TRADE INDUCED TECHNOLOGICAL CHANGE: DID CHINESE COMPETITION REALLY INCREASE EUROPEAN INNOVATION?

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Trade Induced Technological Change: Did Chinese Competition Really Increase European Innovation?[†]

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Abstract

Bloom, Draca, and Van Reenen (2016) find that Chinese competition induced a rise in patenting, IT adoption, and TFP by up to 30% of the total increase in Europe in the early 2000s. Yet average patents per firm fell by 94% for the most China-competing firms in their sample, but also by 94% for non-competing firms. Their findings for patents appear to be driven by the decision to normalize patents by adding one (*i.e.*, patents+1). Since China-competing firms had fewer patents to begin with, adding one induces bias, making it appear as though patents declined by a smaller percentage in the China-competing sectors. When we estimate a negative binomial regression using patents as the dependent variable, correcting several coding errors, we find no (or even negative) correlation between Chinese competition and patent growth.

JEL Classification: F14, F13, L25, L60
Keywords: Patents, China, Europe, Textiles, Trade Shocks, Manufacturing

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1 Introduction

The rise of Chinese import competition in advanced markets is one of the transformative events of the past 30 years of economic history. A major question is thus what the impact of this event has been on innovation. In a recent influential contribution, Bloom et al. (2016, hereafter BDV) find that increased Chinese import competition in Europe in the early 2000s stimulated growth in patenting, IT, and TFP up to 30%. This is a remarkable finding that appears to contradict Autor et al. (forthcoming), who find a negative impact of Chinese competition on US patents. To the best of our knowledge, the discrepancy between these results has not yet been submitted to further scrutiny.[1]

The goal of this paper is to assess whether BDV's seminal finding that the rise of Chinese competition fostered a large rise in patenting across Europe is robust. BDV adopt an intuitive difference-in-difference strategy, comparing patenting in European firms in sectors which were more or less exposed to Chinese competition before and after China joined the WTO and imports rose sharply. While this is a reasonable approach in theory, several aspects of the implementation call their conclusions into question.

First, a simple standard event study diagram including pre-treatment trends shows that their patent data exhibits extreme tapering. Instead of concluding that that Chinese competition fosters patenting, what they really find is that firms in China-competing sectors had a slower collapse in patenting. However, the event study diagrams immediately raise the question of whether the tapering might be in fact driving this result. Why? The reason is that BDV normalize their patent data, which contains many zeros, by adding one and then taking the log (*e.g.*, log(1+Patents)), a solution which is often problematic but particularly so in this instance. The bias induced by this normalization disappears as patents grow large, and the China-competing sectors happened to have had fewer patents to begin with, implying a larger bias. Lastly, BDV adopt a negative binomial regression, in which normalizing patents is not necessary, as a robustness check. However, they make three coding errors on implementation, including continuing to normalize patents by adding one, inducing the same bias. When fixed, the impact of Chinese competition on patents in the regression BDV intended to run is still highly significant, but with the opposite sign. Including sectoral FEs then renders the negative apparent impact of Chinese competition on patents insignificant. We conclude that

1. Intuitively, opposite signs in the estimated effects of competition intensity on patenting could suggest the existence of strong non-linearties, but could also indicate inconsistencies in the empirical approach between the two studies. Non-linearities, however, are also possible as illustrated in a formal model by Aghion et al. (2005), where moderate levels of competition encourage innovation while high levels of competition (after passing a certain threshold) discourage innovation. Yet, levels of Chinese market penetration do not appear to be so different between Europe and the US (see Figure A1).

BDV's optimistic findings on the positive impact of Chinese competition on patents are not robust.

Our findings contribute to the recent literature on the impact of increasing low-wage competition on innovation. Autor et al. (forthcoming) and Hombert and Matray (2018) find a negative impact of increased Chinese competition on patenting in the US and Kueng et al. (2016) find a negative effect of Chinese competition on process innovations in Canada. Our findings for European countries are similar with Xu and Gong (2017), who find no impact of China on R&D in the US. Our paper also contributes to the literature highlighting the importance of replication in applied empirical research, as we show that even in the case of a well-cited, seminal paper, mistakes can be made.[2]

Next we briefly describe the data, present an event-study diagram with pre-treatment trends, show how the tapering and normalization combine to induce bias, and then implement BDV's negative binomial regression with the coding errors corrected.

2 Patent Data & the Bias of Adding One

2.1 Data Description

We use BDV's data. The firm-level variables for 12 European countries mostly come from Bureau Van Dijk's Amadeus, and are then matched to UN Comtrade trade data at the 4-digit level using Pierce and Schott (2012)'s trade data concordance.[3] Other sector-level variables come from Eurostat's Prodcom database. In Figure A2, we plot the number of firms over time in this highly unbalanced sample, and the shrinking number of total recorded patents in the data.

