DISCUSSION PAPER SERIES

DP17960

THE TRANSMISSION OF SECTORAL SHOCKS ACROSS THE INNOVATION NETWORK

Christian Fons-Rosen and Zhaoxin Pu

ORGANIZATIONAL ECONOMICS

CEPR

ISSN 0265-8003

THE TRANSMISSION OF SECTORAL SHOCKS ACROSS THE INNOVATION NETWORK

Christian Fons-Rosen and Zhaoxin Pu

Discussion Paper DP17960
Published 06 March 2023
Submitted 06 March 2023

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

THE TRANSMISSION OF SECTORAL SHOCKS ACROSS THE INNOVATION NETWORK

Abstract

We use a firm-level panel of 13 European countries to assess how a sector-specific shock propagates through technological linkages across innovating firms in the rest of the economy. We find that the competition shock to the European textile sector, induced by the 2001 removal of import quotas on Chinese textiles, had a strong negative effect on non-textile firms' patenting and knowledge sourcing. These firms end up diversifying their patenting across more technological categories and start citing more (geographically and technologically) distant sources of knowledge. When aggregating data at the country level, the negative indirect effect on patenting of non-textile firms can be 3 to 5 times as large as the positive direct effect on textile firms.

JEL Classification: D57, L25, L60, O33, O38

Keywords:

Christian Fons-Rosen - cfons-rosen@ucmerced.edu
University Of California, Merced and CEPR

Zhaoxin Pu - zhaoxin.pu@alumni.ip.mpg.de
DataGuard, Munich

The Transmission of Sectoral Shocks Across the Innovation Network *

Christian Fons-Rosen† Zhaoxin Pu‡

First draft: November 2019; This version: March 6, 2023

ABSTRACT

We use a firm-level panel of 13 European countries to assess how a sector-specific shock propagates through technological linkages across innovating firms in the rest of the economy. We find that the competition shock to the European textile sector, induced by the 2001 removal of import quotas on Chinese textiles, had a strong negative effect on non-textile firms' patenting and knowledge sourcing. These firms end up diversifying their patenting across more technological categories and start citing more (geographically and technologically) distant sources of knowledge. When aggregating data at the country level, the negative indirect effect on patenting of non-textile firms can be 3 to 5 times as large as the positive direct effect on textile firms.

KEYWORDS: technological linkages, spillovers, patents, industrial policy
JEL Classification: D57, L25, L60, O33, O38

*We thank Pere Arque-Castells, Ben Faber, Lisandra Flach, David Heller and Adrien Matray for their very helpful comments. We also thank participants at the CREI Workshop 2017 at the University of Bath, the IO and Trade Seminar 2018 at the LMU Munich, the MPI Junior Researcher Workshop "From Science to Innovation" 2018, the TUM Workshop "Innovation, Technological Change, and International Trade" 2019 and the UC Berkeley International Economics Brown Bag 2019 for valuable comments. We thank Henning Deist and Christopher Schwarting for excellent research assistance. Zhaoxin Pu gratefully acknowledges financial support by Deutsche Forschungsgemeinschaft through CRC TRR 190 (project number 280092119) and Elite Network of Bavaria through the 'Evidence-Based Economics' Doctoral Program.

†University of California in Merced, CEPR & Max Planck Institute for Innovation and Competition in Munich, 5200 North Lake Rd. Merced, CA 95343, United States, cfons-rosen@ucmerced.edu.

‡DataGuard, Munich, zhaoxin.pu@alumni.ip.mpg.de.

1 Introduction

Recent innovation literature has documented the benefits of cross-disciplinary research when ideas are recombined across fields[1] or when inventors with diverse academic backgrounds collaborate[2]. As an illustration, fiber optics technology benefited greatly from the recombination of ideas across industries. In the 1960s, the British Post office approached Corning, a leader in glass manufacturing, to explore whether optical glass fiber could be used for light-transmission in telecommunications. Despite having no prior experience in the telecommunications sector, Corning soon invented the first low-loss optical fiber, which paved the way for long-distance optical communication.[3]

Governments and science funding bodies worldwide acknowledge the importance of an integrative approach in tackling challenges through innovation, explicitly supporting interdisciplinary collaboration. The US defense agency DARPA is a prominent case - funding the first materials-focused interdisciplinary laboratories in the late 1960s and having recently launched a social media platform aimed at facilitating the cross-pollination of ideas between industry and academia.[4] In spite of this evidence, policy evaluation typically focuses only on the direct effects of sector-specific policies, thereby missing possibly sizeable indirect spillover effects across the rest of the economy.

In this paper we ask the following question: when a particular industry changes its innovation strategy in response to an industry-specific competition shock (*direct effect*), how does this effect propagate across the network of innovating firms through technological linkages (*indirect effect*)? As a quasi-natural experiment, we use the 2001 removal of import quotas on textiles following China's accession to the WTO as a shock to the European textile and clothing sector.

We study how patenting decisions by non-textile firms adjust to the changes experienced by the textile industry after the competition shock. We use balance sheet information for a panel of 45,012 European non-textile patenting firms in 13 countries after combining Bureau Van Dijk's ORBIS and Amadeus data sets. Detailed patent information (filings, citations, technology classes) comes from matching the European Patent Office's PATSTAT database to our firm sample, which allows us to calculate firm-pair (dyadic) technological distances.

[1] See e.g., Acemoglu, Akcigit, and Kerr (2016), Uzzi et al. (2013), Jones (2009), Weitzman (1998).

[2] See e.g., Adams et al. (2005), Jones, Wuchty, and Uzzi (2008), Gruber, Harhoff, and Hoisl (2013).

[3] See Cattani (2006) for more details on Corning and the development of optical glass fiber.

[4] See e.g., `https://www.darpa.mil/news-events/2015-08-14` or `https://www.darpa.mil/news-events/2019-03-19`. The German Fraunhofer-Gesellschaft is another example. Instead of being organized by scientific disciplines, its research portfolio is centered on issue-oriented questions that follow an interdisciplinary approach, such as health, security, mobility or communication. `https://www.fraunhofer.de/en/about-fraunhofer/profile-structure.html`. Web links last accessed on March 6, 2023.

Our results can be summarized as follows. In terms of the *direct effect*, the average textile firm experiences a 4% increase in patenting in response to the competition shock, such that a greater quota reduction leads to larger increases in patenting activity (aligned with the finding in Bloom, Draca, and Van Reenen, 2016). However, a more complex pattern emerges once we split textile firms by their technological proximity to the rest of the economy. For textile firms with *distant* technological ties to non-textile firms we replicate the baseline result. By contrast, for textile firms with *close* technological ties to non-textile firms we rather find a negative and significant coefficient, meaning that this subset of textile firms *reduces* the number of patents generated.

Highlighting this heterogeneity in the *direct effect* is critical for this paper, as our main goal is to evaluate how patenting adjustments in textile firms trickle down to firms in the rest of the economy through dyadic technological linkages. Textile firms suffering the largest drop in patenting activity are also those with stronger technological ties to firms in the rest of the economy.

In terms of *indirect effects*, the average non-textile firm reduces patenting by 4% of a standard deviation after the textile industry reduces its patenting by one standard deviation in an OLS estimation. When we instrument textile patenting changes by the Chinese quota shock, the economic magnitude remains stable.

These non-textile firms reduce their innovation activity in textile-intensive technology classes and diversify patenting across a wider set of technology classes. Furthermore, they adjust their knowledge sourcing as they cite fewer textile patents and start searching for new sources of knowledge in more distant geographical and technological spaces. This result is consistent with the finding by Hombert and Matray (2018) where U.S. firms with large R&D stocks escape Chinese import competition by increasing their product diversification.

Furthermore, these non-textile firms react twice as strongly to reductions in patenting by textile firms located in the same country and results are robust to accounting for industrial input-output relationships; similar findings are obtained for quality-adjusted patent counts.

When aggregating the data at the SIC 4-digit industry level, the economic magnitude of the effect doubles, which is aligned with the fact that larger non-textile firms experience the bulk of the impact and are given more weight in these aggregated regressions.

In a final exercise, we aggregate the data at the country level. At the median European country, the negative indirect effect on non-textile firms is 3 times larger than the positive effect on textile firms.

Related Literature

Our paper contributes to several literature strands. First, in the literature on *direct effects* of competition shocks on innovation, Bloom, Draca, and Van Reenen (2016) explore China's opening up to globalization and find a positive effect on innovation by European textile firms. By contrast, Dorn et al. (2020) find a negative effect on U.S. firms across a large variety of sectors. Aghion et al. (2005)'s finding that competition and innovation have an inverted-U relationship can help reconciling these differing results, since the U.S. is understood to be a corporate environment with a higher degree of sectoral competition compared to Europe. We contribute to this literature by highlighting the magnitude of the *indirect effect* across the rest of the economy once technological linkages are carefully accounted for.

For papers looking at total factor productivity as the outcome variable instead of patenting, Pavcnik (2002) uses Chilean data to estimate the direct effect of import competition on productivity and Amiti and Konings (2007) undertake a related exercise in Indonesia. Papers that incorporate the innovation dimension but rather look at the effects of exports include Bustos (2011) using Argentinean data and Aw, Roberts, and Xu (2011) using Taiwanese data. Cai, Li, and Santacreu (2022) develop a theoretical model of trade, innovation and knowledge diffusion to study the role of country and sector heterogeneity on aggregate R&D and welfare. For an extensive literature review on the general relationship between trade liberalization and innovation, we refer to Shu and Steinwender (2019).

Second, our paper contributes to the technology spillovers literature. In particular, our study relates to Bloom, Schankerman, and Van Reenen (2013) who develop an empirical methodology to identify the separate effects of technology and product market spillovers. Using a panel of U.S. firms, they find that positive technology spillovers dominate negative business stealing effects. In subsequent work, Lychagin et al. (2016) add a geographical component to this discussion. Matray (2021) finds that exogenous shocks to innovation by listed firms affect innovation by private firms in the same geographical area due to inventor mobility and learning across firms, whereby these spillovers diminish rapidly with distance. Zacchia (2019) constructs a network of companies and causally shows that individual relationships between inventors of different companies drive knowledge spillovers between firms. We relate to Bloom, Schankerman, and Van Reenen (2013)'s notion of technological linkages and advance this literature by comparing the magnitudes of direct and indirect effects of a sector-specific policy shock on innovation.

Schnitzer and Watzinger (2022) show that venture capital investment in start-ups increases innovation of established companies in technologically related fields due to knowledge spillovers. Moretti, Steinwender, and Van Reenen (2020) uncover both national and international within-industry spillovers from government-funded R&D to private sector R&D. In a regression discontinuity design, Dechezleprêtre et al. (2016) find that patenting spillovers from R&D tax subsidies persist up to seven years for technologically close peer firms. Our empirical strategy allows us not only to gauge the average firm-level response, but also to quantify the relative importance of the indirect effects at the industry and country level.

In a different context, Myers and Lanahan (2022) also find that the indirect effect is quantitatively more important than the direct effect. Using grants awarded to small firms from the U.S. Department of Energy, their estimates suggest that for every patent produced by grant recipients, three additional patents are produced by others who benefit from geographical or technological spillovers. In line with the findings in our paper, they conclude that a large fraction of these patent spillovers take place in technological areas substantially different from those targeted by the grants.

