		(0.048)	(0.047)
$I(\text{Import}^{non-CN}_{f,t-1})$	0.516***	0.463**	0.464**	0.045***	0.043**	0.043**
		(0.113)	(0.213)	(0.010)	(0.018)	(0.018)
N Obs	28,966	28,966	28,966	28,966	28,966	28,966
First-stage F-stat	9.6	4.5	2.3	9.6	4.5	2.3
Firm controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓	✓	✓

Note: Columns 1 and 2, and columns 4 and 5 instrument for firms' imports from China - either $\log(\text{Import variety}^{CN}_{f,t-1})$ or $\log(\text{Import value}^{CN}_{f,t-1})$ - only. Columns 3 and 6 instrument for both $\text{IMP}^{CN}_{k,t-1}$ and $\log(\text{Import value}^{CN}_{f,t-1})$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

$$
\begin{aligned}
\text{RnD}_{f(k),t} = \;& \beta_1 \text{IMP}^{CN}_{k,t-1} + \beta_2 \text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2} + \beta_3 \text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2} \\
& + \beta_4 \text{EXD}^{nEU}_{f,t-1} + \beta_5 \text{EXD}^{nEU}_{f,t-1} * \text{H}_{f,t-2} + \beta_6 \text{EXD}^{nEU}_{f,t-1} * \text{L}_{f,t-2} \\
& + \beta_7 \text{H}_{f,t-2} + \beta_8 \text{L}_{f,t-2} + \gamma \log(\text{Import}_{f,t-1}) + \text{Controls}_{f,t-1} \\
& + \alpha_f + \delta_{s,t} + \nu_{r,t} + \epsilon_{f,t}
\end{aligned}
$$

Columns 1 and 2 in table 4 report the results for log R&D and an R&D dummy, respectively.[31] There is no difference between more productive and less productive firms in their negative response to Chinese competition (the 2nd and 3rd rows). By contrast, I observe

[31] In the first-stage regressions, I use the interactions between the IV for Chinese competition and the productivity dummies ($\text{H}_{f,t-2}$ and $\text{L}_{f,t-2}$) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$ and $\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$.

strong heterogeneity in their response to a positive export demand shock (the 6th and 7th rows). Specifically, firms sitting in the top quarter of the labor productivity distribution increase their R&D expenditure by around 40 percent (=0.037/(0.037+0.057)) more than average firms in response to the export demand shock. This suggests that more productive firms are better poised to take advantage of an increased foreign market demand relative to less productive firms.

As another source of firm heterogeneity, I test whether the competition effect varies over a firm's initial export status:

$$\begin{aligned}\mathrm{RnD}_{f(k),t} = \;& \beta_1 \mathrm{IMP}^{CN}_{k,t-1} + \beta_2 \mathrm{IMP}^{CN}_{k,t-1} * \mathrm{E}_f + \beta_3 \mathrm{EXD}^{nEU}_{f,t-1} \\ & + \gamma \log(\mathrm{Import}_{f,t-1}) + \mathrm{Controls}_{f,t-1} + \alpha_f + \delta_{s,t} + \nu_{r,t} + \epsilon_{f,t}\end{aligned}$$

where E_f denotes a dummy equal to one if firms exported at least once during the initial period (1998-2000). Column 3 in table 4 shows that firms with a prior exporting experience are less hurt by Chinese competition. The interaction term with the initial exporting dummy (the 4th row) is positive and significant at the 10% level. Quantitatively, the adverse impact of Chinese competition on R&D diminishes by more than half (-2.044 = -7.227 + 5.183) for the initially exporting firms, compared to -7.227 for average firms (the 1st row). This could be because firms that had already entered into exporting were better able to reallocate their sales abroad in the face of tougher foreign competition in domestic markets. The coefficient for the interaction term in the R&D dummy regression (column 4) is marginally insignificant, which implies that the advantage of initial exporting is more relevant for adjusting the level of R&D rather than R&D participation.

