Imports, Exports, and Domestic Innovation*

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Abstract

This paper identifies the causal effects of trade integration on domestic innovation. For this purpose, I crawl online data to create a new long-term patenting panel dataset for Germany for the period 1993-2012, and exploit the cross-regional variation in the German industry structure to identify the effect of trade integration with the "East" (i.e., Eastern Europe and China) on patenting. I use trade between the East and other advanced economies as instruments for regional import and export exposure. I find that an increase in net trade exposure (defined as import minus export exposure) causes an increase in regional patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, the effects are heterogeneous across exposure origin. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Increasing integration with China has no effect on innovation. In total, exposure from Eastern Europe accounts for approximately 5.5% of the patenting increase in Germany.

JEL classification: F14, O30, R11, R12.

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1 Introduction

The question of how trade affects domestic innovation has been discussed in the literature for a long time. Theoretically, the effect of trade on innovation is ambiguous.[1] By now, it is a widely held view that the nexus of trade and innovation "remains intrinsically an empirical question" (Autor et al., 2016, p.3). The purpose of this paper is to empirically identify the causal effect of increasing trade integration on innovation. Specifically, I estimate the effects of trade with the "East" (China and Eastern Europe) on innovation in Germany using a regional identification strategy.

To measure innovation, I crawl online patent data from the DPMAregister database of the German Patent and Trademark Office (DPMA). The data cover the period 1993 to 2012 and contain the universe of patent applications (hereafter referred to as "patenting") in Germany. There are several reasons why these data are well suited to study the effect of trade on innovation. First, the data also include innovation from smaller- and medium-sized firms as well as from private persons, whereas most of the existing literature in this field is biased towards larger firms and only captures a fraction of total patenting. Recent studies have shown that, on average, innovation intensity (share of sales invested in innovation) is higher for small firms (see for instance Itenberg (2013), Akcigit (2010) and Akcigit and Kerr, 2018).[2] This suggests that it is important also to consider smaller and medium sized firms when investigating innovation effects, as well as innovation outside of firms such as from suppliers or private entrepreneurs.

Second, the sample period is marked by big changes in patenting in Germany. From the early 1990s, patent applications almost doubled to around 60,000 in the early 2000s. After a peak in 2005, patenting decreased again by two thirds until 2012. Additionally, the period covers two major trade shocks for Germany. The fall of the Iron Curtain in the early 1990s and the opening of China, especially its WTO accession in 2001, increased import competition for Germany, but at the same time, this development created opportunities to tap new export markets. As a result, both German imports from and exports to Eastern Europe and China increased by more than factor 15 and 18, respectively, from 1993 until 2012.

Third, Germany is a big player in global innovation. In 2015, it was the country with the fifth most patent applications worldwide after China, the United States, Japan and Korea, and thus the country with the most patent applications in Europe (WIPO Statistics

[1] Increased trade integration will increase competition for domestic firms, which has ambiguous effects on innovation. See for instance Cohen (2010) for a summary of the literature. Autor et al. (2016) provide a summary of the opposing forces of competition on innovation. See Bloom et al. (2016), for a more detailed discussion on various types of innovation and trade models additionally highlighting the ambiguity. Recent theoretical work by Bloom et al. (2013) and Bloom et al. (2014) explain innovation arising from trade by using a "trapped-factor model" of innovation. Production factors can be either used to produce or innovate. Trade with low-wage countries reduces the profitability of producing the same goods as before and the opportunity cost of innovation decreases. For low-wage countries, the economic literature and policy makers often see trade as a potential channel for technology and knowledge access fostering innovation (see UNCTAD (2014), ICTSD (2011) and Goldberg et al., 2010 a, b).

[2] Previously, this relationship was not observable; firm size did not have effects on innovation intensity. See for instance Cohen et al. (1987) and Cohen and Klepper (1996).

Database, October 2016).

To make use of the universe of patenting, I apply a regional identification strategy. This is possible, because the patent data allow me to use the zip code of the inventor and the applicant to create a regional exposure measure for Germany. In particular, I measure regional trade exposure using a shift-share approach, for instance applied by Autor et al. (2013), and exploit the cross-regional variation in the German industry structure in combination with industry-specific trade flows to identify regional import competition and export intensity. I then explain changes in the innovation activity of 402 counties (in German: "Landkreise") between 1993 and 2012 with changes in regional trade exposures. I combine the regional innovation exposure and trade exposure data with regional labor market information from the Establishment History Panel provided by the German Federal Employment Agency. To address concerns of endogeneity, I instrument for German trade flows with trade flows between other similar high-wage countries and Eastern Europe as well as China. Existing literature, especially in the field of regional economics, stresses the role of regional determinants of innovation that my approach allows me to control for.[3]

I find that, on average, an increase in net trade exposure (defined as import exposure minus export exposure) causes an increase in regional patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, the effects are heterogeneous across exposure origin. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Depending on the specification, I find that a $1000 increase in Eastern European import exposure per worker in a county increases patenting by 0.044 patents per 100,000 inhabitants in that region. This implies that import exposure from Eastern Europe in Germany accounts for approximately 5.5% of patenting increase in the 1993-2012 period. Increasing integration with China has no effect on innovation.

The results are in line with previous papers that find that Chinese trade exposure, compared to Eastern European exposure, plays only a minor role for Europe, and especially Germany, contrary, for instance, to the United States.[4] The estimates show that the effect of import exposure from Eastern Europe on patenting is largest for the most patent-intensive firms. However, the effect also holds for low-patent applicants. I find that there is still a considerable amount of innovation originating from smaller firms or private persons.[5] In general, these applicants are neglected in previous publications, although they make up a significant proportion of total patenting. The results hold for a wide range of robustness checks.

The current paper is most closely related to Bloom et al. (2016) (hereafter referred to

[3]For instance, Jaffe et al. (1993) show that patent citations are more likely to occur within the state of the cited patent than one would expect based only on the preexisting concentration of related research activity.

[4]Pierce and Schott (2016), for instance, show that China's WTO accession caused a decrease in the manufacturing employment in the United States. For the EU, there is no similar effect. The US labor market effects from trade with China estimated by Autor et al. (2013) are much larger than those of Dauth et al. (2014).

[5]Low patent applicants account for a smaller share of total patenting. As compared to firms they usually only hold one or at most a few patents per applicant.

as “BDR”).[6] They match patent data from the European Patent Office with firm-level data from the Bureau Van Dijk’s Amadeus database. For twelve European countries, including Germany, they find that Chinese import competition accounts for approximately 15% of technology upgrading between 2000 and 2007. They argue that import competition led to a reallocation of employment towards innovative firms and an increase in information technology (IT), total factor productivity (TFP), R&D and patenting for exposed firms. In this current paper, I also find a positive effect of import exposure on innovation. Contrary to BDR, I find that this effect is caused by exposure from Eastern Europe, whereas Chinese exposure has no effect on patenting in Germany.

There may be several reasons for why the findings differ. First, the estimation strategy in this paper differs. Using a regional estimation strategy has the advantage that I cover the universe of patenting in Germany - including smaller firms and private applicants. BDR cover on average around 24% of firm patenting and around 20% of total patenting in Germany. Section A.1 in the Appendix provides more details on this comparison and discusses the patent composition in Germany. Second, my sample period covers a longer time span that is marked by major changes in patenting, whereas during the 2000 to 2007 period, studied by BDR, patenting in Germany was at a steady all-time high. Third, BDR use a group of twelve European countries, and results may be driven by countries other than Germany. The industry structure is diverse across different European countries.

Another related paper is by Autor et al. (2016) who match U.S. patents with data for publicly held firms listed in Compustat and find, contrary to my paper, a strong negative effect of import exposure on patenting. It does not come as a surprise that Chinese trade exposure may have different effects for Germany compared to the United States. As discussed previously, the economic literature suggests that the China shock is of much greater importance for the United States.[7] Additionally, as before, differences in results may be explained by the fact that I use a different estimation strategy and include the universe of patents. Similar to BDR, the focus on publicly listed firms in Autor et al. (2016) suggests that their sample is restricted to large firms.

More generally, my paper is also related to studies that link trade liberalization to firm productivity. Shu and Steinwender (2018) provide an excellent summary of the empirical findings for trade impacts on both firm productivity and innovation.[8] Despite the fact that the majority of papers seems to find a positive link between trade and productivity as well as between trade and innovation, different results show that the effects may vary across countries depending on characteristics such as industry and employment structure, competition intensity, exposure origin, sample period, etc. It is all the more surprising that

[6] To my knowledge, their paper is the only other paper that examines the impact of trade exposure on innovation for Germany, albeit only as part of an aggregated group of 12 European countries.

[7] See Pierce and Schott (2016) and the difference in the results of Autor et al. (2013) and Dauth et al. (2014).

[8] Additionally, a number of case studies exist on the issue. See for instance Freeman and Kleiner (2005), who investigate how large US shoe manufacturers respond to import competition from low wage countries or Bartel et al. (2007) and Bugamelli et al. (2008) who look at US valve manufactures and Italian manufacturers, respectively, with similar questions. For the cases under investigation, an increase in innovation to avoid increasing competition from low wage countries seems to be a prominent strategy.

the main focus so far has been on trade exposure from China. More than 70% of the studies published after 2010 listed in Shu and Steinwender (2018) focus on trade exposure from China. Given that exposure from Eastern Europe played a much greater role for Europe, and Germany in particular, I deviate from this practice and also include the exposure from Eastern Europe in this paper.

The remainder of the paper is organized as follows. In the next Section 2, I describe the data and stylized facts about regional innovation and trade exposure in Germany. Section 3 discusses the empirical methodology and presents the baseline results. Section 4 presents further differentiated results and various robustness checks. Conclusions follow in Section 5.

2 Data and Stylized Facts

I combine crawled patent data from the DPMAregister database of the German Patent and Trademark Office and trade data from the UN Comtrade database with the Establishment History Panel (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Centre of the German Federal Employment Office (IAB).[9] The Establishment History Panel is a detailed micro-level dataset that covers a representative 50% sample of all establishments in Germany from 1975 to 2014 (for the 1975-1990 period, it includes only establishments in Western Germany) with at least one employee subject to social insurance contributions. Information on the location of the establishment allows aggregating establishment level variables to the county level. I thus obtain local labor market controls providing information on education (employment shares by skill category), the industry structure (employment shares at the three-digit industry level) and employment (share of foreign workers, male/female worker ratio, age structure and occupational structure by Blossfeld categories). The Blossfeld categories contain information on the number of engineers and scientists, which I use as a proxy for R&D employment. The combined dataset covers the years 1993-2012. Reliable data on establishments and trade in Eastern Germany, as well as patent data based on the current five-digit postal code system, is available from 1993 onwards, determining the first year of observation. The time frame coincides with the rapid increase in trade with Eastern Europe shortly after the fall of the Iron Curtain and with China after its WTO accession in 2001. In the following, I will refer to the combined trade with Eastern Europe and China as trade with the "East".

2.1 Patenting

To measure innovation, I crawl patent data from the DPMAregister database of the German Patent and Trademark Office (DPMA). The data cover the years 1993 to 2012.[10]

[9] This study uses the weakly anonymous Establishment History Panel (Years 1975 - 2014). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and via remote data access (Project Number: fdz1043). For further information concerning the BHP see also Gruhl et al. (2012) (German version) or Hethey-Maier and Seth (2010) (English version).

[10] Patent data is also available from 1980 to 1992. For this time period, however, zip codes are primarily based on the former four-digit system. After the introduction of the current five-digit system the number of

Patents are a widely accepted and common proxy for innovation despite its well-known drawbacks.[11] The data contain the universe of patent applications from applicants and inventors located in Germany.[12] Applicants can be either natural persons (e.g., private entrepreneurs) or legal persons (e.g., corporations). The data provide rich information on every patent and contain details on the applicants (name, zip code, (legal) type), inventors (name, zip code), patent content (title, description and classification as well as subclassifications according to the International Patent Classification,"IPC") and patent history (changes in ownership, different steps in the application process). Using a zip code-municipality crosswalk provided by the German postal service ("Deutsche Post Direkt"), I use the zip code information of the applicants and inventors to create measures for patent intensity at the regional administrative level.[13] The smallest administrative unit for which I calculate regional patenting intensities is the municipality level. For the empirical analysis, however, the data are aggregated to the county level to match the regional aggregation level of the trade exposures. The baseline index for innovation intensity in administrative region i at time t, IA_{it}, is given by:

$$IA_{it} = \frac{\sum_{n=1}^{N} \frac{1}{k^z} \frac{1}{s_n} PAT_{nt}^{z}}{E_{it}}, \qquad z \subset i, \tag{1}$$

where PAT_{nt}^{z} refers to patent n that was filed at time t in zip code area z, which (at least partly) has to be located inside the administrative region i. If the zip code area crosses administrative lines, each administrative unit accounts for fraction $\frac{1}{k^z}$ of the patent, where k^z is the number of administrative regions that are part of the zip code area.[14] Regional innovation is measured either based on the zip code of the inventor or of the applicant (i.e., the owner). Each patent is weighted with $\frac{1}{s_n}$, where s_n is the number of inventors /

zip codes in Germany increased by factor six to around 30,000 allowing for a much more precise allocation of innovation based on the zip code of the inventor or applicant to administrative units.

[11]Deyle and Grupp (2005) provide a brief summary of main drawbacks including 1) limited distinguishability of novelty, 2) limitation to innovation that is subject to patent protection, 3) differing value and quality of patents, 4) limited distinguishability in terms of innovation types such as process or product innovation.

[12]Note: In this paper, "Patenting" (and "Patents") always refer to patent applications. Patent applications are a well suited proxy for underlying innovation activity, as they capture any innovation process that is deemed successful by the applicant. Additionally, the procedure until a patent is eventually granted oftentimes takes several years (and might even be revoked later on) such that patent applications rather than granted patents are the more feasible and immediate measure. Crawling of the dataset began in 2013, such that information on the grant is insufficient. On average, around 42% of total patent applications are eventually granted. This share remains rather constant over the years.

[13]The regional approach is used to establish a link between trade and patenting. Another link, e.g., via the industry to which a patent can be assigned to is not directly accessible. The patents are only classified according to IPC and crosswalks to industry classification have a questionable quality due to the very different nature of the classifications. An industry allocation based on the patent description, for instance, by using machine learning techniques, would also be extremely time-consuming and error-prone.