Third, we speak to the literature on the recombination of ideas. Seminal theoretical work by Levinthal and Cohen (1989) and Bernstein and Nadiri (1989) put at the forefront how firms enjoy knowledge spillovers coming from innovation undertaken in other firms. Weitzman (1998) provides micro-foundations for the knowledge production function, which is modelled as a function of reconfigured old ideas. On the empirical front, Jones, Wuchty, and Uzzi (2008) show that across all scientific disciplines, highest-impact papers are produced by teams that increasingly span university boundaries. Based on 18 million scientific publication, Uzzi et al. (2013) show that the highest-impact papers are those that insert novel features into otherwise conventional combinations of prior work. Acemoglu, Akcigit, and Kerr (2016) analyze citation properties of 1.8 million U.S. patents to provide evidence on knowledge sharing across technological fields. Griffith, Lee, and Straathof (2017) quantify the relative cost for firms to access new ideas across firm boundaries, technology areas and national borders. In line with this literature, we follow the notion that firms build on previous knowledge generated by other firms or industries.We differ from previous work by focusing on the technological linkages between firms, rather than their economic relatedness in the product market.

Fourth, we relate to the literature on the evaluation of industrial policies and the input-output linkages in the economy. In a theoretical framework, Liu (2019) analyzes industrial policy when sectors are vertically linked through an input-output network. Market imperfections in one sector compound through backward linkages to upstream sectors. He shows that the centrality of sectors in the production network matters when policy makers decide which industry to target. We follow a similar idea; instead of production networks, we look at innovation networks and assign more weight to firms that are technologically more central. For papers looking at the amplification of micro shocks see Acemoglu et al. (2012), Acemoglu and Tahbaz-Salehi (2020), Barrot and Sauvagnat (2016) or Carvalho et al. (2021). Compared to them, we focus on the innovation network as opposed to the production network. Carvalho and Draca (2017) study the propagation of U.S. military spending shocks through the production network and their effect on innovation outcomes. Related to our approach, they also highlight the importance of the indirect effect. They investigate how shifts in spending not only affect innovation decisions by main contractors, but also the ones taken by the supplier network of these contractors.

The remainder of this paper is structured as follows: Section 2 describes the empirical strategy. Section 3 provides details on the dataset, the construction of variables and shows descriptive statistics. Section 4 presents the econometric analysis and discusses results. Section 5 concludes.

2 Empirical Strategy

2.1 Baseline OLS Estimation

To measure the indirect effect of how a competition shock to the textile (thereafter, TXTL) sector affects the rest of the economy, our empirical specification estimates within-firm changes in patenting and knowledge sourcing of non-textile (thereafter, NTXTL) firms i as a function of patenting changes of TXTL firms j, weighted by the pairwise technological distance to each of these TXTL firms ($tech_{ij}$). Consider a basic differenced firm-level equation for patents of NTXTL firm i in sector s, country c, and year t as:

$$\Delta lnPat_{isct}^{NTXTL} = \beta \sum_{j} tech_{ij} \Delta lnPat_{jt}^{TXTL} + \gamma_s + \gamma_c + \Delta u_{isct} \tag{1}$$

where Δ denotes the long five-year difference operator. The dependent variable is the within-firm five-year log change in patents by a given NTXTL firm.[5] The regressor of interest is the change in patenting summed across all TXTL firms j, weighted by the corresponding technological proximity at the firm-pair level ($tech_{ij}$). We discuss the calculation of the pairwise technological proximity between two firms in detail in Section 2.5. The specification includes country and industry fixed effects to absorb country-specific and industry-wide shocks. Similar to Bloom et al. (2016), we use overlapping five-year differences (e.g. 2001-1996, or 2002-1997), in order to maximize the use of our data, and cluster the standard errors at the 4-digit industry (SIC4) level.

[5] As we would like to include firms in the regressions with zero patents, we take the log of $1+Pat_{isct}^{NTXTL}$. In alternative specifications, we additionally consider dependent variables that reflect changes in knowledge sourcing and in the direction of patenting.

2.2 Instrumental Variable Estimation

A possible concern is an omitted variable bias by which TXTL and NTXTL firms are likely to face an unobserved common technology shock if their patents belong to related technology fields. Another concern may be reverse causality whereby changes in NTXTL firms cause a change in the innovation decisions of TXTL firms.

We therefore use an instrumental variable approach to address these concerns. We use the removal of import quotas on textiles and clothing from China as an instrument for changes in the innovation output of European TXTL firms, in the spirit of Bloom, Draca, and Van Reenen (2016). Following China's accession to the WTO in 2001, these import quotas were abolished and caused a competition shock for the TXTL firms in Europe. The underlying quotas vary at the 4-digit SIC industry level and reflect their level in the year 2000 prior to their abolishment. Our instrument for the endogenous regressor in equation (1) is the technology-weighted level of quotas across TXTL firms, where again the assigned weights differ for each NTXTL firm. Equation (2) presents the *first stage* of the IV estimation approach:

$$\sum_j tech_{ij} * \Delta lnPat_{jt}^{TXTL} = \lambda \sum_j tech_{ij} * QUOTA_{jt}^{TXTL,2000} + \gamma_s + \gamma_c + \Delta u_{isct} \tag{2}$$

Identification comes from the instrumented change in patenting of TXTL firms [$QUOTA_{jt}^{TXT,2000}$] and from variation across NTXTL firms in their technological exposure to each of the TXTL firms [$tech_{ij}$]. The exclusion restriction is that shocks to the patenting activity of *NTXTL firms* are uncorrelated with the level of quotas faced by *TXTL firms* that were determined in the 1950s-70s. This seems highly plausible, especially when considering that differences in quotas across 4-digit TXTL industries reflect historic bargaining power of the respective industry in richer western economies when the quotas were introduced.[6]

A priori, there are two possible outcomes for the sign of the coefficient on the instrumental variable in equation (2). If $\lambda > 0$, the larger the weighted quota reduction, the stronger the weighted *increase* in domestic TXTL patenting. Instead, $\lambda < 0$ would imply that the larger the weighted quota reduction, the stronger the weighted *drop* in domestic TXTL patenting.

2.3 Reduced Form

One can estimate the reduced form in the following way:

[6] For a more detailed discussion of the quotas instrument, we refer to Bloom, Draca, and Van Reenen (2016).

$$\Delta lnPat_{isct}^{NTXTL} = \delta \sum_{j} tech_{ij} * QUOTA_{jt}^{TXTL,2000} + \gamma_s + \gamma_c + \Delta u_{isct} \tag{3}$$

This equation estimates the (technology-weighted) effect of quota reductions experienced by TXTL firms on five-year log changes in patenting by NTXTL firms. The model is estimated at the NTXTL firm level over time. We again control for industry and country fixed effects.

2.4 Direct Effect on TXTL Firms

While our paper focuses on how a competition shock in the TXTL sector trickles down to the rest of the economy, similarly to Bloom, Draca, and Van Reenen (2016), we also estimate the direct effect of the quota removal on the TXTL sector itself:

$$\Delta lnPat_{jct}^{TXT} = \eta * QUOTA_{jt}^{TXT,2000} + \gamma_s + \gamma_c + \Delta u_{jct} \tag{4}$$

Compared to Equation (3), there are two key differences. First, while throughout the paper we use a panel of NTXTL firms, for this particular exercise we use a panel of TXTL firms (subindex j). Consequently, the dependent variable is now the five-year difference in log patenting by each TXTL firm. Second, each TXTL firm is assigned its own quota in the year 2000 as a regressor. A positive value of η would replicate the finding in Bloom, Draca, and Van Reenen (2016): the stronger the quota reduction faced by a TXTL firm, the greater the increase in patenting activity. In addition to estimating this equation for the full sample of TXTL firms, we will then decompose it as a function of how central these TXTL firms are in the technology network.

2.5 Technological Proximity between Firms

A central element of our empirical specification is the technological proximity ($tech_{ij}$) between two firms. We calculate this pairwise proximity between any NTXTL firm and any TXTL firm based on the overlap in patent portfolios. For each firm, we determine its patent portfolio as of 2001 and construct a vector of patent shares across technology classes, which reflects the firm's technological profile. We then calculate the pairwise un-centered correlation between any two firms' patent portfolio vectors in the following way:[7]

[7] For similar approaches, see Jaffe (1986), Bloom, Schankerman, and Van Reenen (2013), and Lychagin et al. (2016).

$$tech_{ij} = \frac{\sum_c PAT_{ic} * PAT_{jc}}{\sqrt{\sum_c PAT_{ic}^2} * \sqrt{\sum_c PAT_{jc}^2}} \in (0,1), \tag{5}$$

where c stands for technology class, i and j is a firm pair, and PAT is the number patents. In order to determine the technological profile of a firm's patent portfolio, we need to assign each patent to a unique patent technology class. In our main specifications, we use a technology classification that builds on 34 technology areas (TF34), aggregated from the IPC codes following the proposal by Schmoch (2008), which unambiguously assigns each patent to one of these technology areas. In an alternative specification, we use the Cooperative Patent Classification (three-digit CPC codes) to classify each patent into more granular technology classes. Under the three-digit CPC scheme, there are 126 distinct technology classes.[8]

We use technological linkages to define the innovation network. We hold the network constant and study how shocks to one focal area (firms in the TXTL sector) propagate to firms in other (NTXTL) sectors through technological linkages. Ideas can propagate across industries thanks to firms' ability to recombine technologically similar bodies of knowledge. The notion of the mechanism is as follows: if inventions in TXTLs decrease, then spillovers from TXTL to NTXTL firms will diminish; furthermore, inventions will decrease more for those NTXTL firms that are technologically closest to the affected TXTL firms.

Figure 1 shows the patenting levels of NTXTL firms in the period prior to China's accession to the WTO. These NTXTL firms are decomposed into very granular subgroups based on their degree of technological proximity to TXTL firms. The correlation is very weak, suggesting no systematic relationship between a NTXTL firm's patenting intensity in the pre-shock period and its technological linkage to the TXTL industry. For this reason, our regressions should not capture any differential patenting trends between strongly treated NTXTL firms (high exposure to TXTL industry) and weakly treated NTXTL firms (low exposure to TXTL industry) in the years prior to China's entry into the WTO.

2.6 Testing for Alternative Mechanisms

Input-Output Relationships. A concern is that TXTL and NTXTL firms that are technologically close may also be closely linked through vertical input-output industrial relationships. The strength of a NTXTL firm's vertical relationship with the TXTL industry depends on two aspects: first, the share of production output it supplies to the TXTL indus-

[8] We consider only the main technology area or main three-digit CPC code of a patent, even if patents may be assigned to multiple technology classes. CPC codes distinguish between the position and hence importance of the different codes associated with one patent (i.e. cpc-position = "F" first or "L" later). We use this information to determine the unique technology class for each patent.

try; second, the share of inputs it receives from the TXTL industry. We therefore determine each NTXTL firm's input and output exposure to the TXTL industry and test whether these factors drive any of our baseline results.

Industry Level Estimations. In our baseline firm-level estimation, all NTXTL firms are given the same weight, as we use an unweighted estimation specification. This could lead to the following scenario: suppose a 4-digit industry consists of one very large firm that dominates the patenting activity of the industry and many smaller patenting firms. If all the small firms reduce patenting but the one very large firm increases patenting, at the firm level, our regression analysis might suggest that on average patenting decreases. However, at the industry level, aggregate patents may actually increase.