Table 4: Firm heterogeneity (2SLS)

	log(R&D) (1)	I(R&D) (2)	log(R&D) (3)	I(R&D) (4)
$\text{IMP}^{CN}_{k,t-1}$	-3.652**	-0.339**	-7.227***	-0.553***
	(1.615)	(0.136)	(2.369)	(0.201)
$\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$	0.142	0.031		
	(2.069)	(0.180)		
$\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$	-0.598	0.013		
	(2.424)	(0.209)		
$\text{IMP}^{CN}_{k,t-1} * \text{E}_{f}$			5.183*	0.330
			(2.840)	(0.235)
$\text{EXD}^{nEU}_{f,t-1}$	0.057***	0.005***	0.059***	0.005***
	(0.014)	(0.001)	(0.013)	(0.001)
$\text{EXD}^{nEU} * \text{H}_{f,t-2}$	0.037***	0.003***		
	(0.011)	(0.001)		
$\text{EXD}^{nEU} * \text{L}_{f,t-2}$	-0.010	-0.001		
	(0.012)	(0.001)		
$\text{H}_{f,t-2}$	0.024	-0.001		
	(0.133)	(0.012)		
$\text{L}_{f,t-2}$	-0.066	-0.010		
	(0.148)	(0.013)		
$\log(\text{Import}_{f,t-1})$	0.068***	0.006***	0.070***	0.006***
	(0.010)	(0.001)	(0.010)	(0.001)
N of obs	28,966	28,966	28,966	28,966
First-stage F-stat	7.1	7.1	10.5	10.5
Firm controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: In the first-stage regressions for columns 1 and 2, I use the interactions between the IV for Chinese competition and the productivity dummies ($\text{H}_{f,t-2}$ and $\text{L}_{f,t-2}$) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$ and $\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$. Likewise, in the first-stages for columns 3 and 4, I use the interaction between the IV for Chinese competition and firms' initial exporting dummy (E_f) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{E}_f$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

4.5 Robustness

To assess the robustness of the previous results, I begin by examining the importance of firm size. Specifically, columns 1 and 2 of appendix table B4 run 2SLS excluding very small firms with employment of less than 10. And columns 3 and 4 run the same 2SLS dropping very large firms with employment of more than 500. All the results are very similar to the baseline result: The coefficient for Chinese competition is negative and significant while the coefficients for firms' own import and export demand are strongly positive. It suggests that our results are not driven by a group of firms of a certain size.

Next, I estimate via Poisson Pseudo-Maximum Likelihood (PPML) as an alternative empirical model.[32] Appendix table B5 reports the results that are qualitatively similar to those from the baseline regressions.[33] Column 1 does not instrument for Chinese competition. The estimate for Chinese competition is negative and significant at the 5% level, confirming the adverse impact on firm R&D. But its absolute size becomes smaller (-1.88) compared to the OLS counterpart (-3.989 in column 4 of table 1). The estimate for export demand, positive and highly significant, is similar to the OLS result (0.064 vs 0.055). Column 2 implements the control function approach that includes the residual from the first-stage regression of Chinese competition into the second-stage PPML estimation. The estimate for Chinese competition is almost the same in size and is still significant at the 10% level. But note that the coefficient of the first-stage residual is not significant (0.027 with standard error of 1.396), implying that the Chinese competition measure is exogenous and thus the instrumental variable may offer no improvement for consistency with the PPML estimator.

Finally, I attempt to generalize the findings on Chinese competition by using the alternative BSD-R&D sample, which is not combined with the firm-level trade dataset. Despite the drawback of not accounting for firm-level imports and exports, this approach facilitates estimation for a larger number of firms by using the *industry-level* import competition for more firms. Appendix table B6 reports the 2SLS results with 691 more firms included (4,107 → 4,798). The result confirms that Chinese competition significantly inhibited firm R&D. The estimate of -4.033 in column 1 is comparable to -3.925 from the benchmark sample. Column 2 tests potential heterogeneity across the firms' labor productivity. The coefficient of the interaction term for more productive firms (the 2nd row) becomes much greater, but is

[32] As Guceri and Liu (2019) adopted, PPML is known to yield a more consistent estimator in the log-linear specifications when the outcome variable is characterized by a highly skewed distribution with a massive number of zeros like R&D.