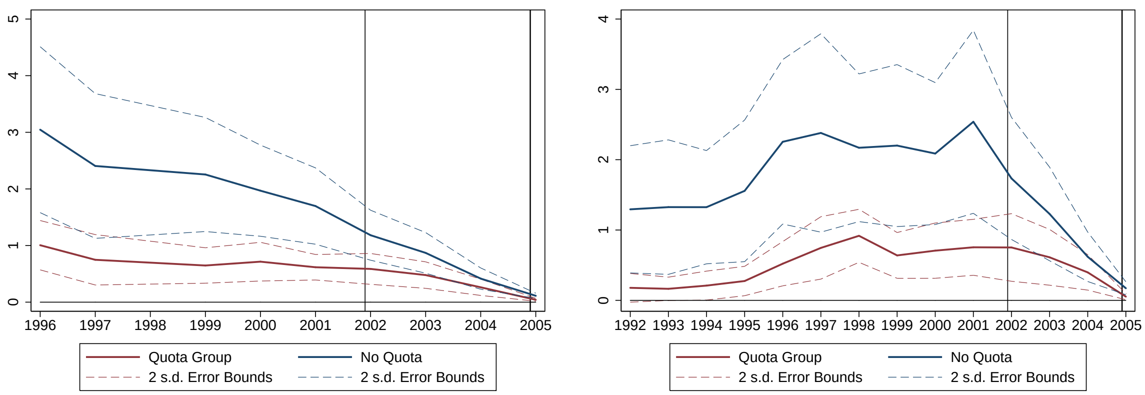
2.2 Difference-in-Difference Diagram

To start, in Figure 1, we present a standard difference-in-difference event study diagram for two of the main data samples used by BDV (the baseline sample, and a longer one). BDV used the removal of textile quotas upon China's WTO entry as a proxy or IV for intensifying competition in some of their specifications. These quotas were originally imposed under the Multifibre Arrangement (MFA) and subsequently removed for

2. For example, the paper has 1,120 citations on google scholar at the time of writing, and featured prominently in a seminar on innovation by Harvard professor Philippe Aghion at the New Economic School in June, 2018.

3. Their data is available here: http://www.stanford.edu/ nbloom/TITC.zip. The countries in the sample are Austria, Denmark, Finland, France, Germany, Ireland, Italy, Norway, Spain, Sweden, Switzerland, and the UK.

WTO members since 1995 in line with the Agreement on Textile and Clothing (ATC). We compare the evolution of patents in textile sectors in which the quotas on Chinese imports were most binding before removal (and thus, the sectors in which Chinese imports increased the most following removal), and compare to sectors in which the quotas did not bind (and thus the removal of quotas mattered less). In Panel (a), the overall decline in patenting is 95.8% for the China-competing group, vs. 96.2% for the control group. There is also a troubling difference in the pre-treatment trends between treatment and control which would be washed out, along with any apparent impact of Chinese competition on patents, by the inclusion of sectoral fixed effects.



(a) Baseline Panel

(b) Long Panel

Figure 1: Avg. Patents by Firm, Textile Sector: Sectors with Quota vs. Others

Notes: The red solid line shows the average patents over time in China-competing textile sectors (firms in sectors which faced textile quotas before they were relaxed and removed), with two standard deviation error bounds (the red dashed lines; computed by regressing patents per firm on a constant for each year). The blue lines show the evolution of average patents for Textile firms in the "No quota" group. The first black vertical line denotes China's accession to the WTO, and the second one shows when the final quotas were removed.

BDV use the long panel to show that their results are in fact robust to controls for sectoral and even firm-level trends. However, the same tapering is present in Panel (b), as patents in the China-competing sectors (red line) also converge toward zero in the period when Chinese competition was purported to have systematically increased innovation in Europe. From 2000 to 2005, the raw percentage decline in both the China-competing and non-competing groups is the same. Including firm-level trends in this case would not necessarily render the results insignificant in the case in which textile quotas are used as a proxy variable for Chinese imports, although it happens that in this case there is no correlation between Chinese imports and patents to begin with (see the Online Appendix).

2.3 The Bias of Adding One

If there are similar percentage declines in patents in the treatment and control groups, why do BDV find a large and significant impact of Chinese competition? The reason is that their results are biased due to: (1) the extreme tapering of the patent data, (2) the decision to normalize patents by adding one, and (3) the differential levels of patents in the China-competing sectors and non-competing sectors. To fix ideas, in Table 1, Panel A, we show that in the baseline sample, average patents per firm actually fell by 94% for the most China-competing firms from 2000 to 2005, but also by 94% for non-competing firms. However, if we first normalize patents by adding one, and then compute the percentage change, we arrive at a 39% decline for the China-competing firms vs. 63% decline for other firms. This difference is merely an artifact of the normalization. In Panel B, it can be seen that the same sleight-of-hand induces bias in the longer sample as well.