We estimate industry-level regressions where the dependent variable is the log change in patents in a 4-digit NTXTL sector k ($\Delta lnPat_{kt}^{NTXTL}$) and the independent variable of interest is the log change in patents in each 4-digit TXTL sector l ($\Delta lnPat_{lt}^{TXTL}$) weighted by the technological proximity at the industry-pair level ($tech_{kl}$).

We account for possible vertical relationships between a NTXTL industry k and a TXTL industry l by using the 4-digit SIC input-output matrix (IO_{kl}). For each NTXTL industry, we use the output share it supplies to a TXTL industry, as well as the input share that it sources from them.

In particular, as an additional regressor we include changes in TXTL sales (ΔlnY_{lt}^{TXTL}), weighted by this IO_{kl} matrix. The term γ_{SIC2D} captures industry fixed-effects at the two-digit SIC code level. In absence of a second instrument for changes in TXTL sales we estimate equation (6) using OLS:

$$\Delta lnPat_{kt}^{NTXTL} = \beta_1 \sum_{l,l\neq k} tech_{kl} \Delta lnPat_{lt}^{TXTL} + \beta_2 \sum_{l,l\neq k} IO_{kl} \Delta lnY_{lt}^{TXTL} + \gamma_{SIC2D} + \Delta u_{kt} \quad (6)$$

Regional Effects. Consistent with the findings by Di Addario, Korchowiec, and Serafinelli (2021) using plant closures in Italy, employees of TXTL firms affected by the shock could relocate to NTXTL firms with a similar technological focus in the same local labor market. In order to test for potential alternative channels at the regional level, we assess if geographical distance plays a role in explaining our results. More precisely, we estimate models where we only consider TXTL firms located in the same country or within a 50 kilometer radius of the NTXTL firm.

3 Data & Descriptive Analysis

For our firm-level analysis, we link Bureau van Dijk's (BvD) ORBIS and Amadeus databases to the PATSTAT database, using ORBIS' embedded BvD-to-PATSTAT link.[9] The ORBIS database is the largest cross-country firm-level database available and includes both public and private firms from all industries. Among others, it includes firm-level data on financial accounts, industry codes, and address data. We use the 2016 Fall version of BvD ORBIS, which includes all historical ORBIS vintages from 2005-2016.[10] We complement ORBIS with the 2006 vintage of BvD's Amadeus database, which includes firm financial data from 1995-2006, in order to improve data coverage for the late 1990s. Amadeus is a similar database of the same data provider (BvD), covering firms in Europe rather than globally.

As Kalemli-Ozcan et al. (2015) discuss, it is advisable to combine different BvD vintages to obtain a consistent coverage of firms over time. We link ORBIS to Amadeus at the firm-year level via BvD's unique firm identifier (BvD-ID), while accounting for duplicate accounts, different currencies and accounting standards as well as possible BvD-ID changes over time. For the harmonization and cleaning of the ORBIS and Amadeus data, we broadly follow Kalemli-Ozcan et al. (2015). In the following, we describe the sample of manufacturing firms and the construction of variables used for our econometric analysis.

Sample of European Manufacturing Firms with Patenting Activity. Consistent with the previous literature (e.g. Bloom et al., 2016; Dorn et al., 2020) our analysis focuses on firms in the manufacturing sector. We use the 4-digit SIC industry information in ORBIS to identify all firms that belong to the manufacturing sector in any of the 13 European countries of Austria, Denmark, France, Germany, Italy, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the UK. From these approximately 2 million firms, we identify those that were active as of 2001, the treatment year when the TXTL import quotas were abolished in China. We use the incorporation date information in ORBIS, where available, and otherwise deduce from non-missing entries for revenue or number of employees, as to whether a firm has been active as of 2001. Keeping only these, we are left with about 1.6 million manufacturing firms. This includes patenting and non-patenting firms.

For our empirical analysis, we are interested in patenting firms. We use ORBIS' embedded BvD-to-PATSTAT link to merge the firm data to patent data. About five percent of the

[9]For the matching of ORBIS and PATSTAT, Bureau van Dijk uses string similarity matching between a company name from ORBIS and the name of the patent applicant from PATSTAT, mapping BvD-IDs to each PATSTAT person ID. Additional information like address information is used to enhance the matching precision.

[10]For representativeness of ORBIS data, see Kalemli-Ozcan et al. (2015).

1.6 million manufacturing firms have a link to the PATSTAT database. In order to calculate a firm's technological proximity to other firms based on its patent filings in the pre-period, we further need to impose the condition that firms in our sample patented at least once before 2001. The above steps result in a final sample of 45,012 NTXTL and 2,380 TXTL firms. Figure 2 shows the ratio of TXTL to NTXTL firms for each region in our sample. The largest concentration of TXTL firms is in Southern Europe (Spain, Portugal and Italy) and in Poland. Nonetheless, the northern part of the United Kingdom and some areas in Norway, France and Germany also have a high ratio of TXTL firms. In Galicia (North-West of Spain), 20% of firms belong to the TXTL sector (90th percentile), whereas in the North of Sweden, the share of TXTL firms is less than 1% (10th percentile).

Patent Filings. Our main dependent variable is the change in the number of patents filed by a firm. We consider patents at the DOCDB patent family level. We refer to patent families interchangeably as patents. Our sample of 45,012 NTXTL firms filed around 615,000 patent families during the years 1996-2005, while the TXTL firms filed approximately 10,000 patent families during the same period.

As we aggregate patent applications to the patent family level, we need to take a few decisions as to how we unify patent attributes. The year is determined by the filing year of the patent member that was filed first within the family. For the technology class, we consider the modal technology area under the TF34 scheme. In the event of ties, we use the numerically lowest technology area. When using the CPC scheme, we prioritize the so-called "F" codes. CPC codes distinguish between the position and hence the importance of different technology classes associated with one patent (i.e. cpc-position = "F" first or "L" later). Where this information is available, we prioritize the "F" codes, and consider the modal code in case there are multiple "F" codes.

We use technology class information to assess changes in the direction and diversity of a firm's patenting activities. Focusing on the patents filed by TXTL firms, we identify those technology classes where TXTL firms are more actively patenting. For each NTXTL firm, we then calculate the fraction of patents filed in these 'TXTL-intensive' technology classes and assess whether there is any redirection of patenting towards or away from them.[11]

Furthermore, we calculate a Herfindahl-Hirschman-Index (HHI) that reflects the level of specialization of a firm's patent portfolio in terms of filings by technology class. We use this index to assess if firms diversify more or less as part of their broader adjustments in

[11] More precisely, we weight the number of patents a firm files in a given technology class by multiplying it with an indicator that reflects the technology class' 'TXTL-intensity'. The indicator value ranges between 0 and 1 and is measured as the share of patents in this technology class filed prior to 2001 by TXTL firms.

patenting and knowledge sourcing decisions.

The technological proximity network is calculated based on firms' pre-2001 technological profiles. That is, we consider patents filed prior to 2001 for the calculation of the pairwise technological proximity between two firms.

Import Quotas Data for the IV Approach. For the import quotas on textiles and clothing that were abandoned following China's entry into the WTO, we use data from Bloom, Draca, and Van Reenen (2016). The quotas variable reflects the toughness of quotas at their initial level in 2000 prior to China's WTO entry and varies at the 4-digit industry level. It is calculated as the proportion of (import value-weighted) HS 6-digit product categories that were covered by a quota within that 4-digit industry. Based on the 4-digit industry codes of each TXTL firm, we can calculate a firm-specific intensity of the quota reduction.[12]

Geocoding & Geographical Distance between Two Firms. We have detailed address data from ORBIS, which allows us to geocode the location of firms. We use the HERE Geocoder API and, where available, a firm's street name, ZIP code, city name and NUTS code to obtain the corresponding longitude and latitude geo-coordinates.[13] We then compute the geographical distance between any NTXTL firm and any TXTL firm in our sample, using the STATA package "geodist".

Patent Citation Data. As a measure of patent value, we use the number of forward citations received from EPO patents within five years after the first filing date (Harhoff et al., 1999). We also use patent citation data to study the knowledge sourcing behavior of firms. Based on patent-to-patent citations, we form dyads consisting of the citing firm and the cited firm. In terms of citing patents, we only consider citations made by EPO patents that were filed with the EPO directly or under the PCT, so as to have consistent citation behavior.[14] In terms of cited patents, we consider all patents, irrespective of the office they were filed at. Due to the restriction to citing patents filed via EPO/PCT, the sample is slightly smaller in those specifications where we evaluate citation behavior.

We can then compare the technological versus geographical distance to the cited firms,

[12] A firm can have multiple primary and secondary SIC 4-digit industry codes. We follow the approach of BDVR, applying a two-third weight to primary codes, a one-third weight to secondary codes, and equal weighting within these groups.

[13] For approximately 97% of the firms in our sample, we know the address at the street level; for 1% the info is at the ZIP or city level; for 2% we have no address info.

[14] See, e.g., Alcácer, Gittelman, and Sampat (2009) and Bacchiocchi and Montobbio (2010) for a discussion of different patent citation behavior between USPTO and EPO.

and evaluate if NTXTL firms have to 'travel further' in the knowledge or geographical space when a given TXTL industry becomes less pivotal as a source of knowledge.

Vertical Industrial Input-Output Relationship. We want to account for potential confounding factors associated with vertical linkages between TXTL and NTXTL firms. In order to capture a NTXTL firm's vertical input and output exposure to the TXTL industries, we use a SIC4 industry-level input-output matrix, as conventionally used in the literature.[15] If a firm has multiple industry SIC codes, we weight them as before: two-third weight to primary codes, a one-third weight to secondary codes. For each NTXTL firm, we calculate the output share it supplies to the TXTL industries, as well as the input share it sources from them. Figure 3 displays histograms for these two measures of vertical input-output relationship to TXTL industries. The correlation with our technological proximity measure is slightly positive but small (0.06 and 0.08, respectively).

Table 1 provides descriptive statistics for our sample of NTXTL firms. The median firm employs 52.5 workers, has annual revenues of 7.4 million Euros and total assets of 4.6 million Euros. It files 0.2 patents per year and the median patent stock amounted to 2.0 patents as of 2001. The sample is skewed in terms of firm size as well as patenting activity.

While in the next section we will present empirical results accounting for endogeneity and alternative channels, a raw look at the data already provides suggestive evidence of our main finding: Figure 4 shows that NTXTL firms that are technologically more connected to the TXTL industry are also the ones experiencing a larger reduction in patenting.

4 Results

4.1 Direct Effect On TXTL Industry

Using a panel of TXTL firms, Table 2 presents the direct effect of the quota removal experienced by a TXTL firm on its patenting activity. As suggested by Campbell and Mau (2021), in all specifications we include both country and industry fixed effects. Column (1) replicates the baseline result found in Bloom, Draca, and Van Reenen (2016). We also obtain a positive estimated coefficient in this unweighted estimation, such that a greater quota reduction leads to larger increases in patenting activity. In Column (2), we weight each TXTL firm by its average technological proximity to the pool of NTXTL firms. The coefficient turns negative (albeit not yet statistically significant), suggesting that the positive coefficient in Column

[15] E.g. Javorcik (2004), Liu (2019).

(1) seems to be driven by TXTL firms with a *low* technological proximity to NTXTL firms. In Column (3) we additionally weight by each firm's patent stock and now the estimated coefficient is both negative and statistically significant. In summary, while Columns (1)-(3) include the same panel of TXTL firms, accounting for both technological proximity to the rest of the economy and also firm size switches the sign of the estimated coefficient from positive to negative. We choose to account for both technological proximity and firm size as these elements will be weights of critical importance when estimating Equation (1).