[33] Due to convergence issues, our PPML estimation does not allow for the stringent sector by year and region by year fixed effects. Instead, I control for firm and year fixed effects.

still marginally insignificant. Regressions using the R&D dummy in columns 3 and 4 provide similar results overall.

4.6 Comparison with the literature

Our finding on the stimulative role of export demand for R&D corroborates the evidence suggested in the previous literature. The heterogeneous effect of export demand in favour of more productive firms is also consistent with the recent findings in Aghion, Bergeaud, Lequien and Melitz (2018) on French firms.

Instead, the adverse impact of Chinese competition found in this paper, while in line with Autor et al. (2020), is at odds with Bloom, Draca and Van Reenen (2015). As Shu and Steinwender (2019) reviewed, empirical evidence remains divided over whether foreign competition encourages or discourages innovation. The difference from Bloom, Draca and Van Reenen (2015), among others, may be partly due to different types of firms considered.[34] Bloom, Draca and Van Reenen (2015) focus on the largest European firms whereas a great fraction of firms in this paper are small and medium sized. These smaller firms are likely to be more affected by the industry's exposure to import competition: In many cases, they would operate within a single industry and thus have little scope for diversification to spread out the competitive pressure.[35] Also noteworthy is the recent finding by Bloom, Romer, Terry and Van Reenen (2020) that even large European firms (the same firms used in Bloom, Draca and Van Reenen (2015)) experienced a significant decline in their sales growth facing Chinese competition, albeit increased patenting. The sales loss due to rising Chinese imports could have given much more pain to smaller firms since their R&D is likely to be more sensitive to cashflows unlike the large firms with more reserved resources. This could also explain why we do not observe a heterogeneous response to the competition shock across firm productivity unlike some previous studies.[36] In the context of the inverted U-shaped relationship between competition and innovation (Aghion et al. (2005)) - one theoretical model of heterogeneity, most firms in our analysis may not be technological leaders within their industries and

[34] It should also be noted that, while several papers use patenting as a measure of innovation, firm patenting may be geared up to protect their existing intellectual properties rather than new innovations. Firms might have a stronger incentive for this so called 'defensive patenting' in the face of increasing threats of imitation by Chinese competitors. For instance, Yamashita and Yamauchi (2020) finds that while Japanese firms increased patenting in the face of Chinese competition, the overall quality of the patents fell in terms of forward citations and the number of international patents. They argue that these findings are related to a defensive nature of patenting.

[35] As one interesting dimension of adjustment, Breinlich, Soderbery and Wright (2018) find that UK manufacturing firms shift their sales from goods to services in response to increasing import competition. And this goods-to-service adjustment takes place among large firms with a high initial R&D intensity.

[36] For instance, see Fernandes (2007), Iacovone (2012) and Bombardini, Li and Wang (2018) who find heterogeneous effects of import competition on firm productivity or patenting.

thus are located on the downward-sloping line of the inverted U-shaped relationship where increased competition stifles innovation.

5 Concluding remarks

How firm innovation is affected by trade shocks has been at the heart of the long-lasting debate on the consequence of globalization. Empirical evidence has been divided. Using administrative datasets for UK firms' R&D expenditure and their trade exposures, this paper thoroughly investigates the impacts of import competition and export demand on firms' R&D investment. I find a strong, detrimental effect of foreign competition ramped up by Chinese imports on UK firms' R&D investment. Increased export demand, by contrast, significantly boosts firm R&D. There is also evidence of heterogeneity in firms' R&D responses to each trade shock. First, exporting firms are less hurt by the rising competition from China. Second, firms with initially higher productivity levels respond more positively to the export demand shock. These findings together suggest that innovation by purely domestic and less profitable firms was most negatively affected by globalization, leading to a widening productivity gap across firms.