Table 1: The Bias of Adding One: Patents-per-Firm

Sample	Measure	Avg. Patents per Firm, 2000	Avg. Patents per Firm, 2005	% Change
Panel A: Baseline Sample				
China-Competing Firms (Quotas Bind)	Patents	0.72	0.042	-94%
	Patents + 1	1.72	1.042	**-39%**
Other Firms (Quotas not binding)	Patents	1.97	0.11	-94%
	Patents + 1	2.97	1.11	**-63%**
Panel B: Long Sample				
China-Competing Firms (Quotas Bind)	Patents	0.71	0.053	-92%
	Patents + 1	1.71	1.053	**-38%**
Other Firms (Quotas not binding)	Patents	2.09	0.17	-92%
	Patents + 1	3.09	1.17	**-62%**

Notes: We compare the % decline in patents between 2000 and 2005, the period in the sample when Chinese competition increases the most, using two different measures: average patents per firm, and average patents per firm plus one, the measure used by BDV. Panel A includes data for BDV's short data set; Panel B uses data from BDV's long data panel.

3 Negative Binomial Regressions

The main empirical strategy BDV employ uses the log of one plus patents as the dependent variable. They use this specification because there are many zero observations in patents, and so a linear regression with log-transformed variables becomes problematic as all zero observations would be lost. Since the influential contributions of Santos-Silva and Tenreyro (2006); 2011, however, this practice has been proven to be no less problematic. Thus, applied empirical research has moved to employing non-linear estimators, at least for robustness checks.[4] Since the bias from adding one is particularly pernicious in this setting as discussed (see Figure 1 and Table 1), we focus on the one set of regressions in BDV in which a normalization is not necessary. This is when BDV run negative binomial regressions, which have have long been the empirical workhorse model in this literature (Hausman et al. (1984)).

They attempt to estimate the following panel regression:

$$PAT_{ijkt} = exp[\alpha IMP^{CHN}_{jkt} + x'_{ikj0}\beta + f_{kt}] + \nu_{ijkt}, \tag{3.1}$$

where IMP^{CHN}_{jkt} are imports from China in sector j in country k at time t, x'_{ikj0} denotes a vector of two controls – initial pre-sample patents and a dummy for zero patents (these are meant to approximate firm FEs due to the incidental parameters problem), and f_{kt} are country*year interactive fixed effects. This (highly unbalanced) panel is then estimated by BDV over the period 1996 to 2005 using annual data. However, when they implement this regression, they appear to have made three coding errors (1) they continued to use one plus patents as their dependent variable, (2) they mistakenly replaced the country*year interactive FEs with separate year and country dummies, and (3) they inadvertently included 4-digit SIC FEs. Thus, we correct these errors one by one. We add that we did not find other coding errors in the paper.[5]

Our results showing the impact of Chinese competition on patents are presented in Table 2. In the first column we replicate BDV's Table 7, column (3), which estimates a negative binomial regression inadvertently using patents plus one as the dependent variable, and contains the other errors as mentioned above. Thus, in column (2) we run the same regression using the actual level of patents (without adding one). When we do so, the sign flips, although the coefficient on Chinese imports is not significant. When we also include country*year FEs, as mentioned in their table notes but not included

4. Despite its great influence in the empirical literature, normalization by adding an arbitrary positive constant appears to be still widely used. Bellego and Pape (2019) show that normalizing by adding one or any other arbitrarily small positive number to a zero observation may result in similarly severe-biased estimates, which further rejects the appropriateness of this strategy.

5. That said, in the long panel (BDV Table 3), we did find there is no relationship between Chinese imports and patent growth to begin with, even using their log of patents plus one setup (they only report results using a proxy for Chinese competition). BDV also censor their observations; uncensoring them reduces significance below threshold levels in some cases, as does using alternative normalizations (see our online appendix).

in the actual regression, we find that the results are now positive, albeit not significant. BDV had argued that these fixed effects are necessary to control for country-specific macroeconomic shocks. In column (4), when we also exclude the 4-digit SIC FEs, which are not mentioned as being in BDV's Table 7, the sign flips to being negative, larger in magnitude than the original coefficient, and significant. Column (4) is the regression that BDV intended to run. A good case could be made, however, that controlling for sectoral FEs is necessary in this context. On the other hand, note that if BDV had controlled for 4-digit FEs in their benchmark Table 1 regressions, none of the results with patents or IT would have survived. These results show that the positive relationship between Chinese imports and patents is fragile at best.