In Columns (4)-(5) we split the sample of TXTL firms by the median technological distance to NTXTL firms. For firms with *distant* technological ties to NTXTL firms, we again replicate the positive and statistically significant coefficient obtained in Bloom, Draca, and Van Reenen (2016) (Column (4)). For firms with *close* technological ties to NTXTL firms, we rather find a negative and significant coefficient (Column (5)). The fact that the TXTL firms most negatively affected by the competition shock are also the ones driving the negative propagation to the rest of the economy - due to their close technological ties to NTXTL firms, as we see in Table 2, Column (5) - is of critical importance for understanding our main result of the paper regarding the indirect effect on NTXTL firms.

4.2 Reduced Form

Moving to our main panel of NTXTL firms, we start by presenting the reduced form estimation results in Table 3. The dependent variable is the within-firm five-year log change in patents by each NTXTL firm. The regressor of interest is the average toughness of quotas faced in the year 2000 by each of the 2,380 TXTL firms in our sample, weighted by the dyadic technological distance between our NTXTL firm and each of these TXTL firms. Consequently, more weight is given to TXTL firms in *close* technological proximity to NTXTL firms. As the technological proximity varies at the firm-pair level, the matrix weights vary for each NTXTL firm.

All columns control for country-specific macro shocks by including a full set of country dummies. Furthermore, Columns (2)-(3) also include sector-year dummies at the SIC 2-digit and 4-digit industries, respectively. We normalize dependent and independent variables in all our regressions, such that results can be interpreted in standard deviation terms. We find that a one standard deviation increase in (tech-weighted) quota toughness faced by TXTL firms is associated with a 2% of a standard deviation decrease in patenting by any given NTXTL firm.

One can think of this finding as follows. Patents by NTXTL firms build on previous knowledge embedded in previous TXTL patents. Knowledge is mostly absorbed from the subset of TXTL firms with stronger technological overlap to NTXTL firms. But it is precisely this subset of TXTL firms (more central in the technological network) that suffer the largest patenting reduction after the competition shock. Consequently, their generated pool of new knowledge shrinks and, as an indirect effect, NTXTL patenting is negatively affected due to a reduction in knowledge absorption.

As an illustrative example, suppose a given NTXTL firm has been learning from the knowledge embedded in patents granted to two different TXTL firms, which we label as Firm A and Firm B. The research and development interests between the NTXTL firm and Firm A are very aligned, but the research and development overlap with Firm B is rather weak. This implies that while Firm A has been a major source of inspiration for the innovation undertaken by the NTXTL firm, Firm B has only had a negligible impact. After the competition shock, Firm A suffers and reduces its innovation effort, while Firm B boosts its innovation activity. These two reactions offset each other, such that the overall *TXTL patenting* activity stays pretty constant. But critically for our line of reasoning, the *NTXTL* firm will indirectly experience the negative consequence of the shock, since it relied much more on the shrinking Firm A than on the growing Firm B. Consequently, a neutral *direct effect* can still lead to a negative *indirect effect* in NTXTL sectors.

4.3 Baseline OLS Results

Table 4 displays the baseline OLS estimation results for the same panel of NTXTL firms. The dependent variable is again the within-firm five-year log change in patents by NTXTL firms. The regressor of interest is now the tech-weighted average patenting change across all TXTL firms. In Column (1) we find an elasticity of 4%, meaning that a decrease in (tech-weighted) TXTL patenting by one standard deviation is associated with a 4% of a standard deviation decrease in the patenting activity of a NTXTL firm. Results remain stable in Columns (2) and (3) after adding a full set of 2-digit and 4-digit industry dummies, respectively.

4.4 Instrumental Variable Estimations

Table 5 presents instrumental variable results. The odd numbered columns report the first stage results and the even numbered columns report the second stage results. The endogenous variable is the tech-weighted average change in patents by TXTL firms, and the instrument is the tech-weighted toughness of quotas faced by TXTL firms. The observed negative coefficient in Column (1) implies that the removal of tougher quotas is related to stronger reductions in TXTL patenting. Column (2) presents the second stage results that show a strong and significant effect of (instrumented) reductions in *TXTL* patenting on reductions in *NTXTL* patenting with a magnitude of 3.6%. Similar to previous tables, the next columns incorporate industry-year dummies leading to only minor changes.

The second stage of the IV estimation in Table 5 indicates that the OLS coefficients (Table 4) are very much in line with IV coefficients. Both the F-test statistic for weak identification (Kleibergen-Paap rk Wald statistic) and the test statistic for under-identification (Kleibergen-Paap rk LM statistic) show that the first stage is very strong in all cases. Given the robust IV results, we prefer the third specification with country fixed effects and industry fixed effects at the 4-digit level; we will consider Column (6) as our baseline specification going forward. Appendix Table A-1 shows that our baseline results also hold when we condition on a sample of firms for which we have non-missing financial data in ORBIS.

4.5 Mechanisms

We claim that the main mechanism driving our results is a classical spillovers channel: if inventions in TXTL firms decrease, then spillovers towards technologically close NTXTL firms will be weaker. Consequently, patenting activity will shrink in those NTXTL firms, leading to a possible readjustment of their knowledge sourcing towards other technological and geographical areas in the innovation network.

Patenting Direction and Citation Behavior. In Table 6 we identify the technology classes with the largest share of patents originating from TXTL firms. Column (1) is our baseline result already discussed in Column (6) of Table 5; in Column (2) we find that the reduction in patenting by TXTL firms leads NTXTL firms to move away from technology classes with a high share of textile patents and to refocus their patenting towards technology areas where TXTL firms are less prevalent. At the same time, in Column (3) the HHI concentration index decreases, meaning that NTXTL firms diversify their patenting across a larger set of technology classes after the shock.

Table 7 addresses the refocusing of innovation efforts by NTXTL firms from a different angle. In line with our previous findings, the result in Column (1) suggests that NTXTL firms are less likely to cite patents of TXTL firms after the China WTO accession. The remaining columns turn to analyzing whether NTXTL firms have to look in more distant locations (both technologically and geographically) to partially substitute for the knowledge absorption lost from TXTL firms. The estimated coefficients in Columns (2) and (3) are negative, implying that NTXTL firms start citing more technologically distant patents; results are mainly driven by large firms, defined as the ones in the fourth quartile of the size distribution. Columns (4) and (5) report that, for the case of large firms, NTXTL firms also start citing patents from more geographically distant firms. Overall, these results are consistent with NTXTL firms trying to mitigate the loss of knowledge coming from TXTL firms by exploring new sources that are in more distant technological and geographical areas.

Geographical Heterogeneity. To address the traditional narrative that spillovers tend to be locally contained, we now describe how the intensity of the observed reduction in NTXTL patenting depends on the average geographical distance to TXTL firms. For illustrative purposes, Column (1) of Table 8 reproduces the baseline result of Column (6) in Table 5, which is based on a (tech-weighted) average of *all* European TXTL firms in our sample. Next, we split these TXTL firms into two groups based on whether they are located in the same country as the NTXTL firm (Column 3) or not (Column 2). The estimated coefficient is substantially larger in Column 3 (0.0575 vs. 0.0324), suggesting that geographical proximity amplifies the impact that TXTL firms have on NTXTL firms, conditional on a given technological distance. One could expect to possibly find heterogeneous effects within the same country, for example, due to local labor markets allowing for the reallocation of affected employees across firms with a similar technological focus. Columns (4) and (5) split the TXTL firms into being closer or further away than 50 kilometers, respectively. Coefficients are similar and do not seem to be consistent with any major labor reallocation mechanism.

Accounting for Input-Output Relationships. A concern is that the main channel driving our results might be industrial input-output relationships that correlate with our technological proximity measures. For example, suppose that certain TXTL firms are input suppliers to a given NTXTL firm. If these TXTL firms suffer from the competition shock, they might be unable to continue trading with the NTXTL firm, which will therefore be negatively affected. To address this concern, for each NTXTL firm, Figure 5 plots the average technological proximity to the TXTL industry against both the share of inputs received from TXTL firms (left panel) and the share of production outputs supplied to TXTL firms (right panel). The correlation between these two input/output exposure measures and our technological proximity measure is positive, albeit small at 0.08 and 0.06, respectively, which mitigates the possibility that our results are driven by this alternative mechanism.

Nonetheless, Table 9 explicitly accounts for these input-output relationships in our econometric framework. As before, Column (1) is the baseline IV result. Columns (2) and (3) split NTXTL firms by the median *output* exposure to the TXTL sector, while Columns (4) and (5) redo the same exercise for the median *input* exposure. We reassuringly do not observe any substantial variation in the magnitude of the estimated coefficient, meaning that the industrial input-output channel seems to be orthogonal to our story. Columns (6) and (7) compare NTXTL firms with weak input *and* output links to the TXTL industry (below 25th percentile on both dimensions) to the ones with strong input *and* output links (above 75th percentile on both dimensions). Both results remain statistically and economically significant. Overall, these results reassure us in the claim that input-output relations are not driving the main result in the paper.

4.6 Robustness

Firm Size Heterogeneity. Appendix Table A-2 reports the IV results by quartiles of NTXTL firm size. While the effect is statistically significant for all four quartiles, the estimated coefficient increases with firm size, and the magnitude for the largest firms (4th quartile) is approximately three times larger than for the smallest firms (1st quartile).

Patent Quality. The distribution of patent quality is known to be skewed. We therefore re-estimate our baseline model restricting the patent count to the subset filed at the European Patent Office (EPO) and using a cite-weighted patent count. Appendix Table A-3 shows that the main result still holds, meaning that the effect is not driven by major changes in patent quality.

Lag Specifications. We further test alternative models that use lagged regressors. The estimated coefficients in Appendix Table A-4 show robust results, with larger effects for the two-year lag on the regressor of interest.

Alternative Measure of Technological Proximity. In addition to calculating the pairwise technological proximity of two firms based on the overlap of their patent filings, we also consider calculating it based on the overlap in their patent citation behavior. The idea is that technological proximity could be understood as two firms building on the same type of pre-existing technology. We can construct a vector of patent citations made to the different patent technology classes for each firm, and again calculate the pairwise uncentered correlation between any two firms' citation vectors. Appendix Table A-5 shows that the estimated effect is smaller in size but qualitatively unchanged. We further check for robustness by using the more fine-grained CPC scheme, instead of the TF34 scheme, for the calculation of the technological proximity measure. We find in non-reported results that the findings also hold.

4.7 Aggregate Analysis: Industry-Level & Regional Effects

Industry-Level Regressions. In all the previous tables we conducted a *within-firm* analysis of NTXTL companies where all firms are given the same weight in the regression. From a policy perspective, it is relevant to understand the evolution of NTXTL patenting at the *industry level*. Industry-level estimations implicitly assign more weight to larger firms and can hence lead to different results if large and small firms respond differently to changes in TXTL patenting.

For the industry-level analysis, we assign each NTXTL firm to its main SIC4 industrial category and estimate the five-year within-industry changes in patenting.[16] To capture possible vertical product market relationships to TXT industries, we include as an additional regressor the changes in TXTL sales at the industry level, weighted by the industry-specific input-output intensity links (see Equation 6).[17] In absence of a second instrument for changes in TXTL sales, we run an OLS instead of an IV estimation.