References

Aghion, Philippe, Antonin Bergeaud, Matthieu Lequien, and Marc J Melitz. 2018. "The Heterogeneous Impact of Market Size on Innovation: Evidence from French Firm-Level Exports." National Bureau of Economic Research Working Paper 24600.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: an Inverted-U Relationship." *The Quarterly Journal of Economics*, 120(2): 701–728.

Aghion, Philippe, Ufuk Akcigit, Antonin Bergeaud, Richard Blundell, and David Hemous. 2018. "Innovation and Top Income Inequality." *The Review of Economic Studies*, 86(1): 1–45.

Amiti, Mary, and Jozef Konings. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." *The American Economic Review*, 97(5).

Autor, David, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu. 2020. "Foreign Competition and Domestic Innovation: Evidence from US Patents." *American Economic Review: Insights*, 2(3): 357–74.

Berthou, Antoine, Jong-Hyun Chung, Kalina Manova, and Charlotte Sandoz. 2020. "Trade, Productivity and (Mis)allocation." IMF Working Paper 20/163, International Monetary Fund.

Bøler, Esther Ann, Andreas Moxnes, and Karen Helene Ulltveit-Moe. 2015. "R&D, International Sourcing, and the Joint Impact on Firm Performance." *The American Economic Review*, 105(12): 3704–39.

Bloom, Nicholas, Mirko Draca, and John Van Reenen. 2015. "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity." *The Review of Economic Studies*, 83(1): 87–117.

Bloom, Nicholas, Paul Romer, Stephen J Terry, and John Van Reenen. 2020. "Trapped Factors and China's Impact on Global Growth." *The Economic Journal*.

Bombardini, Matilde, Bingjing Li, and Ruoying Wang. 2018. "Import Competition and Innovation: Evidence from China." mimeo. https://www7.econ.hit-u.ac.jp/cces/trade_conference_2017/paper/matilde_bombardini.pdf.

Breinlich, Holger, Anson Soderbery, and Greg C. Wright. 2018. "From Selling Goods to Selling Services: Firm Responses to Trade Liberalization." *American Economic Journal: Economic Policy*, 10(4): 79–108.

Bustos, Paula. 2011. "Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of Mercosur on Argentinian Firms." *The American Economic Review*, 101(1): 304–40.

Coelli, Federica, Andreas Moxnes, and Karen Helene Ulltveit-Moe. forthcoming. "Better, Faster, Stronger: Global Innovation and Trade Liberalization." *The Review of Economics and Statistics*.

Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen. 2016. "Do tax Incentives for Research Increase Firm Innovation? An RD Design for R&D." National Bureau of Economic Research Working Paper 22405.

Fernandes, Ana M. 2007. "Trade policy, trade volumes and plant-level productivity in Colombian manufacturing industries." *Journal of International Economics*, 71(1): 52 – 71.

Fowkes, Rigmor Kringelholt, João Sousa, and Neil Duncan. 2015. "Evaluation of Research and Development Tax Credit." Her Majesty's Revenue and Customs Working Paper 17.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India." *The Quarterly Journal of Economics*, 125(4): 1727–1767.

Gray, Rowena, Giulia Montresor, and Greg C. Wright. 2020. "Processing immigration shocks: Firm responses on the innovation margin." *Journal of International Economics*, 126: 103345.

Guceri, Irem, and Li Liu. 2019. "Effectiveness of Fiscal Incentives for R&D: Quasi-experimental Evidence." *American Economic Journal: Economic Policy*, 11(1): 266–91.

Hombert, Johan, and Adrien Matray. 2018. "Can Innovation Help U.S. Manufacturing Firms Escape Import Competition from China?" *The Journal of Finance*, 73(5): 2003–2039.