[14]In Germany, zip codes label areas that are defined for postal delivery which do not always adhere to geopolitical administrative boundaries. However, for 81.55% of the observations zip code areas are municipality-sharp, which means that the zip code area lies within one municipality only. Aggregation to the county level (the preferred aggregation level for the empirical analysis) increases the number of cases, for which the zip code area corresponds to only one administrative region to 99.11%. Accordingly, concerns that inaccurate zip code to administrative unit allocations might bias results can be precluded.

applicants of patent n.[15] To obtain an innovation measure that takes regional population into account, the absolute number of regionally allocated patents (in the numerator) is divided by the population size of this region E_{it}. To deal with the reorganization of municipality boundaries over time, I use municipality crosswalks provided by the German Federal Office for Building and Regional Planning ("Bundesamt für Bauwesen und Raumordnung") to convert regional data to the territorial borders of 2014. This is necessary, since, without territorial reallocation, there would be cases, for which the county of the inventors or applicants changes without the inventors or applicants having actually moved. Additionally, the Establishment History Panel is also based on the territorial borders of 2014.

Figure 1: Patenting in Germany: Total Patenting and Subsections

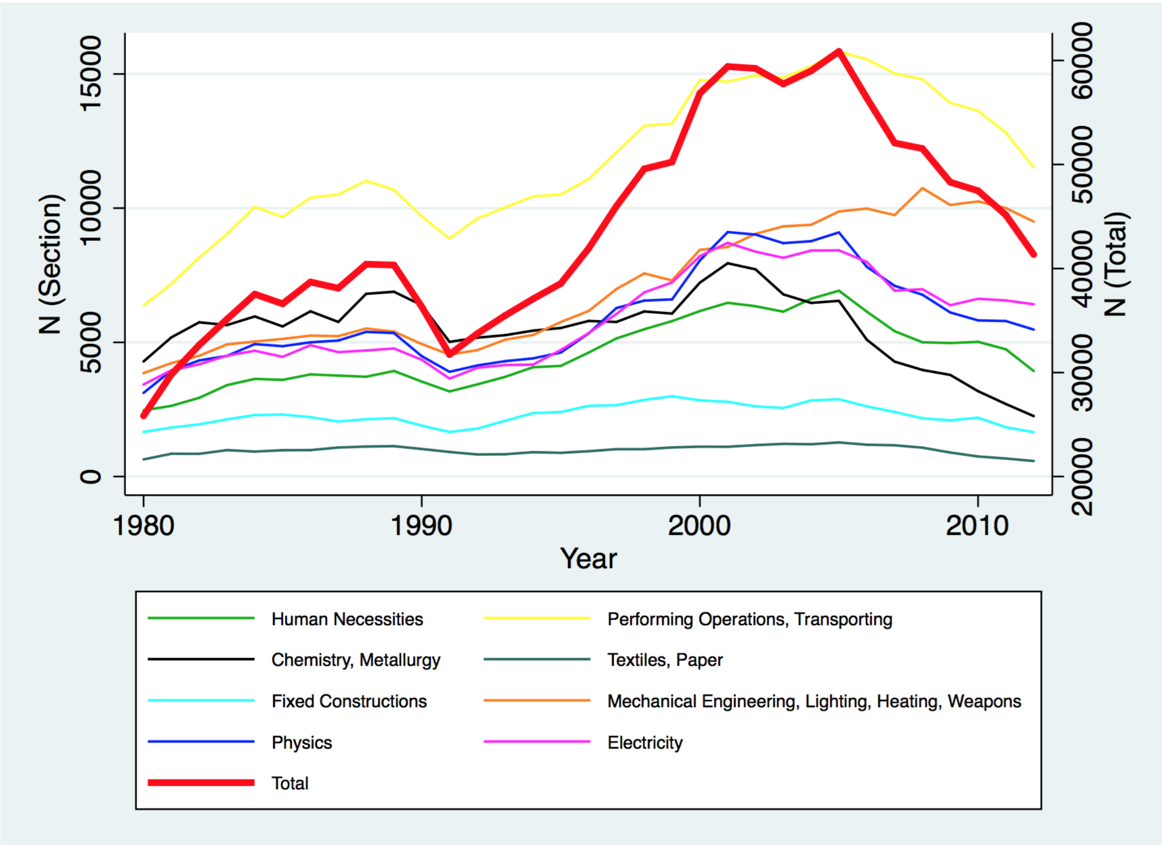


Figure 1 shows the yearly numbers of patent applications in Germany (also including East Germany before German reunification) both in total (right axis) and also broken down by the one-digit level of IPC categories (left axis) from 1980 to 2012. In the 1980s, yearly patenting increased continuously from around 25,000 in 1980 to slightly more than 40,000 in 1989, before a sharp drop around the time of German reunification occured.[16] This trend is similar for all of the eight categories. After 1991, patenting increased quickly throughout the 1990s and the first half of the 2000s to peak at more than 60,000. In the second half of the

[15] In 2012, the average number of inventors per patent was 2.3 and the average number of applicants per patent was 1.1.

[16] Before reunification, the data includes patents filed both at the "German Patent Office" in West Germany and at the "Office of Inventions and Patents" in East Germany. After reunification, both patent offices merged and patenting in Eastern Germany dropped tremendously.

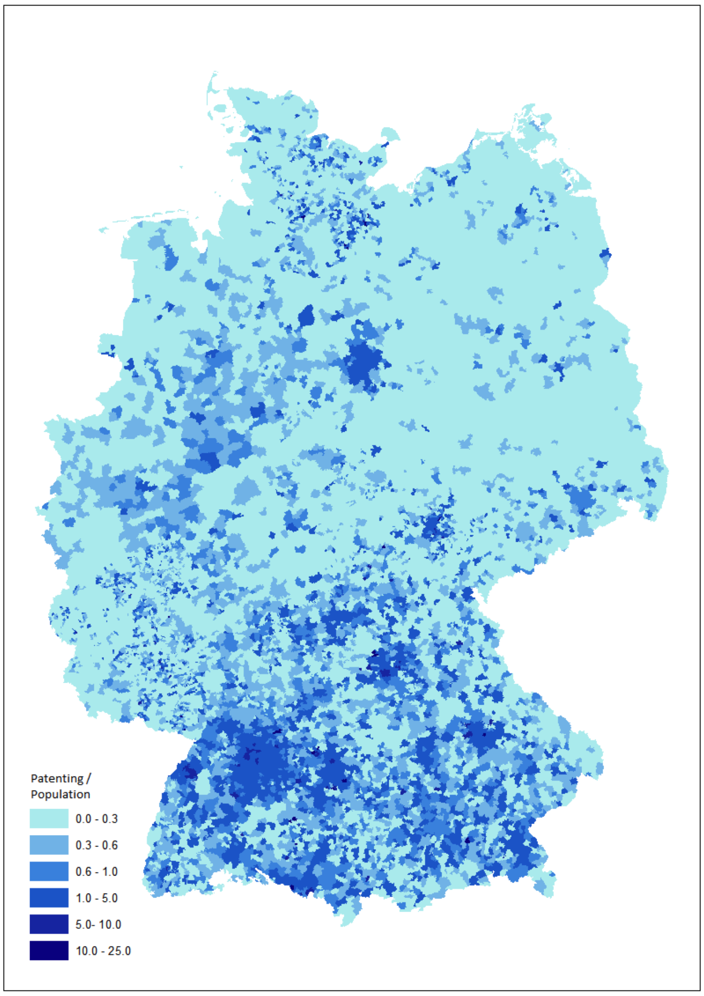
2000s, the number of patent applications dropped continuously to a level of around 41,000 applications in 2012. With around 28%, "Performing Operations, Transporting" accounted for the largest share of patenting, followed by "Mechanical Engineering, Lighting, Heating, Weapons" with a share of about 23%. "Textiles, Paper" (about 1%), "Fixed Constructions" (about 4%) and "Chemistry, Metallurgy" (about 6%) only play a minor role in patenting. Over time, patent growth within the categories roughly follows the growth pattern of total patenting described above. This means that category shares of patenting remain largely unchanged. One interesting exception are the shares of "Mechanical Engineering, Lighting, Heating, Weapons" and "Chemistry, Metallurgy". In 2001, both sections accounted for almost identical shares of 14.4% and 13.4%, respectively. Since then, the share of "Mechanical Engineering, Lighting, Heating, Weapons" has increased to about 23% and the one of "Chemistry, Metallurgy" has decreased to only 5.5% in 2012. For all other sections, shares remain within a 5 percentage point range during the 33 years of observation.

Innovation activity in Germany is very heterogeneous across regions. Figure 2 depicts the number of patent applications in 2012 by the inventor's location for every 1000 inhabitants at the municipality level based on Equation 1. The map shows both a distinct North-South and West-East divide. In the southern states of Baden-Wuerttemberg and Bavaria, patent intensity is much higher than in states that are located further north. At the same time, we can find much more innovation in Western Germany compared to Eastern Germany (inlcuding Berlin). Despite the fact that per capita patenting is comparatively low in some of the largest German cities like Berlin or Hamburg, agglomeration generally seems to favor innovation. Patenting is highest in densely populated areas: In Western Germany, especially the corridor reaching from the Rhine-Ruhr metropolitan area up to the metropolitan area of Hannover, Wolfsburg and Braunschweig in the southern part of Lower Saxony shows the highest per capita innovation. In South Germany, a stretch reaching from Würzburg down to the area around Lake Constance and including the metropolitan regions of Nuremberg, Stuttgart and Munich is patent intensive. Consider that here the inventor's rather than the applicant's location is taken as the origin of innovation. Inventors may live in commuting distance from the firm's location, and thus innovation patterns are regionally more dispersed. Indeed, regional innovation activity is more centralized, when patent applications for every 1000 inhabitants are calculated by the applicant's location (see Figure 9 in the Appendix). Now cities in general, and the centers of metropolitan regions in particular, show relatively high per capita patenting. It is here, where oftentimes the firms or at least the branches that are responsible for the patent applications are located. However, the general picture does not change: The North-South and West-East divide persists and per capita innovation is still relatively high in densely populated areas.[17]

The regional intensity of innovation shows considerable variation over the years. Figure 3 presents the absolute change of patenting per 100,000 inhabitants measured by the location

[17] Unsurprisingly, the picture changes slightly when looking at total patenting rather than per capita patenting (see Figure 10 in the Appendix). Now, the largest German cities like Berlin, Hamburg or Dresden also show high numbers of patent applications.

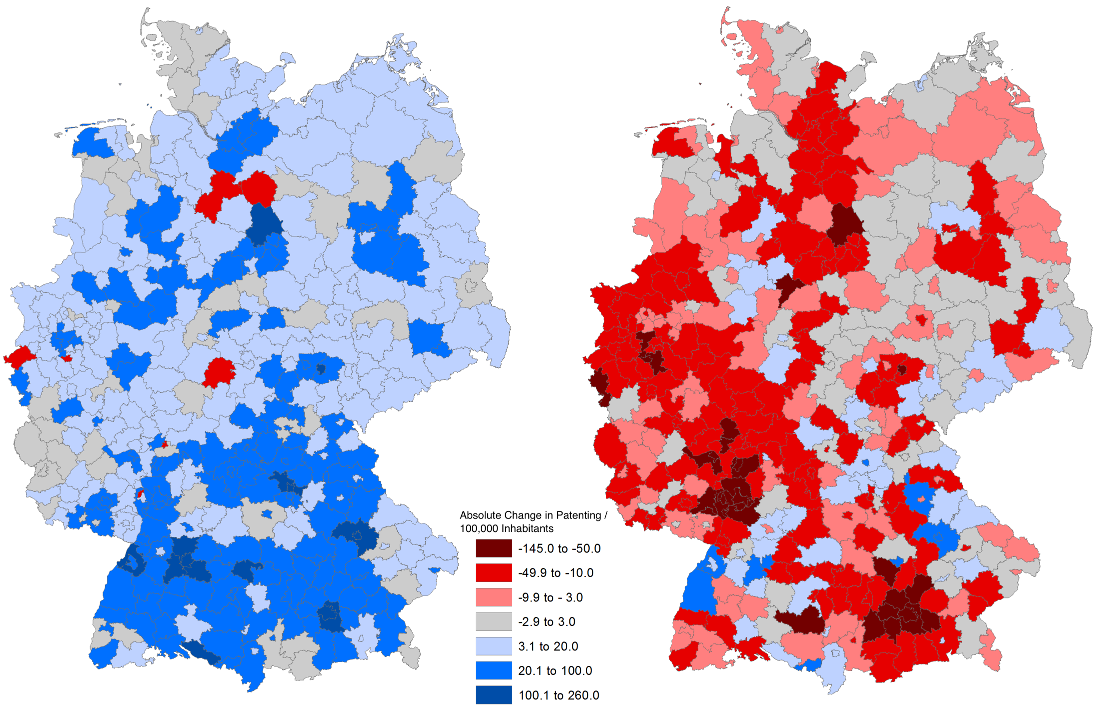
Figure 2: Patenting per 1000 Inhabitants by Municipality of the Inventor



of the inventor at the county level.[18] The map on the left shows the change between the period averages of 1993 to 1995 and 2002 to 2004, $\bar{IA_i}^{02-04} - \bar{IA_i}^{93-95}$, whereas the map on the right depicts the change between the period averages from 2002 to 2004 and from 2010 to 2012, $\bar{IA_i}^{10-12} - \bar{IA_i}^{02-04}$. One immediate observation is that regional growth of patenting differs considerably between the two periods. During the first period, patenting increases in almost all counties with larger growth in the South than in the North and stable values for Eastern Germany. For the second period, the picture is more diverse: Patenting decreases in about 60% of the counties, remains stable in about 20% of the counties and increases in about 20% of the counties as well. Again, most of the regions with increased patenting are located in the South, whereas the Eastern German regions face a decrease in patenting. Regional changes in patenting are a reflection of the diverse regional industry structure in Germany. Previously, it was shown that the numbers of yearly patent applications develop heterogeneously across different IPC categories. This will result in dispersed patterns of regional innovation, as the applicants of patents with certain IPC categories tend to be

[18] The following observations remain largely unchanged when the location of the applicant rather than the location of the inventor is used to calculate regional patenting (see Figure 11 in the Appendix).

Figure 3: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Inventor; $I\bar{A}_i^{02-04} - I\bar{A}_i^{93-95}$ (Left) and $I\bar{A}_i^{10-12} - I\bar{A}_i^{02-04}$ (Right)



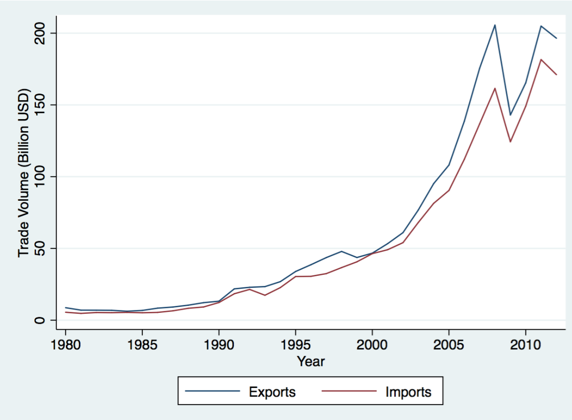
regionally concentrated. In the second period, for instance, patenting decreases strongly in the Ruhr area - a region characterized by traditional manufacturing industries likely to file patents in the field of "Chemistry and Metallurgy" that showed a patenting decrease of more than 50% during that period (cf. Figure 1). Another observation is that regional patenting shows both elements of a clustered and dispersed pattern. On the one hand, we can observe general North-South and East-West patterns and partly also clustering at the more local level such as for the Ruhr area example above. On the other hand, innovation patterns within states are still quite dispersed as patenting intensities vary considerably at the county level within a state.