Table 2: The Impact of Chinese Competition on Patent Growth

	(1) l+Patents	(2) Patents	(3) Patents	(4) Patents
Chinese Imports	0.40**	-0.15	0.12	-0.73**
	(0.17)	(0.47)	(0.49)	(0.34)
Notes	Neg.Bin.	Neg.Bin.	Neg.Bin	Neg.Bin.
Fixed Effects	No Cty*Yr	No Cty*Yr	Cty*Yr	Cty*Yr
Sector FEs	SIC4	SIC4	SIC4	No SIC4
Observations	74038	74038	74038	74038

*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, with errors clustered at the country*4-digit SIC level . The dep. var. is patents plus one in column (1) (BVD's specification) and simply patents in columns (2-4). These are negative binomial regressions using annual data in levels (not changes). The fixed effects and whether the regression is an IV or not is listed in the notes at the bottom of each panel. Column 1 is an exact replication of BDV Table 7, Column (3).

4 Conclusion

BDV find that Chinese competition may have caused a dramatic 30% increase in patent growth over the period 1996-2005, thus exacerbating the puzzle of the slowdown in European growth over this time. Yet, we show that the dramatic decline in patents (in their data) was similar for both China-competing and non-competing sectors. We find that BDV's results are an artifact of the confluence of three factors: (i) the severe tapering of the patent data, as patents-per-firm decline for all firms at the end of the sample, (ii) the lower initial level of patents per firm in the China-competing sectors, and (iii) the decision to normalize the patent data by adding one (*i.e.*, patents+1), even when implementing a negative binomial regression. Fixing the coding errors renders the results insignificant, or even flips the sign. Our conclusion is that the oft-cited optimistic conclusion that Chinese competition increases innovation appears to be fragile.

We believe our research also points to the importance of data-dissemination in applied empirical economics research encouraging replication in economics.

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A Appendix

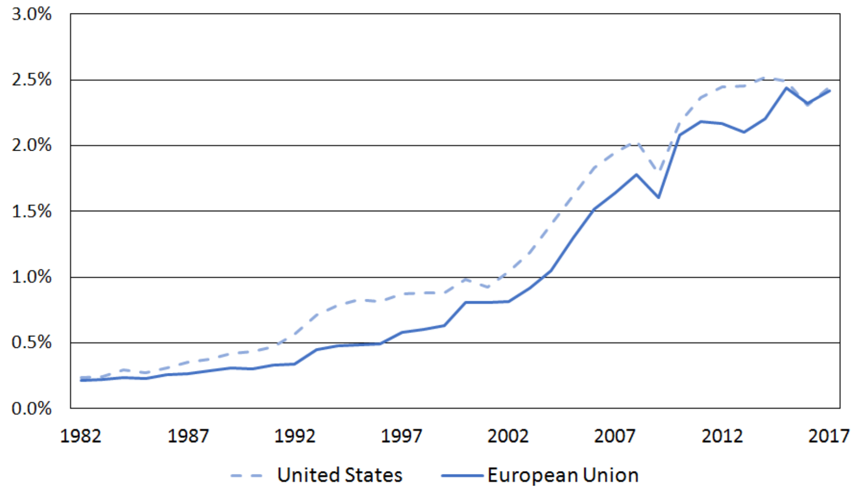

Figure A1: Chinese Imports as a Share of GDP

Notes: This is a graph of total imports from China as a share of GDP in the US vs. Europe. Through 2007, Chinese import intensity was higher in the US, but since then, the gap has closed.

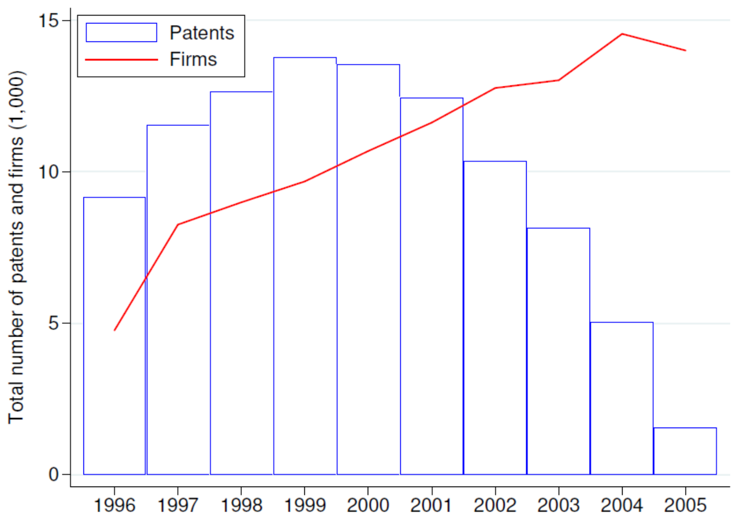

Figure A2: Total Firms and Patents

Notes: These graphs display the total number of firms (left axis), the total number of patents (left axis), and the average patents per firm for all sectors in panel (a) and for Textile sectors in panel (b).