Iacovone, Leonardo. 2012. "The better you are the stronger it makes you: Evidence on the asymmetric impact of liberalization." *Journal of Development Economics*, 99(2): 474 – 485.

Lileeva, Alla, and Daniel Trefler. 2010. "Improved Access to Foreign Markets Raises Plant-level Productivity…For Some Plants." *The Quarterly Journal of Economics*, 125(3): 1051–1099.

Lim, Kevin, Daniel Trefler, and Miaojie Yu. 2018. "Trade and Innovation: The Role of Scale and Competition Effects." Princeton University mimeo. https://ies.princeton.edu/wp-content/uploads/sites/2/2020/12/LTY_061118.pdf.

Mion, Giordano, and Mirabelle Muuls. 2015. "The impact of UKTI trade services on value of goods exported by supported firms." United Kingdom Trade and Investment (UKTI) Project Report.

Pavcnik, Nina. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *The Review of Economic Studies*, 69(1): 245–276.

Shu, Pian, and Claudia Steinwender. 2019. "The Impact of Trade Liberalization on Firm Productivity and Innovation." *Innovation Policy and the Economy*, 19: 39–68.

Topalova, Petia, and Amit Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." *The Review of Economics and Statistics*, 93(3): 995–1009.

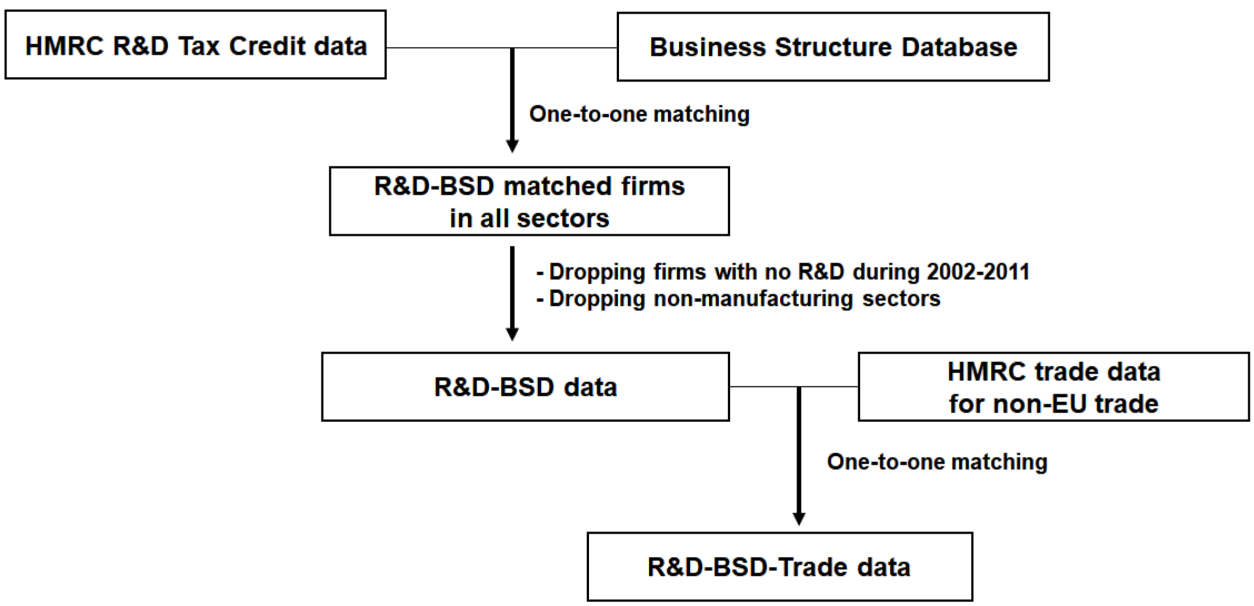
Xu, Rui, and Kaiji Gong. 2017. "Does Import Competition Induce R&D Reallocation? Evidence from the U.S." IMF Working Paper 17/253, International Monetary Fund.