2.2 Trade Exposure

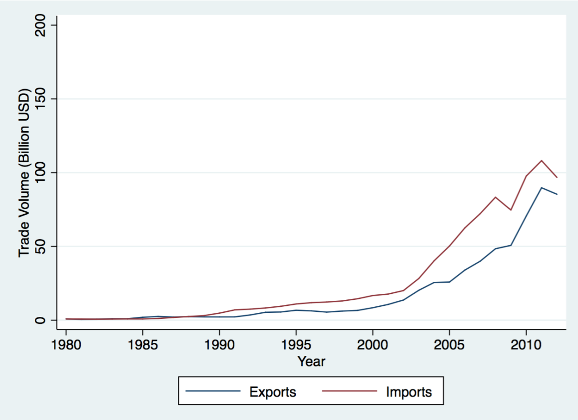
The fall of the Iron Curtain and the opening of China increased import competition for Germany. At the same time, however, this development created opportunities to tap new export markets. German trade relations during the 1993-2012 period are marked by a strong intensification of trade with China and Eastern Europe. Figure 4 shows the increase in German exports to and imports from Eastern Europe (left) and China (right) (measured in billion USD). During the 1980s and early 1990s, trade with either of the two regions was almost non-existent.[19] After the fall of the Iron Curtain in the early 1990s, trade with Eastern Europe picked up pace. Also, trade with China started to increase slowly. However, it was

[19] This observation supports the previous claim that the industry structure in the early 1990s is well suited to allocate trade flows, as it will be unaffected by Eastern trade at that point in time.

not until its WTO accession in 2001 that the trade increase with China became eminent. Accordingly, the import and export exposure in the 1990s primarily originated from trade with Eastern Europe, whereas it was both Eastern Europe and China that contributed to increasing exposures in the 2000s. Overall, German imports from and exports to Eastern Europe and China increased by more than factor 15 and 18, respectively, from the early 1990s until 2012. The nature of the German trade relations with Eastern Europe and China differs substantially. Trade with Eastern Europe is primarily intra-industry, implying that product categories of German export goods are similar to those of the goods imported from Eastern Europe. By contrast, trade with China is primarily inter-industry. Section A.4 in the Appendix discusses the differences in the nature of German-Eastern European and German-Chinese trade in more detail and shows that the weighted Grubel-Lloyd-Index (cf. Figure 14) is much larger for German-Eastern European than for German-Chinese trade.



(a) Eastern Europe



(b) China

Figure 4: German Trade with Eastern Europe and China

To compute regional trade exposures, I use a shift-share approach, for instance applied by Autor et al. (2013), and exploit the cross-regional variation in the German industry structure to regionally allocate trade flows.[20] For this purpose, I obtain trade flows between Germany and Eastern Europe, as well as between Germany and China at the four-digit product level (in SITC 2/3 classification) from the UN Comtrade database. I harmonize trade and IAB employment data using a crosswalk that reclassifies trade flows into the three-digit industry-level classification used in the IAB data.[21] Here, Eastern Europe is defined as the countries of the former Soviet Union plus the member states of the Warsaw Pact and its predecessor states, except Albania, East Germany, and Slovakia.[22] Using a product-industry crosswalk, the trade flows are converted into the industry classifications of the Establishment History

[20]For Germany, this identification strategy was, for instance, used by Dauth et al. (2014) and by Dippel et al. (2015) who measure the effect of trade exposure on voting behavior.

[21]Establishments in the IAB data are classified according to the WZ93 classification ("Industrial Classification of Economic Activities for the Statistical Office of the Federal Employment Agency, 1993 Edition"), which is based on the NACE classification.

[22]To be precise, "Eastern Europe" includes Armenia, Azerbaijan, Belarus, Bulgaria, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Poland, Romania, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

Panel. To obtain the change in regional import exposure ΔImp_{it}^{East} in region i at time t from trade with the East, the following expression is calculated:

$$\Delta Imp_{it}^{East} = \sum_j \frac{E_{ijt}}{E_{jt}} * \frac{\Delta Imp_{jt}^{Ger-East}}{E_{it}}, \tag{2}$$

where the change in imports ΔImp of industry j is allocated to county i according to the share of total employment in industry j that can be found in county i, $\frac{E_{ijt}}{E_{jt}}$. Additionally, the import flows are weighted with the total county employment E_{it}, such that the exposure for a region is, ceteris paribus, larger if overall employment in that region is lower. Taking the sum over all industries then yields the regional import exposure. Likewise, the change in regional export exposure ΔExp_{it}^{East} in region i at time t is calculated as:

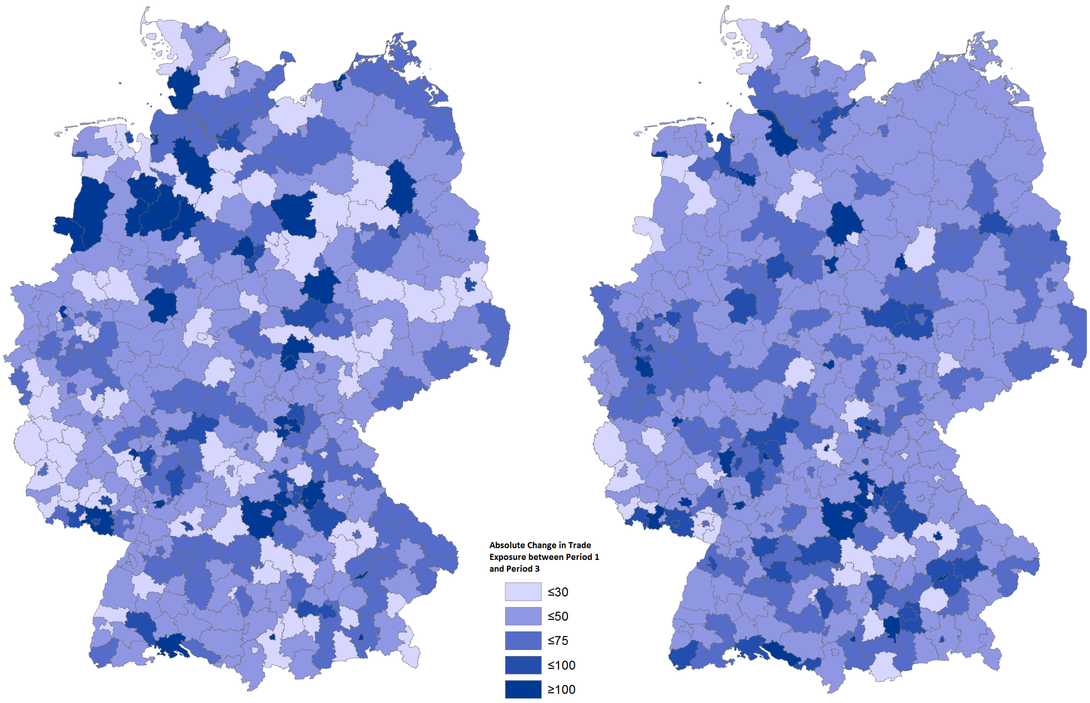
$$\Delta Exp_{it}^{East} = \sum_j \frac{E_{ijt}}{E_{jt}} * \frac{\Delta Exp_{jt}^{Ger-East}}{E_{it}} \tag{3}$$

Figure 5 depicts the change in the computed trade exposure measure separately for import exposure ΔImp_{it}^{East} (left) and export exposure ΔExp_{it}^{East} (right) between the period averages of 2010 to 2012 and 1993 to 1995. As can be seen, the trade shock is spatially rather diverse meaning there is no clear, broad clustering within certain regions. However, certain patterns become visible. First, Eastern Germany is affected less compared to Western Germany. Second, the regions exhibit different import and export exposure, meaning that regions with high import exposure do not necessarily exhibit a high export exposure as well (and vice versa). Third, not only counties that are well-known for their manufacturing industry, such as Wolfsburg (car manufacturing) or Nuremberg-Erlangen (machinery and plant engineering), show relatively high import exposure, but also areas that are not particularly known for their high importance of manufacturing (e.g., certain counties in Lower Saxony). One reason for this pattern might be that the exposures are weighted by the number of manufacturing employees.[23] Figure 12 and Figure 13 in Section A.3 in the Appendix depict the changes in import and export exposure between the period averages of 2010 to 2012 and 1993 to 1995 separately for both origins, Eastern Europe and China. The graphics show that the exposure differs regionally according to the origin, reflecting both the diverse industry structure in Germany but also the differences between the goods traded between Germany and Eastern Europe and between Germany and China.[24]

[23]Note: Compared to Dauth et al. (2014), the figure shows a larger exposure for counties in Eastern Germany. The reason for the difference lies in the different time of observation. I also include Eastern Germany in the first period for the baseline estimation. Shortly after the German reunification, manufacturing in Eastern Germany was hardly existent, explaining why in this paper the change in the exposure in Eastern Germany is larger.

[24]Furthermore, the change in the trade shocks also differs between observation periods (not displayed in this paper), meaning that the change in trade exposure between the period averages of 2010 to 2012 and 2002 to 2014 differs from that between the period averages of 2002 to 2004 and 1993 to 1995.

Figure 5: Absolute Change in Regional Import Exposure $\overline{Imp_i^{East}}^{10-12} - \overline{Imp_i^{East}}^{93-95}$ (Left) and Regional Export Exposure $\overline{Exp_i^{East}}^{10-12} - \overline{Exp_i^{East}}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker



3 Trade Exposure and Innovation

The next subsection contains the baseline estimations for the effects of trade on innovation. I first describe the empirical specification, and then estimate the effect of net exposure on innovation. I break down this effect further into import and export exposure. Finally, I present coefficient estimates separately depending on the origin of the exposure (Eastern Europe and China).

3.1 Empirical Specification

In the baseline specification, I first estimate the effect of changes in the three-year averages of regional net trade exposures on changes in three-year averages in patenting per 100,000 inhabitants with the following equation:

$$\Delta\overline{IA_{it}} = \alpha + \beta\Delta\overline{NetX_{it}^{East}} + \gamma\overline{X_{it}'} + \sigma_i + \kappa_t + u_{it}, \tag{4}$$

with

$$\Delta\overline{NetX_{it}^{East}} = \Delta\overline{Imp_{it}^{East}} - \Delta\overline{Exp_{it}^{East}} \tag{5}$$

where $\Delta\overline{IA_{it}}$ is the change in the three year average of innovation activity, i.e., patenting per 100,000 inhabitants in region i at time t from Equation (1), and $\Delta\overline{NetX_{it}^{East}}$ is the change in the three year average of net trade exposure. The change in net trade exposure is defined as the difference between the change in three year average of import exposure $\Delta\overline{Imp_{it}^{East}}$ and the change in three year average of export exposure $\Delta\overline{Exp_{it}^{East}}$ (cf. Equation (2) and Equation (3)). I deflate the trade flows using the German CPI to the base year 2010. X_{it}' is a vector of regional control variables. Region fixed effects σ_i are implemented at the disaggregated county-level.[25] κ_t are time fixed effects. The standard error u_{it} is clustered at the level of the 402 counties. Note that the estimation approach will generate very conservative estimations for the effects of trade on innovation. The only effects that count here are deviations from the trend, i.e., effects are measured only to the extent that the variation in trade causes a deviation from the linear time trend.

To overcome concerns that shocks that affect German trade and regional innovation simultaneously might drive the results, I follow Autor et al. (2013) and instrument for the trade exposures $\Delta\overline{NetX_{it}^{East}}$, $\Delta Imp_{jt}^{Ger-East}$ and $\Delta Exp_{jt}^{Ger-East}$ using trade flows between other advanced economies and the East. This way, the effect that drives the empirical results originates purely from the exogenous rise in Eastern supply. The selection of the group of countries used for instrumentation for the baseline estimations closely follows Dauth et al. (2014) and includes Canada, Japan, New Zealand, Norway, Singapore, Sweden, and the UK.[26]

I estimate differences between periods that consist of three year averages, as patenting is comparatively volatile, contrary, for instance, to labor market outcomes such as manufacturing employment (e.g., Autor et al., 2013). Taking averages over several years thus prevents that outliers in yearly patenting, i.e., years in which patenting is exceptionally high or low, drive the results.

I study changes between averages of the years 1993, 1994, 1995 (period one) and the averages of the years 2002, 2003, 2004 (period two) and between the averages of the years 2002, 2003, 2004 and the averages of the years 2010, 2011, 2012 (period three). This time frame fits well the patenting time trend in Germany (cf. Figure 1): From period one to period two, patenting in Germany rises to an all time high that persists during the years of period two. The following years from period two to period three are then marked by a steady decline in patenting. Additionally, reliable patent data based on the current five-digit postal code system and establishment data for Eastern Germany is not available before 1993.

[25] Results remain qualitatively unchanged when I implement region fixed effects at more aggregated regional levels of labor market regions, regional planning regions, states and four larger regions (South, North, East and West). This latter regional fixed effects specification follows Dauth et al. (2014); region North covers the states of Schleswig-Holstein, Hamburg, Bremen and Lower Saxony. Region West includes Rhineland-Palatinate, Hessia and Saarland. South contains Bavaria and Baden-Wuerttemberg, and East covers the new eastern states of Germany plus Berlin.

[26] The rationale for the selection of this instrument group, in particular, is well described in their paper. The only difference to Dauth et al. (2014) is that I exclude Australia from the baseline instrument group, as I find Australia negatively affecting the performance of the instruments for German-Chinese trade. As a robustness check, I additionally alter the instrument group by adding other countries and conducting the regressions with various compositions of the instrument group. Results remain unaffected by choice of the instrument group. See Section 4.2.3.

Patenting per 100,000 inhabitants based on the home address of the inventor is the preferred baseline measure of regional innovation. Patenting based on the inventor's location is a frequently used innovation measure in the literature and has been proven to reliably determine the regional origin of innovation.[27] Since inventors will most likely live in close proximity to their workplace, which is the location marking the regional origin of trade exposure, a geographic link between innovation and trade exposure can be established. Patenting based on the applicant's address is less suited to build this link. Firms oftentimes use just one address (generally that of the firm's headquarter) to file patent applications. However, large companies (especially MNEs), which are also responsible for a big share of patent applications, often have multiple locations, holdings, affiliations or subsidiaries, so this procedure could be geographically misleading (see for instance Blind and Grupp, 1999).[28]

In the second baseline estimation (Equation (6)), I then disentangle the net exposure effect and separately include changes in three-year averages of regional import and export exposure:

$$\Delta\overline{IA_{it}} = \alpha + \beta_1\Delta\overline{Exp_{it}^{East}} + \beta_2\Delta\overline{Imp_{it}^{East}} + \gamma\overline{X_{it}'} + \sigma_i + \kappa_t + u_{it}, \tag{6}$$

Finally, in a third estimation, I re-estimate Equation (6) again distinguishing between trade flows from Eastern Europe and China.