Table 10 presents OLS estimations for a panel of SIC4 industries over time including a complete set of SIC2 dummies. The baseline regression in Column (1) presents the main regressor of interest, the five-year log change in (tech-weighted) patenting in TXTL industries. Note that the new technological distances are constructed across *industry pairs* as opposed to firm pairs.

A decrease in (tech-weighted) TXTL patenting by one standard deviation is associated with a 8.13% of a standard deviation decrease in NTXTL patenting. This result, in which the estimated coefficient is two times larger than in our firm-level sample, is consistent with our finding in Appendix Table A-2 that large firms reduce their NTXTL patenting by a greater degree than small firms.[18]

The remaining columns aim to account for vertical product market linkages. In Column (2) we add a regressor capturing changes in sales by the TXTL sector, weighted by how much a NTXTL industry supplies its output to the TXTL sector. In Column (3) we add a similar regressor, but now weighted by how relevant TXTL products are as inputs for each of the NTXTL industries. Column (4) incorporates both variables. Estimation results for our regressor of interest are unchanged, supporting the idea that industrial linkages cannot

[16] The log of industry-level sum of patents is not the same as the sum of the firm-level log of patents (summed to the industry level), as per Jensen's Inequality.

[17] We cannot include such an additional regressor in the firm-level regressions as the input-output level is defined at the industry pair level. Hence, in Table 9 we ran the baseline IV specification with a split sample.

[18] Bloom, Draca, and Van Reenen (2016) also find that industry coefficients are about twice as large as firm-level coefficients.

explain our finding and that the economic magnitude at the industry-level estimations is more than twice as large compared to firm-level results.

Aggregate Magnitudes at the Country Level. In a final exercise, we aggregate the data at the country and European level to gauge the relative magnitudes of the removal of import quotas on TXTL firms (direct effects) and NTXTL firms (indirect effects).

In Figure 6, we plot European regions by the relative magnitude of the direct effect on TXTL firms compared to the indirect effect on NTXTL firms. While there is a positive geographical correlation with the relative number of TXTL firms in the region (Figure 2), strong direct effects are not confined to regions with a high concentration of TXTL firms. This can be explained by the following factors. First, at the firm level, the intensity of quota removals differs across 4-digit industries within the TXTL sector. Second, technological proximity between NTXTL and TXTL firms also differs across regions.

Table 11 documents the steps taken to obtain country-level estimates. First, at the firm level, we estimate the predicted change in the number of patent filings for each single firm. Second, at the country level, we take the median value of the predicted change in patent filings and multiply it by the number of firms in the country. We do this exercise twice: first for TXTL firms; then for NTXTL firms. When looking at the whole of Europe, these estimates illustrate that the (negative) indirect effect on NTXTL firms is 4.97 times as large as the (positive) direct effect on TXTL firms. When looking at the median country, the (negative) indirect effect on NTXTL firms is 3.41 times as large as the (positive) direct effect on TXTL firms. Consequently, the reduction in NTXTL patenting due to China entering the WTO is between 3 and 5 times as large as the increase in TXTL patenting.[19]

Figure 7 visually illustrates the variation across countries of these relative magnitudes just described. The vertical axis is the ratio of the indirect over direct effect. The horizontal axis is the ratio of NTXTL over TXTL firms. We observe a positive association: the larger the relative presence of NTXTL firms, the larger the relative magnitude of the indirect effect. This makes intuitive sense - countries that predominantly have NTXTL firms will be most harmed by the lack of access of knowledge sources coming TXTL firms.

5 Conclusion

Academic research provides different viewpoints on industrial policy: while the innovation literature tends to emphasize the benefits of cross-pollination of ideas across a variety of

[19]For a paper with strong amplification and propagation effects in an input-output production network, see Carvalho et al. (2021).

industries and technology fields, traditional work in the trade literature highlights the gains from specialization and comparative advantage.

This paper addresses this debate by estimating and quantifying the overall impact of an industry-specific policy shock on the innovation network in the whole economy. This includes not only estimating the *direct* impact on firms affected by the policy, but also including the *indirect* impact on innovating firms in the rest of the economy. We construct a firm-level manufacturing panel of 13 European countries with information on innovation activity, knowledge sourcing, and technological distances across each pair of firms and sectors. We use the removal of import quotas on Chinese textile firms in 2001 as an exogenous competition shock to the European textile sector to help identify the induced changes in innovation on non-textile firms through technological linkages to textile firms (Bloom, Schankerman, and Van Reenen, 2013).

Our key result is that an exogenous shock induced by the removal of Chinese import quotas on textile firms strongly propagates through technological linkages across the network of innovating non-textile firms. In fact, the indirect harm on the economy's innovation output turns out to be larger in magnitude than the positive direct impact experienced by patenting increases in the textile sector. Moreover, our analysis shows that non-textile firms shift their innovation away from 'textile-intensive' technology areas, cite fewer patents from textile firms, and instead turn to new sources of knowledge that are further away in both the geographical and technological space. Results are robust when accounting for vertical input-output linkages to the textile sector, are visible at all firm sizes, and the effect upholds when aggregating the panel to the 4-digit industry level or to the country level. These findings highlight the importance of accounting not only for the direct effect, but also for indirect effects, when evaluating the implications of sector-specific industrial policies.

There are a number of avenues that could be explored in future work. First, one could complement our study with an assessment of inventor mobility following the policy shock in order to analyze whether inventors relocate from the textile sector to other industries. Our data do not allow us to undertake a detailed assessment of employment effects. To the extent possible, we test for potential labor reallocation within the local labor market as an alternative mechanism through our geographical analysis. Our estimated coefficients based on firms within a 50km radius (proxy for the local labor market) versus firms outside a 50km radius are very similar to our baseline. This tentatively speaks against a major labor reallocation of inventors. Future research using worker-level data, which may account for labor mobility, could provide additional insights. Second, our empirical strategy uses a policy shock that targeted the European textile sector. This sector is not among the most innovation-intensive sectors, hence our results can be considered a 'lower bound'. Further analysis exploring policy shocks in the context of more innovation-intensive industries would be valuable. Third, a general equilibrium model could help parse out potential mechanisms related to labor reallocation effects and allow for counterfactual analysis of policies that target different types of industries.

References

Acemoglu, D., U. Akcigit, and W. R. Kerr (2016). Innovation network. *Proceedings of the National Academy of Sciences of the United States of America 113*(41), 11483–11488.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Acemoglu, D. and A. Tahbaz-Salehi (2020). Firms, failures, and fluctuations: the macroeconomics of supply chain disruptions. *National Bureau of Economic Research* (WP 27565).

Adams, J. D., G. C. Black, J. R. Clemmons, and P. E. Stephan (2005). Scientific teams and institutional collaborations: Evidence from U.S. universities, 1981-1999. *Research Policy 34*(3), 259–285.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics 120*(May), 701–728.

Alcácer, J., M. Gittelman, and B. Sampat (2009). Applicant and examiner citations in U.S. patents: An overview and analysis. *Research Policy 38*(2), 415–427.

Amiti, B. M. and J. Konings (2007). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. *American Economic Review 97*(5), 1611–1638.

Aw, B., M. J. Roberts, and D. Y. Xu (2011). R&D Investment, Exporting, and Productivity Dynamics. *American Economic Review 101*(4), 1312–1344.

Bacchiocchi, E. and F. Montobbio (2010). International Knowledge Diffusion and Home-bias Effect: Do USPTO and EPO Patent Citations Tell the Same Story? *Scandinavian Journal of Economics 112*(3), 441–470.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Bernstein, J. I. and M. I. Nadiri (1989). Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality. *The Review of Economic Studies 56*(2), 249.

Bloom, N., M. Draca, and J. Van Reenen (2016). Trade induced technical change? The impact of chinese imports on innovation, IT and productivity. *Review of Economic Studies 83*(1), 87–117.

Bloom, N., M. Schankerman, and J. Van Reenen (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica 81*(4), 1347–1393.

Bustos, P. (2011). Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on argentinian firms. *American Economic Review 101*(1), 304–340.

Cai, J., N. Li, and A. M. Santacreu (2022). Knowledge diffusion, trade, and innovation across countries and sectors. *American Economic Journal: Macroeconomics 14*(1), 104–45.

Campbell, D. L. and K. Mau (2021). On "trade induced technical change: The impact of chinese imports on innovation, it, and productivity". *The Review of Economic Studies 88*(5), 2555–2559.

Carvalho, V. M. and M. Draca (2017). Cascading innovation. *Working Paper*.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021). Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Cattani, G. (2006). Technological pre-adaptation, speciation, and emergence of new technologies: How Corning invented and developed fiber optics. *Industrial and Corporate Change 15*(2), 285–318.

Dechezleprêtre, A., E. Einiö, R. Martin, K.-T. Nguyen, and J. Van Reenen (2016). Do tax incentives increase firm innovation? An RD Design for R&D. *National Bureau of Economic Research* (WP 22405).

Di Addario, S., B. Korchowiec, and M. Serafinelli (2021). Cascading innovation. *Working Paper*.

Dorn, D., G. H. Hanson, G. Pisano, P. Shu, et al. (2020). Foreign competition and domestic innovation: Evidence from us patents. *American Economic Review: Insights 2*(3), 357–74.

Griffith, R., S. Lee, and B. Straathof (2017). Recombinant innovation and the boundaries of the firm. *International Journal of Industrial Organization 50*, 34–56.

Gruber, M., D. Harhoff, and K. Hoisl (2013). Boundaries : Scientists vs . Engineers. *Management Science 59*(4), 837–851.

Harhoff, D., F. Narin, F. M. Scherer, and K. Vopel (1999). Citation frequency and the value of patented inventions. *Review of Economics and Statistics 81*(3), 511–515.

Hombert, J. and A. Matray (2018). Can innovation help us manufacturing firms escape import competition from china? *The Journal of Finance 73*(5), 2003–2039.

Jaffe, A. B. (1986). American Economic Association Technological Opportunity and Spillovers of R & D : Evidence from Firms ' Patents , Profits , and Market Value Author (s): Adam B . Jaffe Source : The American Economic Review , Vol . 76 , No . 5 (Dec ., 1986), pp . 984-1. *American Economic Review 76*(5), 984–1001.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? in search of spillovers through backward linkages. *American Economic Review 94*(3), 605–627.

Jones, B. F. (2009). The burden of knowledge and the "death of the renaissance man": Is innovation getting harder? *Review of Economic Studies 76*(1), 283–317.

Jones, B. F., S. Wuchty, and B. Uzzi (2008). Multi-university research teams: Shifting impact, geography, and stratification in science. *Science 322*(5905), 1259–1262.

Kalemli-Ozcan, S., B. Sørensen, C. Villegas-Sanchez, V. Volosovych, and S. Yesiltas (2015). How to construct nationally Representative Firm Level Data from the ORBIS Global Database. *National Bureau of Economic Research* (WP 21558).

Levinthal, D. A. and W. M. . Cohen (1989). Innovation and Learning: The Two Faces of R&D. *The Economic Journal 99*(397), 569–596.

Liu, E. (2019). Industrial Policies in Production Networks. *The Quarterly Journal of Economics 134*(4), 1883–1948.

Lychagin, S., J. Pinkse, M. E. Slade, and J. V. Reenen (2016). Spillovers in Space: Does Geography Matter? *Journal of Industrial Economics 64*(2), 295–335.