Yamashita, Nobuaki, and Isamu Yamauchi. 2020. "Innovation responses of Japanese firms to Chinese import competition." *The World Economy*, 43(1): 60–80.

A Procedure for combining datasets

I combine the three administrative datasets using the look-up tables provided internally by HMRC Datalab across different firm identifiers.[37] One practical challenge is that a firm identifier in one dataset has many-to-many relationships with other identifiers from different datasets.[38] As the most conservative and transparent approach, I keep only a subset of firms whose identifiers are matched one-to-one with one another across datasets. This results in dropping some large firms with multiple identifiers in any of the datasets. I first merge the BSD and the R&D dataset for firms that are matched one-to-one between the two identifiers of each dataset. Among the matched pairs, I keep those in manufacturing sectors that reported non-zero R&D spending at least once between 2002 and 2011. I label the merged dataset up to this stage as 'BSD-R&D' dataset. Finally, I merge the BSD-R&D dataset with the trade dataset to construct the benchmark 'BSD-R&D-Trade' sample.

Figure A1: Flow of dataset construction

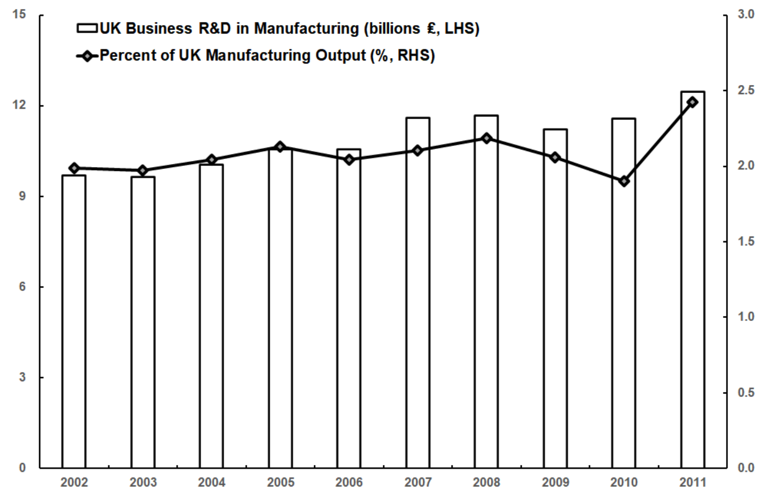


[37]The HMRC Datalab provides separate concordance tables for each pair of identifiers between the unique taxpayer reference number from the corporate tax dataset, enterprise reference number (Entref) from the BSD and value-added tax reference number (VRN). I first concord the Tradeid from the HMRC trade dataset into the VRN, which is then matched with the rest of the identifiers.

[38]As one notable example, firms' overseas transactions are reported at the value-added tax unit level, not at a consolidated national level. Large firms can also consist of multiple subsidiaries that each have own registration numbers. For these reasons, each identifier may have a many-to-many match with one another (Mion and Muuls (2015)).

B Further statistics and results

Figure B1: UK Business R&D in manufacturing sectors



Note: The aggregate manufacturing R&D statistics herein are based on the publicly released Business Enterprise Research and Development (BERD), which is different from the qualifying R&D expenditures for HMRC tax reliefs. The manufacturing output is the sum of the UK manufacturing firms' turnovers in the BSD. Source: Office for National Statistics (ONS) and ONS Business Structure Database (BSD).