3.2 Results

3.2.1 Net Exposure, Import Exposure, and Export Exposure

Table 1 presents the baseline results from Equation (4). Every column pair includes one specification. The first column of the pair always contains the OLS estimates, and the second one the IV results, where I instrument for the trade flows between Germany and the East by using trade flows between other advanced economies and the East. The least conservative specification in the first two columns only includes basic labor market controls, such as the employment shares of skilled workers ("% Skill"), foreigners ("% Foreigner"), women ("% Women"), and workers performing routine tasks ("% Routine"). Additionally, I control for the manufacturing share ("% Manufacturing"). On the one hand, the share of manufacturing drives the trade exposures, and on the other hand, manufacturing accounts for a large proportion of corporate patenting such that regions with larger manufacturing shares are expected to be more patenting intensive. The second specification adds time fixed effects and region fixed effects at the county level. This controls for any unobserved county or period characteristics. Thus, the only remaining identifying variation originates from the county-time dimension. The preferred and most conservative third specification additionally adds controls for the relative importance of specific industries in a given region. These controls account for the fact that patenting in Germany is biased towards larger firms. For the time of

[27] See, for instance, Paci and Usai (2000), Paci and Pigliaru (2002) and Mancusi (2008).

[28] Also see Jaffe et al. (1993) and Jaffe and Trajtenberg (2002) for a profound discussion on the suitable geographical measure of patenting.

observation, the 20 biggest applicants account for almost 25% of total patenting in Germany. Primarily, theses firms are part of the automobile (9 out of 20 of these firms) or chemical industry (5 out of 20 of these firms). Accordingly, I add controls for the employment share in these three-digit industries ("% Chemistry" and "% Automobile") as well as a control for the share of the largest industry ("% Largest Industry") in a region.

Table 1: Effect of Periodic Changes in Regional Net Trade Exposures on Periodic Changes in Patenting per 100,000 Inhabitants

	Baseline Labor Market		**+Region / Time FE**		**+Industry Information**	
Estimation	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta NetExposure$	7.813	6.594	54.367*	36.202*	63.713*	45.766**
	(10.122)	(9.142)	(31.429)	(19.204)	(32.581)	(19.157)
% Manufacturing	93.053***	92.957***	206.701***	207.843***	216.185***	216.784***
	(14.545)	(14.417)	(59.940)	(41.914)	(69.548)	(48.531)
% Skill	-311.130***	-311.358***	-742.855*	-744.803**	-828.788**	-827.581***
	(64.277)	(64.226)	(437.419)	(306.706)	(420.316)	(293.291)
% Foreigner	-51.324***	-51.327***	387.435***	388.539***	379.984***	381.352***
	(18.426)	(18.334)	(133.436)	(93.563)	(131.776)	(92.108)
% Women	191.403***	191.506***	74.693	69.093	96.769	90.624
	(43.801)	(43.641)	(218.777)	(154.085)	(198.563)	(139.089)
% Routine	-207.899***	-207.839***	-272.927*	-273.941***	-276.528*	-277.451***
	(25.366)	(25.190)	(145.235)	(102.062)	(150.768)	(105.577)
% Chemistry					-3.885	- 2.984
					(192.465)	(134.354)
% Automobile					-237.868	-228.359
					(223.421)	(154.515)
% Largest Industry					91.148	87.669
					(139.744)	(97.071)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
	2SLS First Stage Estimates, Dependent Variable: Net Exposure					
$\Delta NetExposure$		0.913***		0.693***		0.692***
(Other Countries)		(0.116)		(0.035)		(0.037)
F-Test excl. Instr.		25.52		59.22		39.74

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

The effect of changes in regional net trade exposure on changes in patenting ("Δ Net Exposure") is insignificant for the estimations with only basic labor market controls, but turns statistically significant and is positive when adding fixed effects and industry information. IV estimates are similar to the OLS results. As the change in net exposure is defined in units of $1000 per worker, the coefficient of 45.77 in the preferred 2SLS estimation implies that a $1000 increase in the net exposure per worker in a county increases patenting by

45.77 patents per 100,000 inhabitants in that county. The coefficient for the IV estimation is slightly smaller and indicates greater significance compared to the OLS estimate consistent with an upward bias of the OLS estimate. Additionally, the results show that an increase in the share of foreigners is positively linked to innovation and that - as expected - patenting increases with the share of manufacturing. Patenting is smaller when the number of routine workers increases. Innovation requires complex tasks that are generally conducted by non-routine occupations. Surprisingly, patenting is also negatively related to the share of skilled workers. A probable explanation is that a large proportion of high-skilled workers is employed in the service sector, which, in turn, is significantly less patent intensive than manufacturing. The first stage estimations are displayed at the bottom of the table and indicate strong and fitting instruments. The F-tests show that the hypotheses that instruments are excluded can be rejected, and the instruments are strongly correlated with the endogenous explanatory variable.

To identify whether the positive coefficients are either explained by changes in import exposures or by changes in export exposures, estimating Equation (6) disentangles the effects. The results are displayed in Table 2. As before, I apply the three specifications "baseline labor market","fixed effects" and "industry controls". Again, the first column for every specification shows the OLS estimate, whereas the second column shows the IV results.

The results show that the positive effect on changes in innovation from increasing net exposure is completely driven by import exposure effects. $\Delta\overline{Exp_{it}^{East}}$ ("Δ Export Exposure") is insignificant for all specifications, whereas $\Delta\overline{Imp_{it}^{East}}$ ("Δ Import Exposure") is statistically significant and positive for specification 2 and 3. The coefficient of 0.051 in the preferred 2SLS estimation implies that a \$1000 increase in the import exposure per worker in a county increases patenting by 0.051 patents per 100,000 inhabitants in that county.[29] Again, first stage estimations displayed at the bottom of the table show strong and fitting instruments. The results for the control variables are in similar ranges as in the previous estimate.

3.2.2 Heterogeneity between Eastern Europe and China

To disentangle the findings, I now break down the effects by further distinguishing between the origin of trade exposure, and estimate Equation (6) separately for both Eastern European and Chinese exposure. This distinction is well justified, as exposures from Eastern Europe and China are rather diverse. First, trade exposure from Eastern Europe kicked in much earlier after the fall of the Iron Curtain in the early 1990s, whereas the exposure from China primarily began to increase after its WTO accession in 2001. Second, exposure from Eastern Europe is much higher compared to China. Both imports from and exports to Eastern Europe are approximately 10 times larger in the 1990s and still twice as high in

[29] Compared to estimation (4) coefficients might seem small in magnitude at first glance. However, it has to be considered that the values of net exposure $\overline{NetX_{it}^{East}} = \Delta\overline{Imp_{it}^{East}} - \Delta\overline{Exp_{it}^{East}}$ are much smaller compared to the values for the import or export exposure. The values for the import exposure are only slightly larger than those for the export exposure during the years of observation (cf. Figure 4). Additionally, the figures for average patenting per county are not large either. For the observation period, total yearly average patenting in Germany reached a number of 49,712. Taking into account that there are 402 counties in Germany, average yearly patenting per county amounts to a number of around 124.

Table 2: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants

	Baseline Labor Market		**+Region / Time FE**		**+Industry Information**	
Estimation	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta ImportExposure$	0.004	0.002	0.059*	0.042**	0.067*	0.051***
	(0.007)	(0.007)	(0.034)	(0.018)	(0.035)	(0.018)
$\Delta ExportExposure$	-0.178**	-0.201*	0.060	0.142	0.029	0.122
	(0.080)	(0.114)	(0.194)	(0.242)	(0.237)	(0.302)
% Manufacturing	95.378***	95.583***	219.624***	227.962***	225.475***	233.606***
	(14.582)	(14.423)	(60.871)	(44.126)	(69.989)	(50.893)
% Skill	-262.803***	-255.979***	-724.646	-716.577**	-818.569*	-809.073***
	(76.293)	(81.187)	(440.874)	(307.585)	(421.272)	(289.373)
% Foreigner	-42.202**	-40.856**	389.015***	391.031***	382.315***	385.580***
	(17.988)	(18.234)	(133.510)	(94.093)	(133.052)	(94.255)
% Women	175.785***	173.622***	54.987	38.285	87.432	73.690
	(45.810)	(45.862)	(223.020)	(169.619)	(201.849)	(146.414)
% Routine	-195.450***	-193.520***	-258.712*	-251.890***	-267.113*	-260.409***
	(26.727)	(27.932)	(142.725)	(93.250)	(145.210)	(94.195)
% Chemistry					-8.736	-11.762
					(192.454)	(134.219)
% Automobile					-202.735	-164.705
					(247.574)	(195.777)
% Largest Industry					99.438	102.661
					(149.750)	(112.006)
County FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
	2SLS First Stage Estimates, Dependent Variable: Import Exposure					
$\Delta ImportExposure$		0.878***		0.652***		0.650***
(Other Countries)		(0.072)		(0.021)		(0.021)
F-Test excl. Instr.		169.98		151.47		151.48
	2SLS First Stage Estimates, Dependent Variable: Export Exposure					
$\Delta ExportExposure$		0.551***		0.591***		0.559***
(Other Countries)		(0.091)		(0.119)		(0.106)
F-Test excl. Instr.		180.71		161.75		131.63

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

2012. Third, the nature of trade differs: As shown previously, trade between Germany and Eastern Europe is primarily intra-industry (cf. Section A.4 in the Appendix), whereas for China, the inter-industry component is much larger.

Table 3 shows the OLS and IV estimations for both Eastern Europe and China, using again the three specifications from above. Unsurprisingly, changes in export exposure remain widely insignificant for both Eastern Europe and China. Interestingly, the results show that the import exposure effect is purely driven by Eastern Europe: For all specifications including fixed effects, the effect is positive and significant, whereas exposure from China is largely insignificant. The coefficient of 0.044 in the preferred IV estimation implies that a \$1000 increase in Eastern European import exposure per worker in a county increases patenting by 0.044 patents per 100,000 inhabitants in that county. A simple calculation reveals that import exposure from Eastern Europe in Germany accounts for approximately 5.5% of the patenting increase in the 1993-2012 period.[30] This corresponds to the average annual number of 1,215 patent applications.

The result that trade with Eastern Europe affects Germany more than trade with China is in line with previous findings in the literature. Dauth et al. (2014), for instance, show that imports from Eastern Europe affect manufacturing employment in Germany way more than Chinese imports. Effects from trade with China on labor market outcomes for the United States estimated by Autor et al. (2013) are much larger than those estimated by Dauth et al. (2014) for German labor markets - presumably due to Germany's different industry structure that is characterized by a large share of skill-intensive manufacturing. Pierce and Schott (2016) show that China's WTO accession caused a decrease in the manufacturing employment in the United States. For the EU, there is no similar effect.

[30] The exposure per worker in \$ 1000 increased by a factor of 33.36. The calculated coefficient results in an increase of approximately 1.5 patents per 100,000 inhabitants. The actual increase of patenting per 100,000 inhabitants in this period was 27.4, so the import exposure from Eastern Europe accounts for about 5.5% of the patenting increase.

Table 3: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Change in Patenting per 100,000 Inhabitants - Exposure Origin

	Baseline Labor Market				**+Region / Time FE**				**+Industry Information**			
	Eastern Europe		**China**		**Eastern Europe**		**China**		**Eastern Europe**		**China**	
Estimation	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta ImportExposure$	0.004	0.003	-0.015	-0.090	0.044*	0.036**	0.155**	0.163	0.049**	0.044***	0.177**	0.242
	(0.007)	(0.005)	(0.041)	(0.077)	(0.024)	(0.016)	(0.079)	(0.203)	(0.022)	(0.015)	(0.077)	(0.230)
$\Delta ExportExposure$	-0.271**	-0.093	-0.277*	-0.525*	0.261	0.707	0.002	0.150	0.278	0.546	-0.091	0.089
	(0.126)	(0.213)	(0.144)	(0.302)	(0.414)	(0.890)	(0.277)	(0.506)	(0.465)	(1.105)	(0.320)	(0.620)
% Manufacturing	95.385***	93.535***	93.851***	94.953***	224.901***	252.120***	221.470***	229.470***	233.233***	249.218***	231.951***	245.295***
	(14.412)	(14.469)	(14.598)	(14.541)	(62.433)	(61.581)	(60.736)	(45.343)	(72.093)	(73.626)	(70.543)	(54.383)
% Skill	-274.510***	-299.463***	-272.019***	-230.086***	-707.472	-650.111**	-733.180*	-729.752**	-796.688*	-768.755***	-813.282*	-808.103***
	(73.401)	(81.397)	(74.528)	(86.148)	(439.765)	(314.483)	(438.993)	(311.195)	(418.766)	(291.501)	(422.446)	(296.382)
% Foreigner	-39.962**	-47.400***	-47.436**	-40.004**	384.403***	374.559***	385.582***	390.911***	378.525***	373.148***	374.083***	380.226***
	(18.005)	(17.984)	(18.571)	(19.607)	(131.197)	(93.599)	(133.826)	(99.985)	(129.249)	(90.477)	(134.384)	(103.994)
% Women	185.419***	189.835***	174.255***	160.889***	49.321	27.707	65.042	46.197	76.768	69.452	93.461	82.231
	(44.258)	(45.126)	(46.788)	(49.837)	(218.565)	(163.152)	(225.331)	(187.175)	(197.579)	(140.932)	(203.547)	(157.676)
% Routine	-196.954***	-204.001***	-198.889***	-189.811***	-252.281*	-220.095**	-264.423*	-257.394***	-257.497*	-239.831**	-268.801*	-258.448***
	(26.687)	(27.762)	(26.139)	(29.552)	(139.253)	(105.158)	(144.603)	(94.593)	(142.234)	(104.543)	(148.766)	(97.553)
% Chemistry									-3.573	-8.144	-21.467	-36.065
									(190.322)	(133.298)	(193.747)	(138.923)
% Automobile									-189.141	-171.534	-248.038	-195.766
									(221.535)	(178.546)	(259.516)	(256.010)
% Largest Industry									99.690	109.426	88.900	101.317
									(148.994)	(121.074)	(144.867)	(114.958)
Region FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	2SLS First Stage Estimates, Dependent Variable: Import Exposure											
$\Delta ImportExposure$		1.005***		0.343***		0.76***		0.39***		0.761***		0.376***
(Other Countries)		(0.022)		(0.027)		(0.032)		(0.111)		(0.034)		(0.106)
F-Test excl. Instr.		11858.01		68.03		48.75		3.38		36.66		5.76
	2SLS First Stage Estimates, Dependent Variable: Export Exposure											
$\Delta ExportExposure$		0.505***		0.278***		0.354***		0.357***		0.344***		0.32***
(Other Countries)		(0.111)		(0.07)		(0.1)		(0.125)		(0.094)		(0.1)
F-Test excl. Instr.		102.03		90.12		48.7		62.3		36.89		36.88

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

The fact that trade exposure from Eastern Europe is much larger in magnitude may be an explanation for the findings. Furthermore, results are in line with the observed trend in patenting (cf. Figure 1). During the time of increasing import exposure from Eastern Europe in the 1990s, patenting in Germany increases tremendously. However, during the second wave of import exposure during the 2000s, when trade from China was picking up pace, patenting in Germany was on the decline. One potential explanation is that during the first exposure wave, Germany adapted its product mix to avoid competition with low-wage countries in Eastern Europe resulting in an increase of patenting. When China, almost a decade later, entered the world market (at the beginning with low quality goods that were partly similar to the initial Eastern European product mix), Germany did not face immediate competition anymore as it already had adjusted. Lastly, and probably most importantly, the fact that German-Eastern European trade (contrary to German-Chinese trade) is primarily intra-industry (cf. Section A.4 in the Appendix) is likely to imply that German firms face much larger import competition from Eastern Europe. Increased competition decreases the opportunity costs of innovation as existing products become less profitable.