Matray, A. (2021). The local innovation spillovers of listed firms. *Journal of Financial Economics 141*(2), 395–412.

Moretti, E., C. Steinwender, and J. Van Reenen (2020). The intellectual spoils of war? Defense R&D, Productivity and International Spillovers. *National Bureau of Economic Research* (WP 26483).

Myers, K. R. and L. Lanahan (2022). Estimating spillovers from publicly funded r&d: Evidence from the us department of energy. *American Economic Review 112*(7), 2393–2423.

Pavcnik, N. (2002). Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants. *Review of Economic Studies 69*(1), 245–276.

Schmoch, U. (2008). Concept of a Technology Classification for Country Comparisons. *Final Report to the World Intellectual Property Organisation (WIPO).*

Schnitzer, M. and M. Watzinger (2022). Measuring the spillovers of venture capital. *Review of Economics and Statistics 104*(2), 276–292.

Shu, P. and C. Steinwender (2019). The impact of trade liberalization on firm productivity and innovation. *Innovation Policy and the Economy 19*(1), 39–68.

Uzzi, B., S. Mukherjee, M. Stringer, and B. Jones (2013). Atypical combinations and scientific impact. *Science 342*(6157), 468–472.

Weitzman, M. L. (1998). Recombinant Growth. *The Quarterly Journal of Economics 113*(2), 331–360.

Zacchia, P. (2019). Knowledge Spillovers through Networks of Scientists. *The Review of Economic Studies* (May), 1–30.

Tables

Table 1: Summary Statistics for Non-textile Firms

	Mean	p5	p25	Median	p75	p95	Obs
No. of Employees	538.31	2.00	16.75	52.50	169.40	1,138.00	29,510
Revenue (1000s Euros)	120,285.28	250.00	2,150.00	7,372.25	26,896.50	240,868.70	29,338
Total Assets (1000s Euros)	13,8861.30	98.85	1,177.23	4,597.00	19,871.80	240,714.80	24,389
Patent Stock	29.03	0.20	1.00	2.00	7.20	53.00	45,012
Patent Filings per year	1.35	0.00	0.00	0.20	0.40	3.00	45,012
No. of Primary SIC Codes	1.50	1.00	1.00	1.00	2.00	4.00	45,012
No. of Secondary SIC Codes	1.07	0.00	0.00	0.00	1.00	5.00	45,012
Observations	45,012						

Notes: This table presents summary statistics for our sample of non-textile firms. The first three financial variables are provided by Bureau Van Dijk and approximately a third of the sample has missing values. Patent stock and patent filings come from PATSTAT, the industry SIC codes come from Bureau van Dijk; these variables are available for all firms.

Table 2: Direct Effects of Quotas Removal on Textile Firms

Dep. Var.:	Base	Weighted by		Sample split	
ΔlnPat textile firms	(1)	(2)	(3)	(4)	(5)
		tech-connect.	tech-connect. & pat.stock	tech-connect. <p50	tech-connect. >p50
Toughness of quotas	0.0401***	−0.0166	−0.1344**	0.0977***	−0.0248**
	(0.007)	(0.020)	(0.049)	(0.008)	(0.010)
Country FE	Yes	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes	Yes
No. of clusters	13	13	13	13	13
Observations	11,900	11,900	11,900	5,905	5,995
Unique Firms	2,380	2,380	2,380	1,181	1,199

Notes: This table presents the direct effects results for the panel of 2,380 textile firms in our sample. The dependent variable is the change in the log of patents by textile firms. The regressor of interest is the quota toughness prior to China's accession to the WTO faced by each of these textile firms. Column (1) is an unweighted regression on the full sample of textile firms. Column (2) weights each textile firm by its average technological proximity to the pool of non-textile firms, Column (3) additionally weights each textile firm by its patent stock. Columns (4) and (5) split the textile firms by the median technological proximity to non-textile firms. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 3: Reduced Form Results

Dep. Var.: Δ lnPat non-textile firms	(1)	(2)	(3)
Toughness of quotas in 2000	-0.0196^{***}	-0.0191^{***}	-0.0176^{***}
	(0.003)	(0.003)	(0.003)
Country FE	Yes	Yes	Yes
Industry(SIC-2D) FE	No	Yes	No
Industry(SIC-4D) FE	No	No	Yes
No. of clusters	471	471	471
Observations	225,060	225,060	225,060
Unique Firms	45,012	45,012	45,012

Notes: This table presents the reduced form results for the full panel of non-textile firms. The dependent variable is the change in the log of patents by non-textile firms. The regressor of interest is the quota toughness prior to China's accession to the WTO for each textile firm, weighted by the technological proximity between a given non-textile firm and each textile firm. To clarify, given that we have 2,380 textile firms in our sample, each regressor is a weighted average of 2,380 quota changes, and the closer the technological proximity to the non-textile firm, the greater the weight assigned. Column (1) is the baseline specification that controls for country fixed effects. Columns (2) and (3) additionally include a full set of industry 2-digit and 4-digit dummies, respectively. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 4: OLS Results

Dep. Var.: Δ lnPat of non-textile firms	(1)	(2)	(3)
Δ lnPat of textile firms	0.0421^{***}	0.0420^{***}	0.0417^{***}
	(0.004)	(0.003)	(0.003)
Country FE	Yes	Yes	Yes
Industry(SIC-2D) FE	No	Yes	No
Industry(SIC-4D) FE	No	No	Yes
No. of clusters	471	471	471
Observations	225,060	225,060	225,060
Unique Firms	45,012	45,012	45,012

Notes: This table presents the baseline OLS results for the full panel of textile firms. The dependent variable is the change in the log of patents by non-textile firms. The regressor of interest is the change in the log of patents by textile firms, weighted by the technological proximity between a given non-textile firm and each textile firm. To clarify, given that we have 2,380 textile firms in our sample, each regressor is a weighted average of 2,380 changes in the log of patenting, and the closer the technological proximity to the non-textile firm, the greater the weight assigned. Column (1) is the baseline specification that controls for country fixed effects. Columns (2) and (3) additionally include a full set of industry 2-digit and 4-digit dummies, respectively. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 5: IV Results - First and Second Stage

Dep. Var.: Δ lnPat textile firms						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
Toughness of quotas	-0.5341^{***}		-0.5325^{***}		-0.5340^{***}	
	(0.004)		(0.004)		(0.004)	
Δ lnPat of TXT firms		0.0367^{***}		0.0360^{***}		0.0329^{***}
		(0.006)		(0.006)		(0.006)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry(SIC-2D) FE	No	No	Yes	Yes	No	No
Industry(SIC-4D) FE	No	No	No	No	Yes	Yes
Underidentification test	59.8		54.1		51.9	
Weak identification test	14,995.1		14,502.9		15,613.3	
No. of clusters	471	471	471	471	471	471
Observations	225,060	225,060	225,060	225,060	225,060	225,060
Unique Firms	45,012	45,012	45,012	45,012	45,012	45,012

Notes: This table presents the instrumental variable estimation results for the full panel of NTXTL firms. The dependent variable is the same as in Tables 2 and 3. The instrument is the weighted change in the quota toughness prior to China's accession to the WTO for each TXTL firm, as described in Table 3. The endogenous regression is the weighted change in the log of patents by TXTL firms, as described in Table 2. Columns (1), (3), and (5) present first stage results, while columns (2), (4), and (6) present second stage results. Columns (1) and (2) are the baseline specification that control for country fixed effects. Columns (3) and (4) additionally include a full set of industry 2-digit dummies. Columns (5) and (6) include instead a full set of industry 4-digit dummies. The table reports test statistics for underidentification (Kleiberger-Paap rk LM statistic) and weak identification (Kleibergen-Paap rk Wald statistic). ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 6: Patenting Direction: 'Textile-Intensity' and Diversity of Tech Classes

	(1) Δ in patent filings (baseline)	(2) Δ in Share pat. 'txt-int.' classes	(3) Δ in HHI (1/diversity)
Δ lnPat of textile firms	0.0329***	0.1421***	0.0354***
	(0.006)	(0.012)	(0.008)
Country FE	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes
Underidentification test	51.9	51.9	51.9
Weak identification test	15,613.3	15,613.3	15,613.3
No. of clusters	471	471	471
Observations	225,060	225,060	225,060
Unique Firms	45,012	45,012	45,012

Notes: Column (1) is our baseline IV result (as in Table 5 Column (6)). The dependent variable in Column (2) is the share of patents granted in textile-intensive technology areas. Column (3) has the HHI concentration index as dependent variable. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 7: Citation Behavior

	Δ in % Cites to textile firms	Δ in TechDist		Δ in GeoDist	
	(1) all	(2) all	(3) large firms	(4) all	(5) large firms
Δ lnPat of textile firms	0.0683**	−0.0044	−0.0851**	0.0027	−0.1072***
	(0.034)	(0.031)	(0.039)	(0.028)	(0.038)
Country FE	Yes	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes	Yes
Underidentification test	37.3	31.7	19.5	32.4	20.8
Weak identification test	1,010.5	622.3	440.1	708.7	446.1
No. of clusters	283	243	198	239	197
Observations	12,010	8,482	4,805	8,213	4,653
Unique Firms	5,690	3,996	1,815	3,855	1,754

Notes: In Column (1), the dependent variable is the share of citations made to textile firms. Columns (2) and (3) look at the technological distance to cited patents, for the full sample and for the 25% of largest non-textile firms, respectively. Columns (4) and (5) repeat the exercise but with geographical distance to cited patents instead. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 8: Geographical Heterogeneity

Dep. Var.: Δ lnPat of non-textile firms	(1)	(2)	(3)	(4)	(5)
Δ lnPat of textile firms: all	0.0329***				
	(0.006)				
Δ lnPat of textile firms: other countries		0.0324***			
		(0.006)			
Δ lnPat of textile firms: same country			0.0575***		
			(0.011)		
Δ lnPat of textile firms: same country, <50km				0.0570***	
				(0.019)	
Δ lnPat of textile firms: same country, >50km					0.0516***
					(0.011)
Country FE	Yes	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes	Yes
Underidentification test	51.9	53.3	47.5	26.6	46.8
Weak identification test	15,613.3	6,759.4	1,177.9	203.4	1,162.8
No. of clusters	471	471	471	469	469
Observations	225,060	225,060	225,060	204,485	216,170
Unique Firms	45,012	45,012	45,012	40,897	43,234

Notes: This table introduces geographical variation into the analysis. Presented are the second stages of IV estimations where each regressor differs in its geographical scope. The dependent variable is the same as in Table 5. The endogenous regressor is the weighted change in the log of patents by textile firms, as in Table 5. In column (1) the regressor encompasses all textile firms at its weighted average; in Columns (2) and (3) it is limited to the sample of textile firms outside, or respectively inside, the same country as the non-textile firm. Considering only textile firms in the same country, Column (4) restricts the sample to those within a 50km radius of the non-textile firm; finally, Column (5) restricts the sample to the ones outside of a 50km radius of the non-textile firm. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table 9: Accounting for Input-Output Relationships

Dep. Var.: Δ lnPat of non-textile firms	Base	Output Exposure to Textiles		Input Exposure to Textiles		Input & Output	
	(1)	(2) Below Median	(3) Above Median	(4) Below Median	(5) Above Median	(6) <p25	(7) >p75
Δ lnPat of textile firms	0.0329***	0.0297***	0.0331***	0.0336***	0.0313***	0.0493**	0.0207*
	(0.006)	(0.010)	(0.007)	(0.009)	(0.008)	(0.022)	(0.012)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test	51.9	48.0	25.1	35.3	24.1	25.8	25.4
Weak identification test	15,613.3	9,080.6	10,553.4	9,891.4	11,037.9	6,574.6	4,676.6
No. of clusters	471	354	337	344	340	224	228
Observations	225,060	110,475	107,505	110,000	108,465	25,800	41,420
Unique Firms	45,012	22,095	21,501	22,000	21,693	5,160	8,284

Notes: ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level. In this table we account for the impact of industrial input-output relationships in the production network. The dependent variable and regressor of interest are as in Table 4. Column (1) repeats the baseline IV result of Table 5 Column (6). Columns (2) and (3) split the non-textile firms by the median output exposure to the textile sector, while Columns (4) and (5) split them by the median input exposure to textiles. Columns (6) and (7) estimate the effect for the non-textile firms with the weakest vs. the strongest input and output exposure to textiles (below 25th percentile vs. above 75th percentile on both dimensions).