Table B1: Descriptive Statistics

	BSD-R&D-Trade sample			BSD-R&D sample		
Variable	N	Mean	SD	N	Mean	SD
Turnover	33,958	7,671.6	68,291.5	39,736	8,850.7	67,584.3
Employment	33,958	52.1	239.9	397,36	59.3	235.8
Firm age	33,958	18.4	10.6	39,736	18.7	10.5
R&D expenditure	33,958	130.8	1204.4	39,736	160.9	1,802.6
R&D dummy	33,958	0.403	0.490	39,736	0.410	0.492
Non-EU import competition	33,958	0.114	0.138	39,736	0.111	0.133
Chinese import competition	33,958	0.027	0.067	39,736	0.026	0.064
Export to non-EU	33,958	1,418.6	13,300			
Import from non-EU	33,958	932.2	14,600			
Export dummy	33,958	0.653	0.475			
Import dummy	33,958	0.613	0.486			
Import from China	33,958	58.5	755.5			

Note: All variables are at the firm level except for non-EU and Chinese import competitions at the UK SIC 4-digit level. Turnover, R&D expenditure, exports and imports are in thousands of pounds sterling. Firm age is in years. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table B2: First-stage regressions

	$\text{IMP}^{CN}_{k,t-1}$ (1)	$\log(\text{import variety}^{CN}_{f,t-1})$ (2)	$\log(\text{import value}^{CN}_{f,t-1})$ (3)
IV for $\text{IMP}^{CN}_{k,t-1}$	0.031***		
	(0.007)		
IV for $\log(\text{import}^{CN}_{f,t-1})$		0.030***	0.098**
		(0.010)	(0.046)
N Obs	28,966	28,966	28,966
Other controls	✓	✓	✓
Firm FE	✓	✓	✓
Sector-year FE	✓	✓	✓
Region-year FE	✓	✓	✓

Note: Column 1 is the first-stage regression for column 5 of table 1. Columns 2 and 3 are the first-stage regressions for columns 1 and 2 of table 3, respectively. Each regression includes all other regressors in the second-stage regressions. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table B3: Using the industry-level measure of export demand

	log(R&D)		I(R&D)	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.057***	-3.995**	-0.371***	-0.347**
	(1.059)	(1.529)	(0.089)	(0.137)
EXD $\text{sic}^{nEU}_{k,t-1}$	-0.030	-0.030	-0.003	-0.003
	(0.022)	(0.022)	(0.002)	(0.002)
EXD $\text{sic}^{nEU}_{k,t-1} * \text{E}_f$	0.063***	0.063***	0.005***	0.005***
	(0.012)	(0.012)	(0.001)	(0.001)
log($\text{Import}_{f,t-1}$)	0.070***	0.070***	0.006***	0.006
	(0.010)	(0.010)	(0.001)	(0.001)
log($\text{Employment}_{f,t-1}$)	0.220***	0.220***	0.016**	0.016**
	(0.079)	(0.078)	(0.007)	(0.007)
Δ log($\text{Turnover}_{f,t-1}$)	0.032	0.032	0.002	0.002
	(0.064)	(0.064)	(0.005)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.171	-0.171	-0.015	-0.015
	(0.149)	(0.149)	(0.013)	(0.013)
	(0.117)	(0.117)	(0.010)	(0.010)
N Obs	28,966	28,966	28,966	28,966
adj R2	0.416	-	0.3716	-
First-stage F-stat	-	20.1	-	20.1
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: Columns 3 and 4 run 2SLS instrumenting for Chinese competition. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table B4: Robustness to firm size (2SLS)

	Employment>10		Employment<500	
	log(R&D)	I(R&D)	log(R&D)	I(R&D)
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.630**	-0.378**	-4.051**	-0.350**
	(2.114)	(0.180)	(1.579)	(0.141)
$\text{EXD}^{nEU}_{f,t-1}$	0.063***	0.005***	0.063***	0.005***
	(0.022)	(0.002)	(0.013)	(0.001)
$\log(\text{Import}_{f,t-1})$	0.074***	0.006***	0.069***	0.006***
	(0.012)	(0.001)	(0.010)	(0.001)
$\log(\text{Employment}_{f,t-1})$	0.083	0.002	0.222***	0.016**
	(0.141)	(0.012)	(0.078)	(0.007)
$\Delta\log(\text{Turnover}_{f,t-1})$	0.070	0.004	0.029	0.002
	(0.100)	(0.008)	(0.063)	(0.005)
$\text{Foreign}_{f,t-1}$	-0.134	-0.012	-0.142	-0.013
	(0.162)	(0.014)	(0.155)	(0.014)
N Obs	20,464	20,464	28,635	28,635
First-stage F-stat	28.8	28.8	20.8	20.8
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: All columns run 2SLS instrumenting for Chinese competition. Columns 1 and 2 are from the sub-sample for firms with employment of more than 10 and columns 3 and 4 are for firms with employment of less than 500. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table B5: Poisson Pseudo-ML estimation