4 Further Differentiation and Robustness

Following the identification of Eastern Europe as the driving force behind positive trade effects on German innovation, I will now use the breakdown by import and export exposure and exposure origin to differentiate the baseline results further and to conduct a wide range of sensitivity checks to validate the robustness of the results. The findings are all based on the most sophisticated specification (3) that includes labor market and industry controls as well as time and county fixed effects.[31]

4.1 Further Differentiation

4.1.1 Final and Intermediate Good Trade

The explanation that import exposure from Eastern Europe and not from China causes innovation due to the higher proportion of intra-industry trade, and thus higher competition, implies that the effects are caused by trading final goods. Intra-industry imports can either be final products that are directly consumed by German consumers, and thus stand in competition with German products, or intermediate goods that are used as inputs by German industries. If the latter was the case, the imports would not imply competition, but instead offshoring of upstream production to Eastern Europe. In this case, German firms will receive a larger share of intermediate goods for assembly from abroad. Thus they may specialize in high-skilled tasks and allocate more production factors to R&D activities. To examine the effect of final goods trade on innovation, I use the import matrix from the input-output tables provided by the Federal Statistical Office to compute industry specific final good

[31] Note, however, that the results of the robustness check also confirm the results of the other specifications and also those of Equation (4) and Equation (6) (in all specifications). These results are not published in this paper but are available upon request. The same applies to first-stage results. The results indicate strong and fitting instruments for all differentiation (unless stated otherwise) and are also available upon request.

shares. Using these shares, I adjust the trade flows and re-estimate the baseline equation. See Section A.5 in the Appendix for more details. The results are presented in Table 4 and confirm the explanation that competition causes an increase in patenting: Still, the effect for import exposure from Eastern Europe is positive, statistically significant, and even larger compared to total trade. The effects on innovation from Chinese import exposure, as well as from Chinese and Eastern European export exposure, remain insignificant.

Table 4: Final vs. Intermediate Good Trade

Estimation	Final Good Trade
Eastern Europe	
$\Delta ImportExposure$	0.435*** (0.168)
$\Delta ExportExposure$	0.417 (1.113)
China	
$\Delta ImportExposure$	0.268 (0.243)
$\Delta ExportExposure$	0.187 (0.58)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

4.1.2 Patent Applicants

The results presented so far are based on the universe of patenting in Germany. This, of course, does not only include firms, but also private persons, research institutions, foundations, government institutions, etc. Using the name of the patent applicant allows me to distinguish between certain types of applicants (see Section A.1 in the Appendix for more details). To control which type of applicant drives the results, I identify five different applicant categories ("firms", "research", "foundation / club", "government" and "not classified") and re-estimate the baseline equation for each category separately. The "not classified" category primarily consists of private persons. The results are presented in Table 5. As expected, it is primarily firms that are affected by Eastern trade exposure. However, innovation in research institutions also increases. One potential explanation is that firms may collaborate with research institutes in order to innovate. Indeed, around 24% of patents from research institutions are commonly filed together with a firm. Again, it is only trade exposure from Eastern Europe driving the results. Import exposure from China and export exposure do not affect innovation for any of the applicant types significantly.

Table 5: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin and Applicant Type

Estimation	Company	NC	Research	Foundation/ Club	Government
Eastern Europe					
$\Delta ImportExposure$	0.041***	0.001	0.002**	0.001	-0.000
	(0.014)	(0.002)	(0.001)	(0.000)	(0.000)
$\Delta ExportExposure$	0.807	-0.142	-0.096	-0.024	0.000
	(1.022)	(0.101)	(0.105)	(0.029)	(0.004)
China					
$\Delta ImportExposure$	0.231	0.025	-0.027	0.016	-0.002
	(0.212)	(0.038)	(0.025)	(0.019)	(0.003)
$\Delta ExportExposure$	0.144	0.021	-0.060	-0.018	0.001
	(0.517)	(0.095)	(0.070)	(0.027)	(0.003)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

4.1.3 Patenting by firm's innovation activity

Patenting in Germany is highly concentrated. Very few firms - mostly MNEs - account for the lion's share of patenting (see Section A.1 in the Appendix). One advantage of the regional identification strategy in this paper is that it allows me to cover all patents and not only patenting by larger firms.[32] Focusing on larger firms, as commonly done in the literature, may cover the majority of patents, but will fail in covering the majority of innovating companies. To disentangle the effects by patent intensity of the firm, I subdivide the data into three categories depending on the number of patents by applicant. Each category accordingly includes approximately the same number of patent applications.[33] Table 6 shows the properties of each category and presents the results for separately re-estimating the baseline equation for each category. The first category consists of 94,337 different applicants. This corresponds to a share of 97.7% of all applicants, and thus the majority of applicants. On average, these applicants file approximately 0.18 patents per year (or 1 patent every five years). The 2,154 applicants in the second category file on average 7.85 patents per year. The 64 most patent intensive firms in the third category account for the same share of total patenting as the 94,337 least patent intensive applicants in the first category and file approximately 273 patents every year. The estimates show that the effects of import exposure from Eastern Europe on patenting is largest for the patent-intensive firms. However, also

[32]Note: The data do not contain any firm level information except the firm's name. The number of patent applications, however, seems to be closely related to common size definition such as the number of employees or turnover. The firms with the largest amount of patenting are well-known multinationals (cf. Section A.1 in the Appendix). On the contrary, a random check of the names of firms with only a small number of patent applications largely reveals unknown small- and medium sized firms.

[33]Note: The categories do not include exactly the same amounts of patents, as the same applicants are attributed to one category only.

for the less patent-intensive firms, the coefficients are positive and significant. The size of the effect doubles approximately from the first to the second category and again from the second to the third category. The third category accounts for slightly more than 50% of the total estimated effect from Eastern European import exposure on patenting. Focusing on larger firms only, would thus only capture part of the total trade effect on innovation.

Table 6: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Applicant Categories

Estimation	1. Category	2. Category	3. Category
Eastern Europe			
$\Delta ImportExposure$	0.006*	0.013*	0.025***
	(0.000)	(0.007)	(0.01)
$\Delta ExportExposure$	-0.058	0.458	0.146
	(0.187)	(0.637)	(0.841)
China			
$\Delta ImportExposure$	-0.033	0.173	0.102
	(0.053)	(0.126)	(0.196)
$\Delta ExportExposure$	0.037	-0.096	0.149
	(0.118)	(0.41)	(0.333)
Applicants	94337	2154	64
Avg. Patents / Year	0.18	7.854	273.025

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

4.1.4 Patent Properties

In this section, I check if trade exposure has any effect on patent properties. The patent data contain information on the number of foreign and domestic inventors as well as the number of foreign and domestic applicants per patent. Furthermore, the number of countries for which protection has been requested is known. In the absence of other patent quality measures such as patent citations, this measure is the best proxy for patent quality available. When applying for a patent, firms have to decide on the countries the patent should grant protection for. Adding countries entails additional costs both in terms of application fees as well as information costs (e.g., knowledge about the local patent law). Acknowledging other factors that may influence the number of protection countries[34], this figure could be seen as the firm's self-evaluation of the patent quality. If applicants deem the patent to be valuable, they might be willing to bear additional costs and add countries of protection. They might, however, decide for protection in fewer countries if the patent is believed to be less valuable. The results in Table 7 show that the number of countries for which protection has been requested is unaffected by trade exposure. I thus conclude that the patent quality remains unchanged. Also, the number of inventors per patent is unaffected. This holds true for both the number of domestic and foreign inventors (partition not displayed in the table). Import exposure from Eastern Europe increases, however, the number of applicants per patent. This is caused by an increase in the number of domestic applicants, whereas the number of foreign applicants is unaffected. One potential explanation is that domestic companies form cooperations to jointly innovate to avoid competition.

4.1.5 R&D Employment

I now deviate from patenting as the dependent variable and estimate the effect of trade exposure on R&D employment instead. For this purpose, I again differentiate between Eastern European and Chinese exposure and estimate the following equation:

$$\Delta\overline{R\&D_{it}} = \alpha + \beta_1\Delta\overline{Exp_{it}^{East}} + \beta_1\Delta\overline{Imp_{it}^{East}} + \gamma\overline{X_{it}'} + \sigma_i + \kappa_t + u_{it}, \tag{7}$$

The estimation approach and all controls are identical to Equation (6), except that now R&D is the left hand side variable. R&D employment $R\&D_{it}$ is defined as the total number of engineers and natural scientists in region i at time t. The measure is provided by the Establishment History Panel and serves as a "proxy to measure establishment's R&D" according to the data description. Table 8 displays the results. In line with the previous findings, import exposure from Eastern Europe significantly increases absolute R&D employment. Companies are increasing R&D employment as a result of import competition from Eastern Europe, allowing them to innovate more. Import exposure from China, as well as

[34]One likely alternative factor influencing this measure is company size. Larger companies are potentially more likely to apply for a larger number of countries as they may operate internationally and thus have lower information costs. To control for this potential explanation, I re-estimate the following estimation by the firms innovation category. For every category, the results are identical to results for the whole sample.

Table 7: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patent Properties

Estimation	# Inventors	# Applicants	# Foreign Applicants	#Domestic Applicants	# Protected Countries
Eastern Europe					
$\Delta ImportExposure$	-0.000	0.000***	0.000	0.000***	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
$\Delta ExportExposure$	0.011	0.000	0.000	0.000	0.012
	(0.013)	(0.002)	(0.001)	(0.002)	(0.140)
China					
$\Delta ImportExposure$	-0.003	0.001	-0.000	0.001	-0.025
	(0.003)	(0.001)	(0.000)	(0.001)	(0.037)
$\Delta ExportExposure$	0.011	0.003	0.000	0.003	-0.033
	(0.007)	(0.002)	(0.000)	(0.002)	(0.060)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

export exposure, does not show significant effects. The result implies that for every $2000 increase in Eastern European import exposure per worker in a county, one additional R&D job is created in that county.

Table 8: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in R&D Employment

Estimation	# R&D workers
Eastern Europe	
$\Delta ImportExposure$	0.505**
	(0.227)
$\Delta ExportExposure$	-19.383
	(15.147)
China	
$\Delta ImportExposure$	-2.109
	(3.128)
$\Delta ExportExposure$	3.56
	(4.118)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

4.2 Robustness

4.2.1 Alternative Innovation Measures

In this section, I deviate from the previous innovation measure of patenting per 100,000 inhabitants based on the home address of the inventor. Table 9 in Section A.6 in the Appendix shows the results, when, instead, various other regional innovation measures are used. In column one, innovation is measured as the absolute number of patents based on the home address of the inventor instead of the population weighted number. In columns two and three, I use the zip code of the applicant instead of that of the inventor in order to regionally compute both population weighted patenting (column two) and total patenting (column three). Using land size as weight is common in the regional economics literature (see for instance Nordhaus, 2006). Accordingly, I use patenting per hectare based on the home address of the inventor (column four) and based on the address of the applicant (column five) as additional alternative innovation measures. So far, I computed regional patent exposures based on the five-digit zip code system. There are a few observations (less than 1%), for which the inventor's or the applicant's zip code is based on the old four-digit zip code system (from before the 1993 reform). Correspondence tables between former four-digit postal codes and administrative units are rather inaccurate, such that I did not take these observations into account before. Instead of dropping these observations as before, I now use correspondence tables to reclassify the origin of the innovation and re-estimate the regressions, also taking former four-digit zip codes into account. Results are displayed in column six (patenting per 100,000 inhabitants based on the inventor's home address) and seven (total patenting based on the inventor's home address). All alternative measures confirm the previous findings and show that only import exposure from Eastern Europe has positive and significant effects on patenting.

4.2.2 Regional Sensitivity

Using a regional identification strategy, it is crucial to check the robustness of the results with respect to regional sensitivity. The following section discusses the robustness with respect to the distinction between Western and Eastern Germany, the aggregation level of the administrative units and the consideration of commuter flows.

Western and Eastern Germany

As a robustness check, I re-estimate Equation (6) differentiated by Eastern European and Chinese trade exposure for Western Germany and Eastern Germany separately. One concern could be that the inclusion of Eastern Germany distorts the results. Especially during the first observation period shortly after German reunification, extensive restructuring processes make it difficult to identify the effects. After reunification, much of the manufacturing industry collapsed in Eastern Germany. Accordingly, the calculation of import exposures could be misleading for Eastern Germany and instrumentation could be difficult, bearing in mind that there were only a few companies still importing or exporting. Still today, large fractions of the patent intensive manufacturing sector are located in Western Germany, whereas manufacturing in Eastern Germany is comparatively scarce. Thus it does not come as a surprise to find the results in Table 10 in Section A.6 in the Appendix confirming the hypothesis that the effects discussed so far mainly originate in Western Germany. Although the Eastern German regions also show a significant positive effect of import competition from Eastern Europe on innovation, the effect is almost twice as large for Western Germany only and also approximately twice as large as the baseline estimates for Western and Eastern Germany combined (see Table 3). Furthermore, almost all previously discussed control variables are insignificant for Eastern Germany.[35]

Commuter Flows and Aggregation of Local Labor Markets

I use patenting per 100,000 inhabitants based on the home address of the inventor as the preferred baseline measure of regional innovation. Even though this regional innovation measure is commonly accepted, widely used, and has been proven to reliably determine the regional origin of innovations, one concern may be that the geographic link between innovation and trade exposure fails to hold for commuters. The regional trade exposure is based on the industry structure and thus on the location of the firm. My measure for regional innovation, however, is based on the home address of the inventor. If the county of the inventor's workplace deviates from the county of his home address (and he thus commutes across county borders for work), the geographic link between innovation and trade exposure fails to hold. First and foremost, this may imply underestimating patenting in larger cities compared to the surrounding area as the commuting balance is generally positive for cities and negative for the hinterland. Commuter flows provided by the German Federal Employment Office show that in 2013 around 13.9% of the population in Germany commuted across county borders.[36]

To control for the potential commuter bias, I adjust regional patenting using the commuter flows between counties in 2013. For each of the 402 counties, I compute the share of commuters to the 401 other counties relative to the county's labor force and to the county's population, and adjust county based patenting according to these shares.[37] The results for the commuter adjusted estimations are displayed in column one to column four of Table 11 in Section A.6 in the Appendix and confirm the previous results. Results remain in a very similar range as before, independent of the innovation measure both for patenting per population (column one and two) and total patenting (column three and four) and independent from the measure of the commuter share both when measured as commuters relative to the

[35]Note additionally that the IV estimation for Eastern Germany only shows weak instruments. The F-tests show that the hypotheses that instruments are excluded can be rejected. However, the instruments are not significantly correlated with the endogenous explanatory variable. This finding does not come as a surprise, given the fact that after German reunification the manufacturing industry collapsed and trade was almost non-existent. For Western Germany, instruments are strong and fitting.