Table 10: Industry-Level (SIC4) Regressions: OLS

Dep. Var.: Δ lnPat of non-textile industries (SIC4)	(1) Base	(2) Output	(3) Input	(4) Input & Output
Δ lnPat of $tech_{ij}$-weighted textile industry	0.0813***	0.0874***	0.0835***	0.0871***
	(0.011)	(0.013)	(0.012)	(0.013)
Δ lnY of IO_{ij} output-weighted textile industry		−3.8394		−6.6127
		(3.653)		(5.915)
Δ lnY of IO_{ij} input-weighted textile industry			−2.0646	4.3505
			(4.507)	(7.296)
Industry(SIC-2D)-Year FE	Yes	Yes	Yes	Yes
Observations	2,065	2,065	2,065	2,065
Unique SIC4 Industries	413	413	413	413

Notes: This table presents 4-digit SIC industry-level regressions, including 2-digit SIC industry fixed effects in all specifications. The dependent variable is the change in the log of patents by non-textile firms in each 4-digit industry. The regressor of interest is the change in the log of patents by textile firms, weighted by the technological proximity between a given non-textile 4-digit industry and each textile 4-digit SIC industry. Similar to Table 9, Columns (2)-(4) control for industrial input-output relationships. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

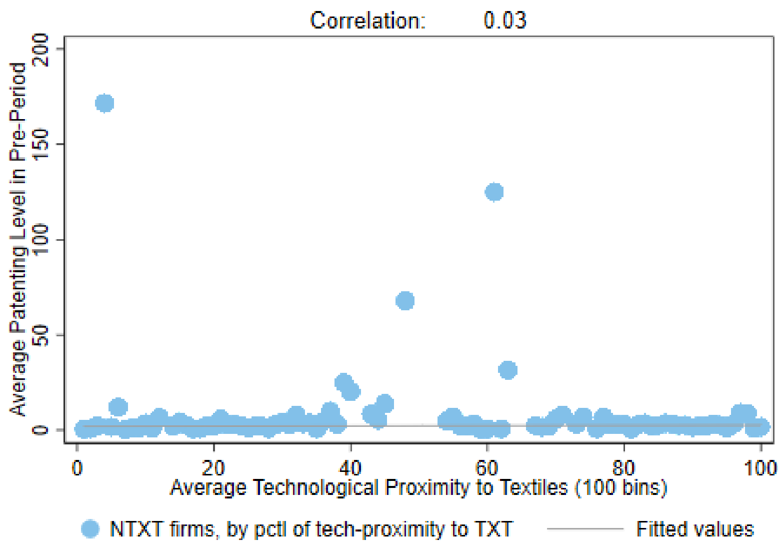
Table 11: Direct vs. Indirect Effects at the Aggregate Level

Predicted change in patent filings ($\hat{y}$)	Formula
Firm Level	
Direct effect	$\hat{y}_j^{dir} = \hat{\eta} * QUOTA_j^{TXTL} * PatInt_j$
Indirect effect	$\hat{y}_i^{indir} = \hat{\delta} * (\sum_j tech_{ij} * QUOTA_j^{TXTL}) * PatInt_i$
Country level	
Direct effect	$\hat{y}_c^{dir} = Median[\hat{y}_{j,c}^{dir}] * N_{c,TXTL}$
Indirect effect	$\hat{y}_c^{indir} = Median[\hat{y}_{j,c}^{indir}] * N_{c,NTXTL}$
Ratio [Europe]	$\hat{y}_{EU}^{indir} / \hat{y}_{EU}^{dir} = 4.97$
Ratio [Median Country]	$\hat{y}_c^{indir} / \hat{y}_c^{dir} = 3.41$

Notes: This table estimates the ratio of the indirect effect of patenting divided by the direct effect of patenting, aggregated at the country and European levels, as a consequence of the removal of import quotas on Chinese textiles.

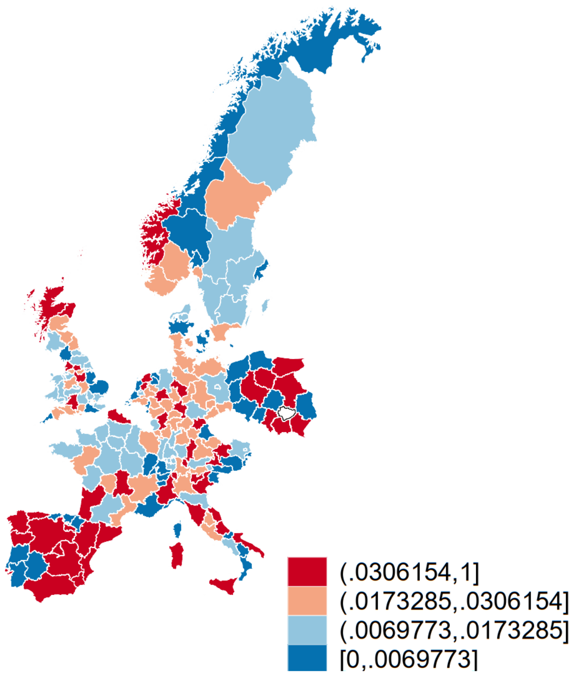
Figures

Figure 1: Patenting in Pre-Period vs. Technological Proximity to textile firms



Notes: The scatter plot shows the average pre-period patenting levels of non-textile firms by percentiles of their technological proximity to textile firms. The greater the variable on the horizontal axis, the closer the technological proximity to textile firms. We split our sample of non-textile firms into 100 bins.

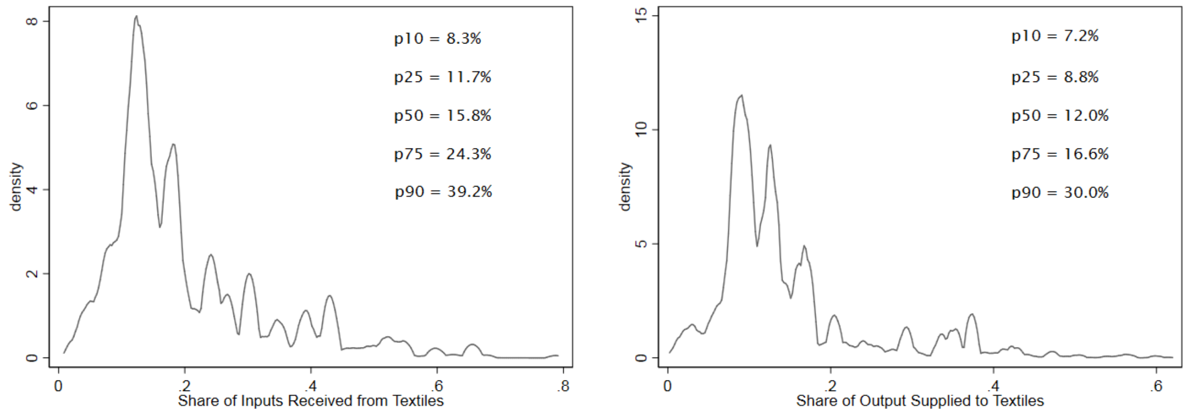
Figure 2: Number of TXTL vs. NTXTL Firms



Country	Non-Textile Firms	(in %)
AT	839	1.86
CH	3,114	6.92
DE	15,366	34.14
DK	661	1.47
ES	1,655	3.68
FR	5,525	12.27
GB	8,672	19.27
IT	5,164	11.47
NL	1,849	4.11
NO	571	1.27
PL	92	0.20
PT	67	0.15
SE	1,437	3.19
Total	45,012	100.00

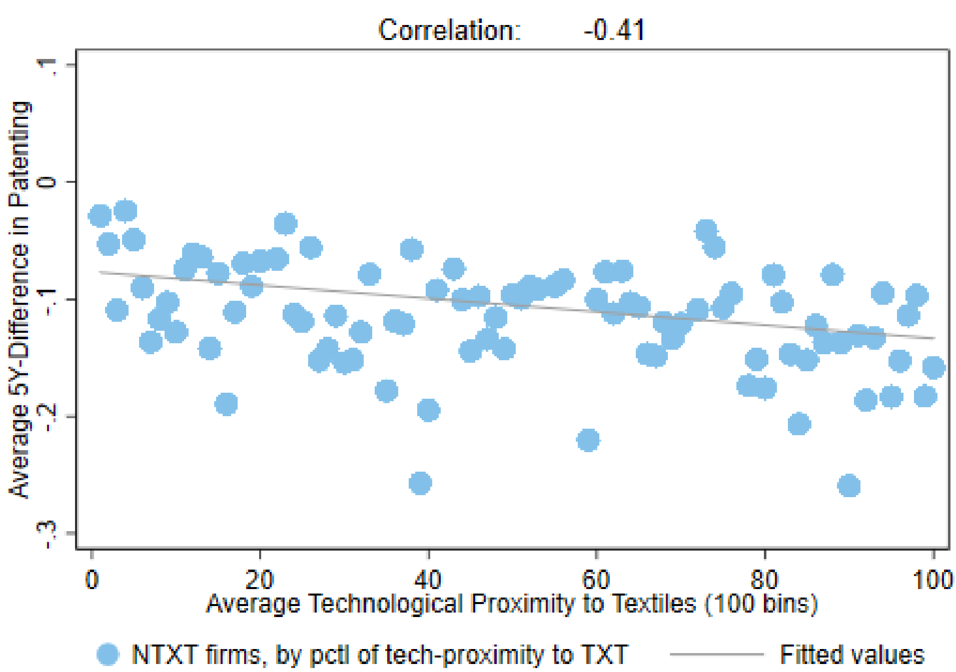
Notes: The map shows the relative number of textile firms to non-textile firms in each NUTS2 region in the 13 European countries of our sample. Red-shaded regions have a relatively high share of textile firms, blue-shaded regions have a relatively low share of textile firms.