	no-IV	IV
	(1)	(2)
$\text{IMP}^{CN}_{k,t-1}$	-1.887**	-1.896*
	(0.781)	(1.044)
$\text{EXD}^{nEU}_{f,t-1}$	0.055***	0.055***
	(0.015)	(0.015)
$\log(\text{Import}_{f,t-1})$	0.029***	0.029***
	(0.007)	(0.007)
$\log(\text{Employment}_{f,t-1})$	0.091	0.091
	(0.063)	(0.063)
$\Delta \log(\text{Turnover}_{f,t-1})$	-0.010	-0.010
	(0.035)	(0.035)
$\text{Foreign}_{f,t-1}$	-0.056	-0.056
	(0.116)	(0.115)
N Obs	28,966	28,966
1st-stage residual	-	0.027
		(1.396)
Firm FE	✓	✓
Year FE	✓	✓

Note: Column 2 implements the control function approach of adding the residual from the first-stage regression for Chinese competition as an additional regressor in the second-stage Poisson estimation. Robust standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.

Table B6: Estimation from the larger BSD-R&D sample (2SLS)

	log(R&D)		I(R&D)	
	(1)	(2)	(3)	(4)
$\text{IMP}^{CN}_{k,t-1}$	-4.033**	-4.461***	-0.348**	-0.399***
	(1.57)	(1.604)	(0.140)	(0.134)
$\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$		2.715		0.241
		(2.227)		(0.187)
$\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$		-0.353		0.027
		(2.347)		(0.203)
$\text{H}_{f,t-2}$		0.198*		0.014
		(0.107)		(0.009)
$\text{L}_{f,t-2}$		-0.155		-0.016
		(0.120)		(0.010)
$\log(\text{Employment}_{f,t-1})$	0.247***	0.263***	0.018***	0.02***
	(0.064)	(0.066)	(0.005)	(0.005)
$\Delta \log(\text{Turnover}_{f,t-1})$	0.067	0.114*	0.004	0.008
	(0.063)	(0.067)	(0.005)	(0.006)
$\text{Foreign}_{f,t-1}$	-0.152	-0.151	-0.014	-0.014
	(0.139)	(0.139)	(0.012)	(0.012)
N of obs	33,993	33,993	33,993	33,993
First-stage F-stat	24.0	8.0	24.0	8.0
Firm FE	✓	✓	✓	✓
Sector-year FE	✓	✓	✓	✓
Region-year FE	✓	✓	✓	✓

Note: This table is based on the BSD-R&D dataset - not combined with the firm-level trade dataset. In the first-stage regressions for columns 2 and 4, I use the interactions between the IV for Chinese competition and the productivity dummies ($\text{H}_{f,t-2}$ and $\text{L}_{f,t-2}$) as the instruments for $\text{IMP}^{CN}_{k,t-1} * \text{H}_{f,t-2}$ and $\text{IMP}^{CN}_{k,t-1} * \text{L}_{f,t-2}$. Standard errors are clustered by UK SIC 4-digit industry. Significance: *** p<0.01, ** p<0.05, * p<0.1. Data source: HMRC Overseas Trade in Goods Statistics, HMRC R&D Tax Credit Dataset and ONS Business Structure Database.