[36]2013 is the first year for which commuter flows are available at the county level.

[37]Note: This procedure is based on the assumption that the share of commuters among the inventors is equal to that of the total labor force. I use commuters relative to the county's population as one measure, since the inventors and applicants may be private persons that do not necessarily belong to the working population.

county's workforce (column one and three) and commuters relative to the county's population (column two and four).

The choice of the regional aggregation level is crucial, especially in light of the innovation measure used in this paper. To establish a geographic link between innovation and trade exposure, it is important that workplace and place of residence of the inventor are located within the same regional unit. Thus, one concern could be that counties are too small to capture this link. The smaller the geographic entities, the higher the chance that inventors commute across county borders. Accordingly, I additionally repeat the estimation at the level of 258 labor market regions (in German: "Arbeitsmarktregionen") and at the level of 96 regional planning regions (in German: "Raumordnungsregionen"). Labor market regions cover the center of functional labor markets and its surroundings. Its boundaries are formed under the condition that commuting flows across regions are minimized. Regional planning regions are even more aggregated and represent the observation and analysis grid of the federal spatial order. Naturally, the share of commuters decreases as the spatial units become more aggregated. Approximately 9.37% of the population commutes across the borders of the labor market regions and around 7.2% commutes across the borders of the regional planning regions. Results for the estimation at the level of labor market regions (column five) and for the estimation at the level of regional planning regions (column six) are shown in Table 11 in Section A.6 in the Appendix. Regression results for both spatial units do not differ qualitatively from the results at the county level.

4.2.3 Instrument Group

As another robustness check, I vary the selection of the country group that I use to instrument the trade flows between Eastern Europe / China and Germany. Table 12 in Section A.6 in the Appendix exemplarily shows three alternative instrument groups.[38] For the first reported alternative specification, I delete the UK, Sweden, and Norway from the sample and add Korea and the United States instead (column one). This specification deals with concerns that other European countries are too much integrated with Germany (common market, member of the Schengen Area, no tariffs, etc.). Next, I include only countries that are member of the European Union (France, the Netherlands, and Italy, see column two).[39] Finally, column three shows the results when the instrument group consists of all countries previously mentioned. As can be seen, the results remain largely unaffected by choice of the instrument group. The instruments generally perform well for all specifications, except for the last specification, where contrary to the baseline specification the instruments

[38]Note: The reported results represent only a small part of the performed robustness check variations in the group of instruments. In general, no deviations were found in any of the alternative instrument groups. This also holds true for the over-identification case, in which I include the trade flows of all countries in the instrument group as separate instruments instead of the aggregate. The list of countries whose trade flows I use in different combinations for instrumentation is limited to advanced economies and includes Australia, Canada, France, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Singapore, Sweden, the UK, and the United States.

[39]Naturally, this way the instrumental variable is most likely not independent from the left hand side variable as trade integration is very high among the countries. This, in turn leads to a high and significant correlation between instrument variable and endogenous explanatory variable.

are not significantly correlated with the endogenous explanatory variable for German-Chinese trade.

4.2.4 Time Framing

Finally, I alter the time framing to check the robustness of the results. First, I do not use value changes between three year averages, but conduct estimations based on single year data instead. I use all 27 three-year combinations from the years that are covered in the baseline scenario.[40] Results remain qualitatively unchanged and are not driven by choice of the years.

The time frame also matters for the computation of the regional trade exposures. In the baseline estimation, the start-of-period industry composition is used to regionally allocate industry-level trade flows. Even though Eastern trade is still very limited during the first period, I additionally use the industry composition ten years prior to the start-of-period to compute regional exposures.[41] Both approaches generate qualitatively identical results. Using the start-of-period industry composition or the pre-start-of-period industry composition guarantees that the industry structure is unaffected by Eastern trade. This should help alleviate concerns about reverse causality. However, it is also well established that changes in trade exposure affect the regional industry structure (see for instance Dauth et al. (2014)). Thus over time, regional exposures will, in fact, also vary, because the industry structure changes. To account for this fact, I replicate the estimations using trade exposures based on time varying industry structures. Again results are qualitatively unaffected.

In summary, the robustness checks show that neither alternative innovation measures, nor the choice of regional units and consideration of commuter flows, nor the choice of instruments, nor the time frame, influence the results. These findings reinforce the observation that trade with Eastern Europe drives innovation in Germany.

5 Conclusion

So far, we have little systematic empirical evidence on the effect of increasing trade integration on innovation. The purpose of this paper is to shed some light on the issue and identify the causal effect of increasing trade integration of Germany with Eastern Europe and China on innovation. For this purpose, I create a regional measure of innovation activity by crawling online patent data and apply different regional trade exposure measures. The findings show that, on average, an increase in net trade exposure (defined as import minus export exposure) causes innovation to increase. Disentangling the effect further, I find that it

[40]In detail, this means that changes between the following year-year-year combinations are estimated: 1993-2002-2010, 1994-2002-2010, 1995-2002-2010, 1993-2003-2010, 1994-2003-2010, 1995-2003-2010, 1993-2004-2010, 1994-2004-2010, 1995-2004-2010, 1993-2002-2011, 1994-2002-2011, 1995-2002-2011, 1993-2003-2011, 1994-2003-2011, 1995-2003-2011, 1993-2004-2011, 1994-2004-2011, 1995-2004-2011, 1993-2002-2012, 1994-2002-2012, 1995-2002-2012, 1993-2003-2012, 1994-2003-2012, 1995-2003-2012, 1993-2004-2012, 1994-2004-2012, 1995-2004-2012

[41]Note: This specification only includes West Germany, as data for the East German industry structure is not available for that time period.

is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Contrary to existing studies, this paper also shows that exposure effects are heterogeneous across exposure origins. The positive link between import exposure and innovation is fully explained by trade integration with Eastern Europe. Increasing integration with China has no effect on innovation.

I find that trade induced innovation primarily affects firms, but interestingly also the innovation activity of research institutions increases as a result of increased Eastern European trade exposure. The regional identification approach of this paper allows me to cover the universe of patenting, unlike most other papers in this field. This makes it possible to subdivide the effects according to the applicant's patent intensity. Patenting is highly concentrated, meaning that few firms account for the majority of patenting. Although the estimates show that the effects are greatest for the most patent intensive applicants, I also find a positive effect on innovation originating from applicants with low patent intensity. These low patent applicants represent the majority of the applicants, contribute in their entirety significantly to total patenting and are generally excluded from previous publications. The estimated effects are robust for a wide range of sensitivity checks and remain largely unchanged by choice of instruments, the time framing, and the choice of regional units and controls.

The findings on the relation between trade and innovation have important policy implications: First, it is an interesting insight that innovation effects are heterogeneous with respect to the country of exposure origin. One potential explanation for the finding that exposure from Eastern Europe but not from China drives innovation is that German-Eastern European trade (contrary to German-Chinese trade) is primarily intra-industry. This likely implies that German firms face much larger import competition from Eastern Europe. Additionally, trade exposure from Eastern Europe is much larger in magnitude. Another potential explanation is that during the first exposure wave in the 1990s, Germany adapted its product mix to avoid competition with low-wage countries in Eastern Europe resulting in an increase of patenting. When China, almost a decade later, entered the world market, Germany did not face immediate competition anymore as it already had adjusted. Second, and more generally, the results show that arguments that trade with low wage countries is bad for innovation have to be rejected. The fear that trade with low-wage countries might block innovation is unfounded. In fact, for Germany increasing trade integration on average even fosters innovation.

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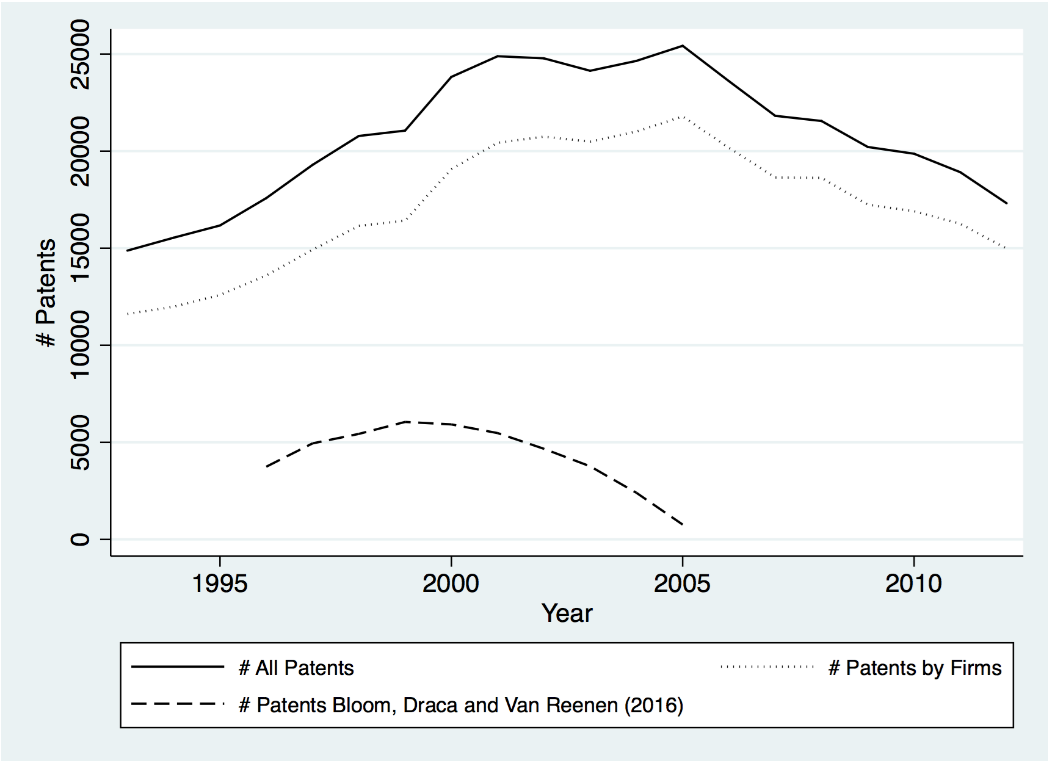
(UNCTAD/DTL/STICT/2013/8)

A Appendices

A.1 Patenting in Germany

Figure 6: Coverage of Patenting



Note: Bloom et al. (2016) use granted patents, whereas in this paper I use patent applications as a proxy for innovation. To conduct a simple comparison, I multiply the total number of patent applications (cf. Figure 1) with the average number of granted patents during the time of observation.

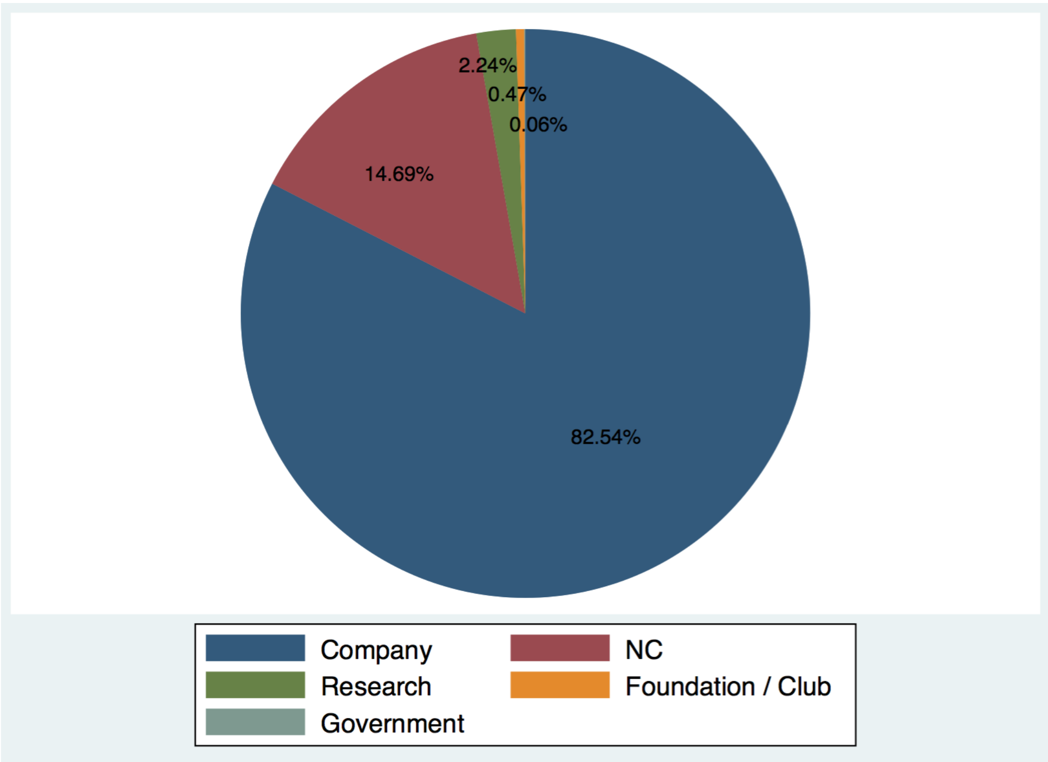
Figure 6 compares the number of patents covered in this paper with that of Bloom et al. (2016). In their study, Bloom et al. (2016) combine Bureau Van Dijk's Amadeus data with patent data from the European Patent Office for twelve European countries, one of which is Germany. The advantage of obtaining firm level data comes at the expense of only capturing a fraction of total patenting. Using a regional approach addresses this disadvantage and allows considering the universe of patenting in Germany. The solid black line shows a proxy for the total number of granted patents and the dotted line shows a proxy for the total number of patents applied by firms in Germany covered in this study. The dashed line shows the number of patents covered by Bloom et al. (2016), which, on average, accounts for approximately 24% of firm patenting and around 20% of total patenting.[42]

As can be seen, firms account for the vast majority of patenting in Germany. Since the data does not contain any further information about the applicant, I use the applicant's name in the patent document to distinguish between certain types of applicants. Companies must use the name with which they are officially registered in the commercial register. In Germany,

[42] Bloom et al. (2016) use granted patents, whereas in this paper I use patent applications. To conduct a simple comparison, I multiply the total number of patent applications (cf. Figure 1) with the average number of granted patents during the time of observation.

the official firm name contains an abbreviation identifying the legal structure of the firm (e.g., “AG” and “GmbH” for corporations). This abbreviation allows uniquely identifying firms. Additionally, I classify three other applicant types using different key words. These types are “research”, using key words such as “Universität” (= university) or “Fachhochschule” (= university of applied sciences), “foundation / club”, using key words such as “Stiftung” (= foundation) or “e.V.” (= abbreviation for registered society) and “government”, using key words such as “Bundesrepublik” (= federal republic) or “Ministerium” (= ministry). I label any applicant that cannot be uniquely defined as “not classified”. Most of these applicants are private persons (as can be seen by the fact that the applicant’s name is the name of a person). Figure 7 gives an overview of the type composition of patent applicants between 1993 and 2012. With more than 82%, firms account for the vast majority of patenting in Germany. “Not classified” types (mostly consisting of private persons) represent the second largest share with around 15%. Patenting shares of research institutions (2%), foundations and clubs (0.5%) and government entities (0.05%) are neglicable.