Figure 3: Vertical Production Links in the Input/Output Matrix



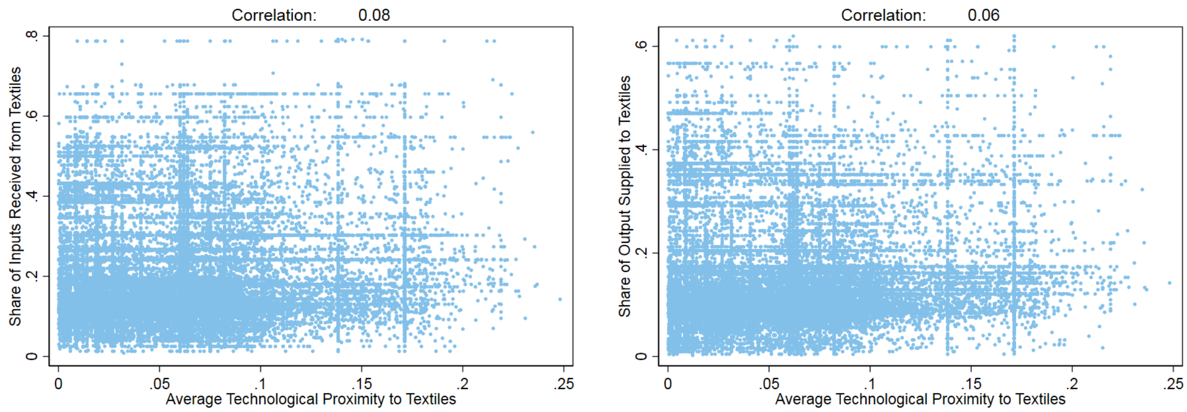
Notes: This figure plots the distribution of the vertical input & output exposure measures across the non-textile firms. The left panel shows the histogram for the share of inputs received from textile industries, the right panel shows the histogram for the share of output supplied to textile industries.

Figure 4: Changes in Log-Patenting vs. Technological Proximity to TXT



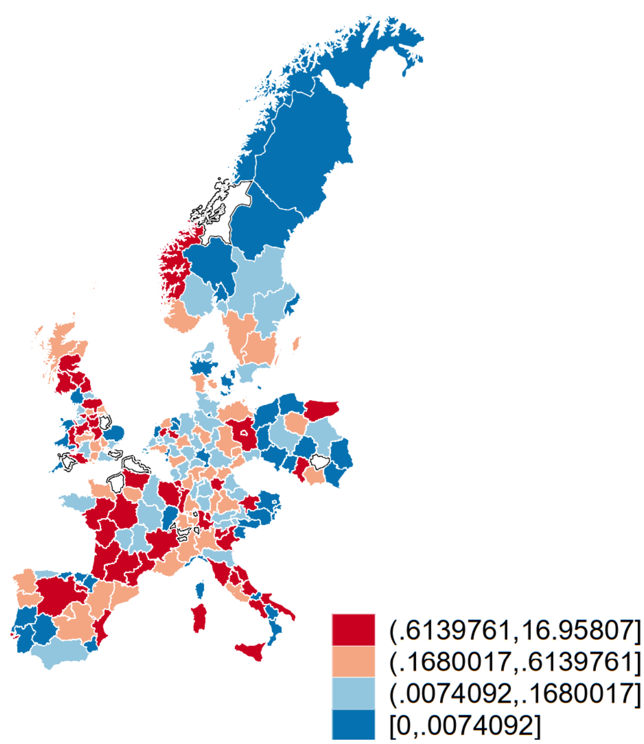
Notes: The scatter plot shows the average changes in log-patenting of non-textile firms in the post-period, by percentiles of their technological proximity to textile firms.

Figure 5: Technological Connectedness vs. Vertical Connectedness to TXTL Firms



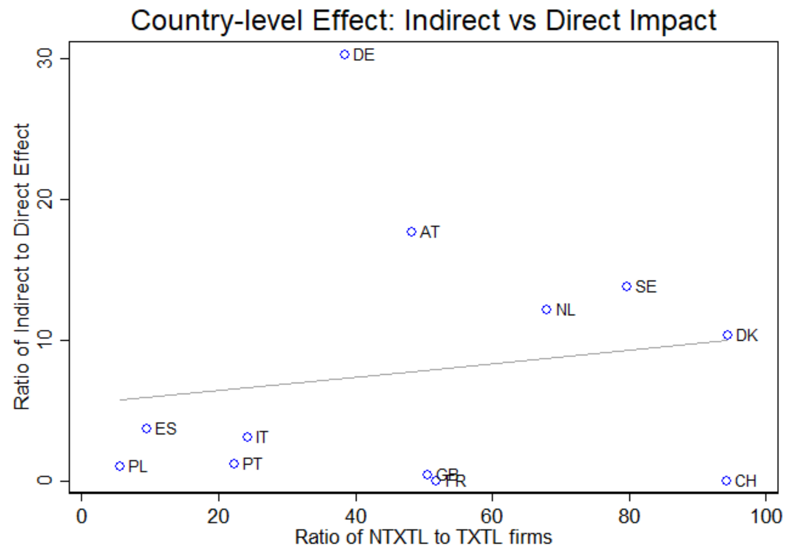
Notes: This figure shows the correlation between technological proximity and vertical input & output exposure measures for the sample of non-textile firms: share of inputs received from textile industries (left) and share of outputs supplied to textile industries (right).

Figure 6: Aggregate Effects at the Regional (NUTS2) Level



Notes: The figure maps the relative magnitude of the indirect effect at the NUTS2 regional level.

Figure 7: Country-level Estimates: Relative Importance of Indirect Effect



Notes: This figure collapses firms at the country level and measures how the relative impact of the China shock on non-textile firms is a function of the relative number of non-textile firms.

A Appendix: Tables

Table A-1: Baseline Results
Conditional on Financial Data Availability for Sample Firms

Dep. Var.: Δ lnPat of non-textile firms	(1) IV 1st stage	(2) IV 2nd stage	(3) Reduced Form	(4) OLS
Toughness of quotas in 2000	-0.5334^{***}		-0.0183^{***}	
	(0.005)		(0.005)	
Δ lnPat of textile firms		0.0343^{***}		0.0377^{***}
		(0.008)		(0.004)
Country FE	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes
Underidentification test	41.1			
Weak identification test	13,971.7			
No. of clusters	441	441	441	441
Observations	121,945	121,945	121,945	121,945
Unique Firms	24,389	24,389	24,389	24,389

Notes: This table estimates the same models as in the baseline IV, Reduced Form and OLS specifications, but restricted to the sample of firms for which we have non-missing financial data in ORBIS. Columns (1) and (2) correspond to Table 5 Columns (5) and (6). Column (3) corresponds to Table 3 Column (3), and Column (4) to Table 4 Column (3). All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table A-2: Heterogeneity by Firm Size

Dep. Var.: Δ lnPat of non-textile firms	(1) all (baseline)	(2) all w/ revenue info	(3) 1st quartile	(4) 2nd quartile	(5) 3rd quartile	(6) 4th quartile
Δ lnPat of textile firms	0.0329***	0.0334***	0.0188**	0.0194**	0.0321**	0.0636**
	(0.006)	(0.007)	(0.007)	(0.010)	(0.013)	(0.026)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification test	51.9	50.0	38.3	38.1	45.5	56.0
Weak identification test	15,613.3	14,519.3	12,353.9	9,030.0	9,258.2	11,615.6
No. of clusters	471	444	324	305	307	369
Observations	225,060	146,690	36,735	36,610	36,675	36,670
Unique Firms	45012	29338	7347	7322	7335	7334

Notes: This table shows heterogeneous effects by non-textile firm size in an IV framework, where the second stage is presented. Firm size is determined by revenue, where firms in the 1st quartile are the smallest. The dependent variable and regressor of interest are as in Table 4. Column (1) repeats the baseline result of Table 5 Column (6). Column (2) conditions on non-missing revenue info in ORBIS. The remaining Columns (3)-(6) split the non-textile firms by size into quartiles. Column (3) restricts the sample to the smallest non-textile firms and Column (6) does the same for the largest non-textile firms. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table A-3: Accounting for Patent Quality

Dep. Var.: Δ lnPat of non-textile firms	(1) All patents	(2) EPO patents	(3) EPO cit.-weight
Δ lnPat of textile firms	0.0329***	0.0191***	0.0135 **
	(0.006)	(0.006)	(0.005)
Country FE	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes
Underidentification test	51.9	51.9	51.9
Weak identification test	15,613.3	15,613.3	15,613.3
No. of clusters	471	471	471
Observations	225,060	225,060	225,060
Unique Firms	45,012	45,012	45,012

Notes: In this table we address patent quality by non-textile firms in an IV framework where the second stage is presented. Column (1) is our baseline IV result (as in Table 5 Column (6)), which includes patents filed with any patent authority. Column (2) restricts the patent count to those filed with the European Patent Office (EPO); as citations across patent authorities cannot be directly compared, we believe it is sensible to focus only on the most important patent authority for our European manufacturing firms. Finally, Column (3) weights the change in the log of patents by the number of citations received in the first five years post-grant. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table A-4: Alternative Lag Specification

Dep. Var.: Δ lnPat of non-textile firms	(1)	(2)	(3)
Δ lnPat of textile firms	0.0329***		
	(0.006)		
L.Δ lnPat of textile firms		0.0381***	
		(0.008)	
L2.Δ lnPat of textile firms			0.0588***
			(0.014)
Country FE	Yes	Yes	Yes
Industry(SIC-4D) FE	Yes	Yes	Yes
Underidentification test	51.9	52.4	52.4
Weak identification test	15,613.3	4,830.5	2,373.4
No. of clusters	471	471	471
Observations	225,060	180,048	135,036
Unique Firms	45012	45012	45012

Notes: Column (1) repeats our baseline IV result. Columns (2) and (3) use one-year and two-year lags of the regressor, respectively. All specifications include country fixed effects and industry 4-digit fixed effects. ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.

Table A-5: Alternative Technological Proximity Measure

Dep. Var.: Δ lnPat of non-textile firms						
	(1)	(2)	(3)	(4)	(5)	(6)
Method	1st stage	IV	1st stage	IV	1st stage	IV
Quotas removal	-0.2128^{***}		-0.2139^{***}		-0.2156^{***}	
	(0.002)		(0.002)		(0.001)	
Δ lnPat textile (all) - cites		0.0094^{***}		0.0093^{***}		0.0078^{***}
		(0.002)		(0.002)		(0.002)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry(SIC-2D) FE	No	No	Yes	Yes	No	No
Industry(SIC-4D) FE	No	No	No	No	Yes	Yes
Underidentification test	55.0		50.3		48.9	
Weak identification test	9,009.5		18,038.7		24,970.2	
No. of clusters	455	455	455	455	455	455
Observations	123,035	123,035	123,035	123,035	123,035	123,035
Unique Firms	24,607	24,607	24,607	24,607	24,607	24,607

Notes: This table presents the instrumental variable estimation results for the full panel of non-textile firms, using an alternative measure of $tecih_{ij}$ that is based on the overlap in citation behavior between a firm-pair. The dependent variable is the change in the log of patents by non-textile firms. The instrument is the weighted change in the quota toughness prior to China's accession to the WTO for each textile firm. The endogenous regression is the weighted change in the log of patents by textile firms. Columns (1), (3), and (5) present first stage results, while columns (2), (4), and (6) present second stage results. Equations (1) and (2) are the baseline specification that control for country fixed effects. Equations (3) and (4) additionally include a full set of industry 2-digit dummies. Equations (5) and (6) include instead a full set of industry 4-digit dummies. The table reports test statistics for underidentification (Kleiberger-Paap rk LM statistic) and weak identification (Kleibergen-Paap rk Wald statistic). ***/**/* indicate significance at the 1%/5%/10% level. Standard errors are clustered at the SIC4 industry level.