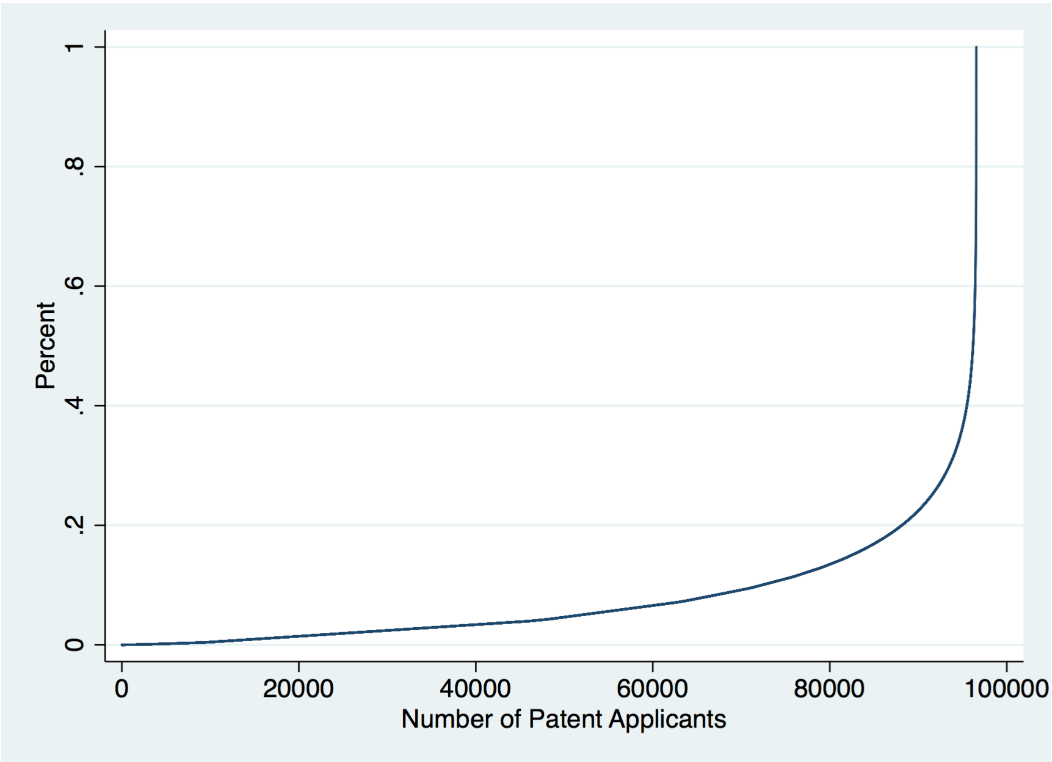
Figure 7: Patent Applicants by Type



Patenting in Germany is very unequally distributed across the applicants. This means that a small number of different applicants accounts for a large share of patent applications. Figure 8 shows the Lorenz Curve for the distribution of patenting between the years 1993 and 2012 with the cumulative number of patent applicants on the x-axis and the percentage share of applied patents on the y-axis. The figure suggests that patenting is highly concentrated. This impression is confirmed by the Gini coefficient of 0.849. The 10 applicants with the highest number of applications account for approximately 20% of total patenting in Germany.

The top applicants are all well known multinationals such as “Robert Bosch GmbH” (with a patenting share of 5.5%), Siemens AG (with a patenting share of 5.4%), BASF AG (with a patenting share of 1.6%), BMW AG (with a patenting share of 1.2%) or DaimlerChrysler AG (with a patenting share of 1.2%). At the same time, a share of 47.5% of the patent applicants, applied for not more than 1 patent during the smple period. These 47.5% of applicants account for merely 3.9% of total patenting in Germany.

Figure 8: Distribution of Patents by Applicants



A.2 Regional Patenting Structure in Germany

Figure 9: Patenting per 1000 Inhabitants by Location of the Applicant

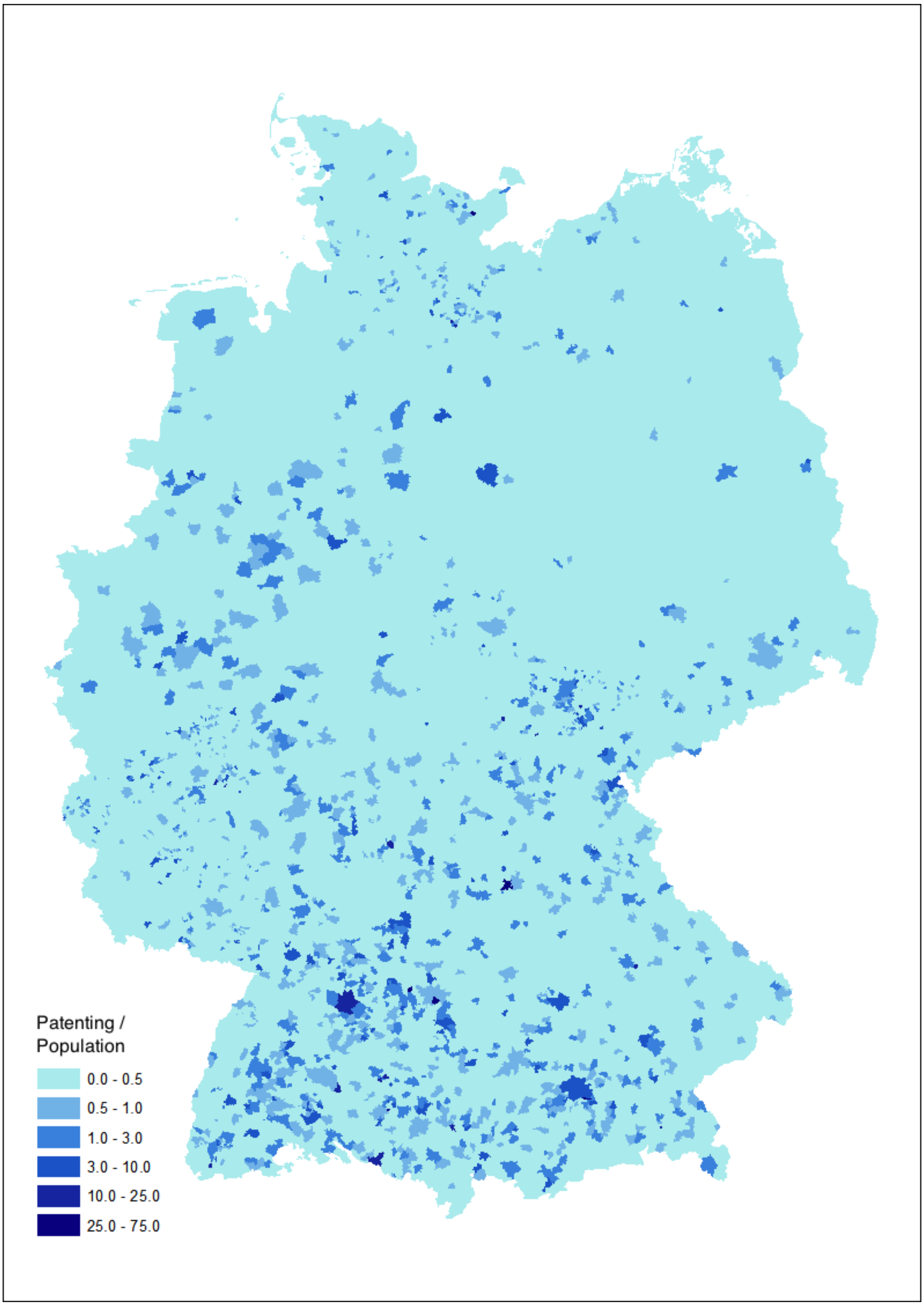


Figure 10: Total Patenting by Location of the Applicant

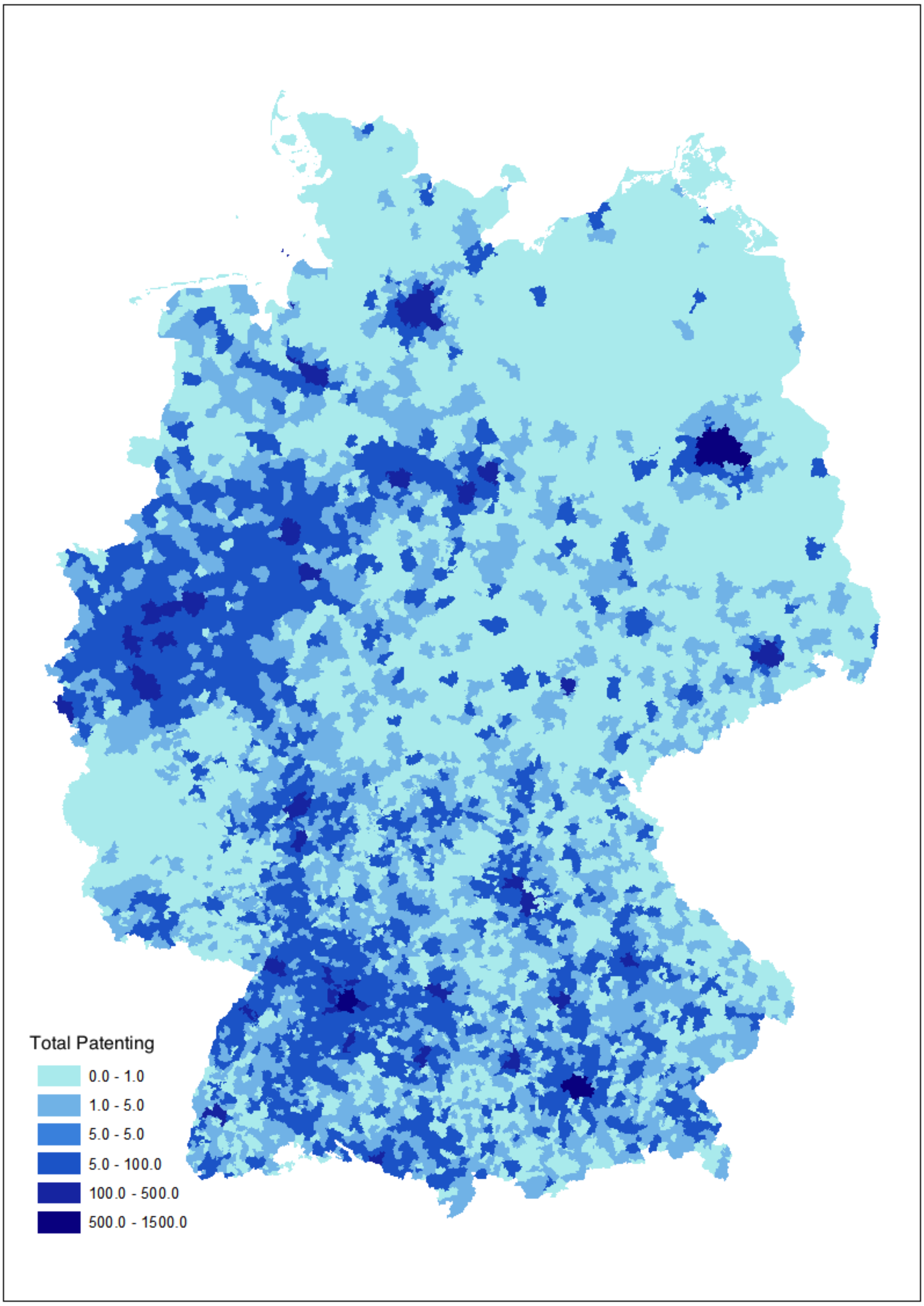
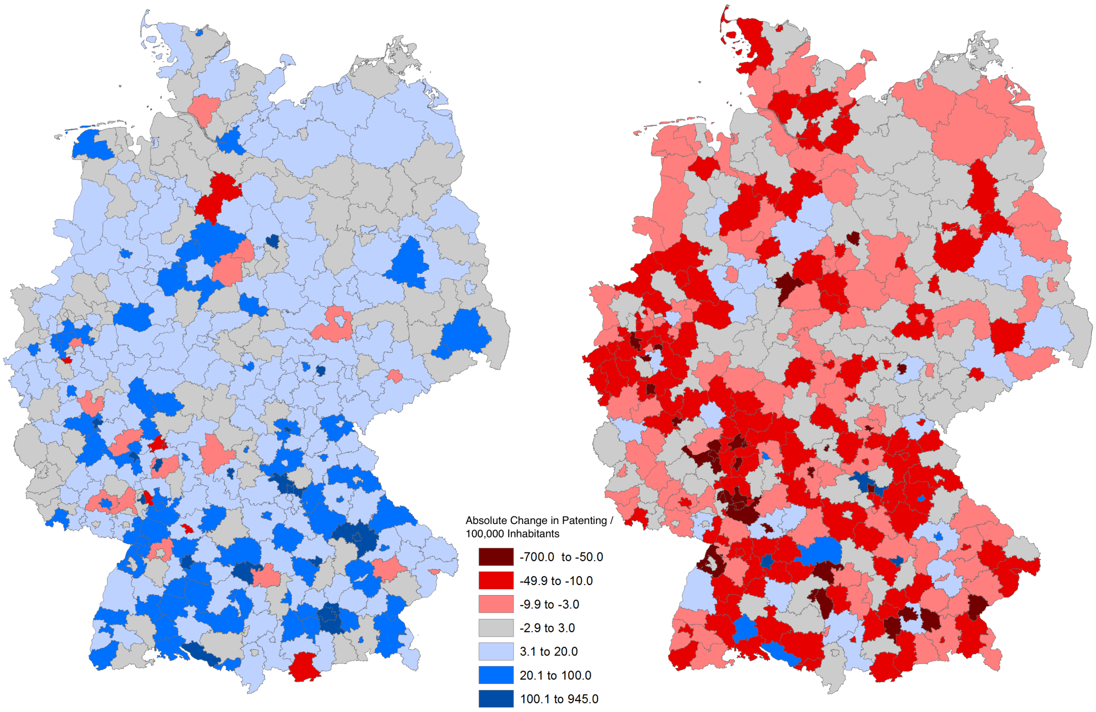


Figure 11: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Applicant; $\bar{IA_i}^{93-95} - \bar{IA_i}^{02-04}$ (Left) and $\bar{IA_i}^{02-04} - \bar{IA_i}^{10-12}$ (Right)



A.3 Regional Trade Exposure in Germany

Figure 12: Absolute Change in Regional Import Exposure from Eastern Europe $\overline{Imp_i^{EE}}^{10-12} - \overline{Imp_i^{EE}}^{93-95}$ (Left) and China $\overline{Imp_i^{China}}^{10-12} - \overline{Exp_i^{China}}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker

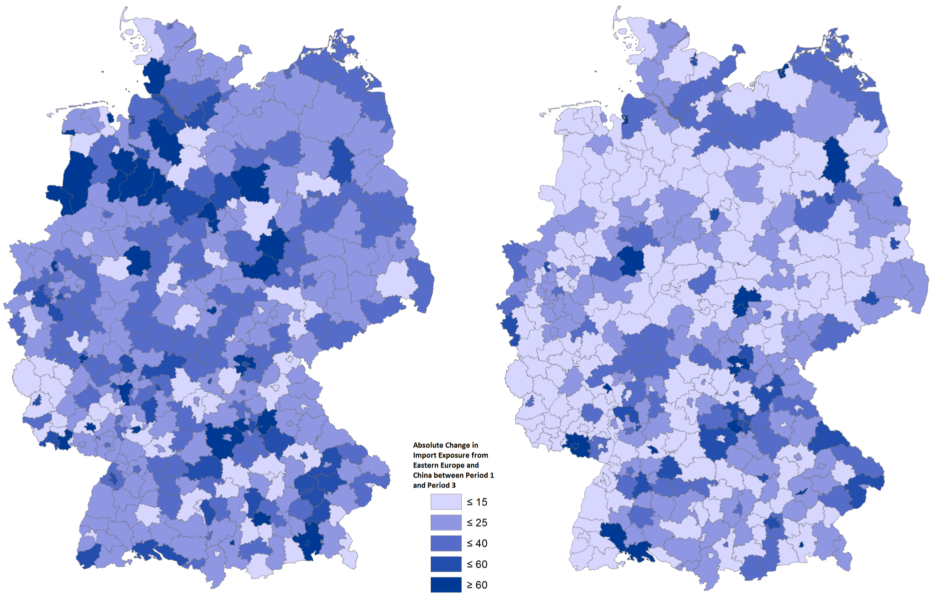
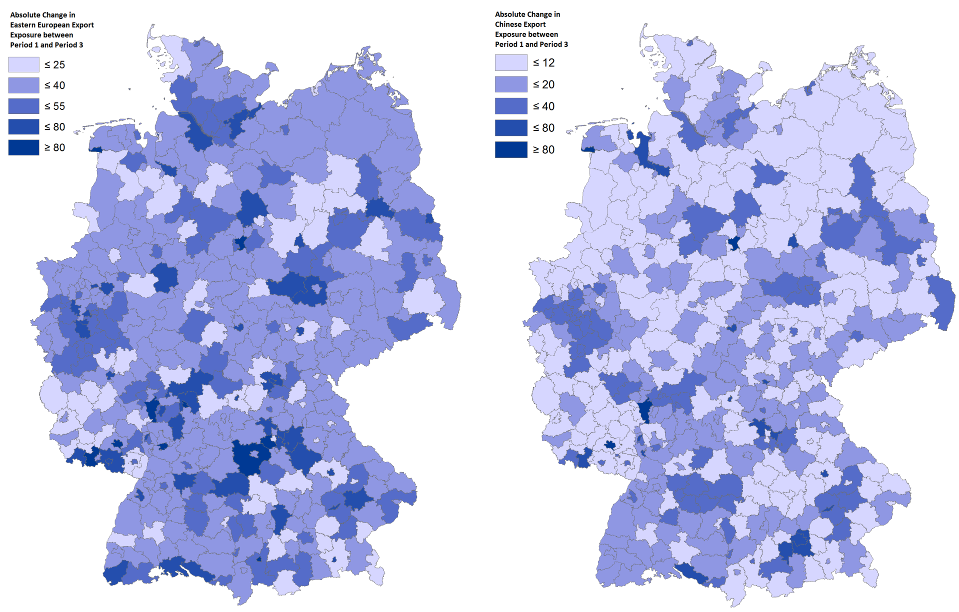


Figure 13: Absolute Change in Regional Export Exposure from Eastern Europe $\overline{Exp_i^{EE}}^{10-12} - \overline{Imp_i^{EE}}^{93-95}$ (Left) and China $\overline{Exp_i^{China}}^{10-12} - \overline{Exp_i^{China}}^{93-95}$ (Right) in \$ 1000 per Manufacturing Worker



A.4 German Trade with Eastern Europe and China

Figure 14: Weighted Grubel-Lloyd-Index for German Trade with Eastern Europe and China between 1980 and 2012

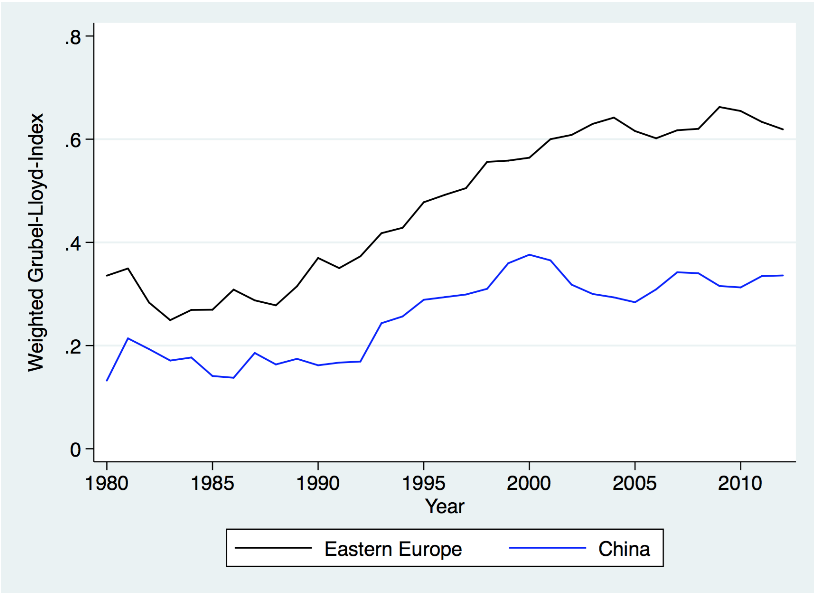


Figure 14 depicts the weighted Grubel-Lloyd-Indices for trade between Germany and Eastern Europe as well as between Germany and China computed as

$$GL_{jt} = \sum_j w_{jt} \frac{|Exp_{jt}^{Ger-East} - Imp_{jt}^{Ger-East}|}{Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}}, \quad \text{with } \mathrm{w}_{jt} = \frac{Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}}{\sum_j Exp_{jt}^{Ger-East} + Imp_{jt}^{Ger-East}} \tag{8}$$

A.5 Final and Intermediate Good Trade

Similar to Autor et al. (2013) and Dauth et al. (2014), I use the input-output table for the year 2002 provided by the Federal Statistical Office to compute industry specific final good shares. To be precise, I use the share of imports that is used for final consumption or investment (rather than for inputs) to calculate the final good shares at the two-digit or three-digit industry level. The classification of the input-output tables can be easily transferred into the industry classification of the IAB. The choice of the year is driven by data limitations. For the years of the first period, input-output tables are not available, for the years of the third period the industry classification cannot be transferred into that of the IAB. As a robustness check, I additionally use the years 2000 and 2001 to calculate final trade shares, but results remain unchanged.

A.6 Robustness

Table 9: Effect of Periodic Changes in Regional Import and Export Exposures by Exposure Origin on Periodic Changes in Various Innovation Measures

Innovation Measure	Total Pat. by Inventor	Pat. / Pop by Applicant	Total Pat. by Applicant	Pat./ Area by Inventor	Pat. / Area by Applicant	Pat. / Pop by Inventor zip codes II	Total Pat by Inventor zip codes II
Eastern Europe							
$\Delta ImportExposure$	0.071**	0.077***	0.227*	0.000***	0.001**	0.036***	0.063*
	(0.036)	(0.028)	(0.129)	(0.000)	(0.000)	(0.012)	(0.034)
$\Delta ExportExposure$	1.412	-3.591*	-13.564	-0.011	-0.052	0.256	0.737
	(3.101)	(1.963)	(10.081)	(0.014)	(0.036)	(1.067)	(2.955)
China							
$\Delta ImportExposure$	-1.139	-0.099	-1.780	-0.004	-0.010	0.121	-1.210
	(0.760)	(0.357)	(1.099)	(0.003)	(0.007)	(0.214)	(0.736)
$\Delta ExportExposure$	0.928	-1.430	-1.113	-0.004	-0.017	0.016	0.759
	(1.094)	(1.120)	(1.769)	(0.007)	(0.014)	(0.599)	(1.053)

Note: N=804; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 10: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Western and Eastern Germany

	Only Western Germany		**Only Eastern Germany**	
Estimation	Eastern Europe	China	Eastern Europe	China
$\Delta ImportExposure$	0.070**	0.007	0.046*	1.919
	(0.032)	(0.282)	(0.026)	(1.762)
$\Delta ExportExposure$	1.142	0.525	-4.781	-4.126
	(1.173)	(0.477)	(3.917)	(6.876)
% Manufacturing	204.354*	125.639	-215.688	563.728
	(113.617)	(89.063)	(487.091)	(528.182)
% Skill	-917.912	-997.312*	298.762	-305.369
	(618.718)	(593.031)	(389.029)	(512.601)
% Foreigner	429.197***	467.945***	292.147	-168.899
	(136.080)	(143.499)	(211.984)	(461.890)
% Women	12.677	9.326	247.956	403.291
	(183.054)	(194.324)	(276.925)	(446.359)
% Routine	-338.164**	-362.672***	139.311	-30.021
	(140.624)	(128.046)	(263.661)	(438.585)
% Chemistry	20.125	22.174	-561.713**	-818.521
	(157.437)	(161.084)	(281.886)	(592.712)
% Automobile	-160.061	-41.047	-754.837	-393.867
	(198.273)	(234.719)	(512.334)	(501.720)
% Largest Industry	229.191	235.814	9.028	291.938
	(151.724)	(156.598)	(141.659)	(428.238)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: N=650 for Western Germany, N=154 for Eastern Germany; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 11: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants - Commuters and Alternative Administrative Units

Innovation Measure	Pat. / Pop by Inventor com. adj. I	Pat. / Pop by Inventor com. adj. II	Total Pat. by Inventor com. adj. I	Total Pat. by Inventor com. adj. II	Pat. / Pop by Inventor AMR aggr.	Pat. / Pop by Inventor ROR aggr.
Eastern Europe						
$\Delta ImportExposure$	0.047***	0.049***	0.079**	0.084**	0.097***	0.357*
	(0.014)	(0.013)	(0.037)	(0.039)	(0.036)	(0.194)
$\Delta ExportExposure$	-0.000	-0.275	0.200	-0.439	-3.970	9.024
	(1.080)	(1.081)	(3.204)	(3.296)	(3.448)	(12.913)
China						
$\Delta ImportExposure$	0.156	0.110	-1.410*	-1.558*	-1.483	0.687
	(0.220)	(0.219)	(0.825)	(0.867)	(1.352)	(2.257)
$\Delta ExportExposure$	-0.102	-0.190	0.723	0.629	-1.691	4.221
	(0.609)	(0.606)	(1.138)	(1.171)	(1.717)	5.757

Note: N=804 for commuter adjusted estimations in column one to four. N=516 for AMR, N=192 for ROR; Clustered standard errors (by county) in parentheses; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.

Table 12: Effect of Periodic Changes in Regional Import and Export Exposures on Periodic Changes in Patenting per 100,000 Inhabitants by Exposure Origin - Different Instrument Groups

Estimation	Instr. Group 1	Instr. Group 2	Instr. Group 3
Eastern Europe			
$\Delta ImportExposure$	0.064***	0.046***	0.062***
	(0.021)	(0.015)	(0.021)
$\Delta ExportExposure$	-1.467	0.802	-1.232
	(1.745)	(0.666)	(1.846)
2SLS First Stage Estimates; Dependent Variable: Import Exposure			
$\Delta ImportExposure$	0.636***	0.477***	0.358***
(Other Countries)	(0.025)	(0.01)	(0.014)
F-Test excl. Instr.	32.19	25.40	38.72
2SLS First Stage Estimates; Dependent Variable: Export Exposure			
$\Delta ExportExposure$	0.297***	0.724***	0.14***
(Other Countries)	(0.074)	(0.181)	(0.032)
F-Test excl. Instr.	31.28	66.15	32.25
China			
$\Delta ImportExposure$	-1.886	0.089	0.166
	(2.68)	(0.093)	(0.198)
$\Delta ExportExposure$	0.079	-0.165	-3.046
	(0.259)	(1.127)	(2.967)
2SLS First Stage Estimates; Dependent Variable: Import Exposure			
$\Delta ImportExposure$	0.215***	1.24***	0.0223
(Other Countries)	(0.078)	(0.315)	(0.087)
F-Test excl. Instr.	5.85	4.40	2.94
2SLS First Stage Estimates; Dependent Variable: Export Exposure			
$\Delta ExportExposure$	0.099*	0.524***	0.029
(Other Countries)	(0.03)	(0.156)	(0.018)
F-Test excl. Instr.	24.57	12.26	26.2

Note: N=804; Clustered standard errors (by county) in parentheses; Instrument group 1 includes: Canada, Japan, Korea, New Zealand, Singapore, the United States; Instrument Group 2 includes: France, Italy, the Netherlands; Instrument Group 3 includes: Australia, Canada, France, Italy, Japan, Korea, the Netherlands, New Zealand, Norway, Singapore, Sweden, the UK, the United States; *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level; All regressions include a constant; First stage estimates also include the same control variables that are indicated in the columns for the second stage estimates.