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Imports, Exports and Domestic Innovation

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Imports, Exports and Domestic Innovation^a

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Abstract

By crawling online data, I create a new long-term patenting panel dataset for Germany to identify the causal effect of trade integration with Eastern Europe and China on patenting in the period 1993-2012. I exploit the cross-regional variation in the German industry structure and use trade flows to other advanced economies as instruments for regional import and export exposure. I find that an increase in the 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 effects on innovation.

JEL classification: F14, O30, R11, R12.

1 Introduction

The purpose of this paper is to identify the causal effect of increasing trade integration on innovation using a regional identification strategy. To do so, I focus on German trade with China and Eastern Europe. The opening of China and the fall of the Iron Curtain 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 and exports from and to Eastern Europe and China increased by more than factor 15 and 18, respectively from 1993 until 2012.

We have little systematic evidence, especially empirically, on the effect of increasing trade integration on innovation in high-wage countries. While the economic literature and policy makers often see trade as a channel for technology and knowledge access for low-wage countries¹, the effect on innovation for high-wage countries is theoretically unclear. Increased trade integration with low-wage countries will increase competition for domestic firms. Generally, an increase in competition has ambiguous effects on innovation.² Additionally, increasing trade integration has been linked with a decrease in manufacturing employment; see for instance Pierce and Schott (2013) and Autor, Dorn and Hanson (2013). At the same time, manufacturing accounts for the vast majority of patenting. In 2012, manufacturing firms were responsible for around 85% of corporate patenting in Germany.³ Thus, employment shifts to less patent-intensive sectors may suggest a decrease in innovation. Innovation, however, may still increase, as remaining firms are more productive (Melitz 2003). In addition, Bernard, Jensen and Schott (2006) show that exposure to low-wage country imports leads to a reallocation of manufacturing activity to high-tech firms. Being often more patent-intensive, this reallocation may imply an increase in technology and innovative power. For firms that engage in offshoring, domestic productivity of

¹See for instance UNCTAD (2014), ICTSD (2011) and Goldberg et al. (2010 a, b).

²See 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, Draca and Van Reenen (2016), for a more detailed discussion on various types of innovation and trade models additionally highlighting the ambiguity.

³Similar numbers can be observed from other high income countries. For instance, in the U.S. manufacturing accounts for about 75% of corporate patents (Autor et al., 2016).

remaining tasks may increase. These tasks are generally skill intensive tasks such as R&D activities (Grossman and Rossi-Hansberg, 2008). 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.

Even though the nexus of trade and innovation “remains intrinsically an empirical question” (Autor et al., 2016), we have much less evidence on the empirical side. An interesting exception is a paper by Bloom, Draca and Van Reenen (2016), who match patent data from the European Patent Office with Amadeus. For twelve European countries, they find that Chinese import competition accounts for approximately 15% of technology upgrading between 2000 and 2007. Import competition led to a reallocation of employment towards innovative firms and an increase of IT, TFP, R&D and patenting for exposed firms. These results are similar to those of Arora, Belezon and Patacconi (2015), who find a positive relationship between import competition and patenting in their correlational analysis. Another exception is a paper by Autor et al. (2016). They match U.S. patents with publicly held firms listed in Compustat and find a strong negative effect of import exposure on patenting. Similarly, Kueng, Li and Yang (2016) observe a decrease of process and product innovation for a set of Canadian firms.⁴ Opposing results show that the effects may vary across countries depending on characteristics such as industry structure, employment structure, competition intensity, etc., and highlight the necessity for additional empirical research in this field.

In this paper, I explain changes in the innovation activity of 408 local labor markets (in German: “Landkreise”)⁵ between 1993 and 2012 with regional trade ex-

⁴Additionally 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, Ichinowski and Shaw (2007) and Bugamelli, Schivardi and Zizza (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.

⁵Note: In the following, “counties” and “Kreise” are used interchangeably to label the local labor

posures. I crawl online patent data from the DPMAregister database of the German Patent and Trademark Office (DPMA) and combine this data with county-level information from the “Establishment History Panel” provided by the German Federal Employment Agency and regional exposure measures. Regional trade exposure is measured twofold: Firstly, I follow the approach by Autor, Dorn and Hanson (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. Dauth, Findeisen and Südekum (2014) apply this method to the German case. Secondly, I use regional trade exposures from Bröcker and Meier (2018), who compute exposures using a CGE model. To address concerns of endogeneity I instrument for German trade flows using trade with other similar high-wage countries.

To my knowledge, this paper is the first to use a regional identification strategy to study the impact of trade exposure on innovation. Existing literature, especially in the field of regional economics, stresses the role of regional factors for innovation.⁶ Asheim, Smith and Ought (2011) provide a detailed overview of the regional innovation systems literature. The regional approach has the advantage that the entire universe of patenting in Germany - including smaller firms and private applicants - is covered, whereas most of the existing literature in this field is biased towards larger firms. Despite the fact that patenting undoubtedly is also biased towards larger firms⁷, there still is a large amount of innovation from smaller firms or private persons. In Germany, private persons alone account for almost 40% of patent applicants.⁸ Additionally, 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, 2010).⁹ These facts

markets

⁶For instance Jaffe, Trajtenberg and Henderson (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.

⁷In 2012, the 10 largest inventors account for almost 30% of total patenting in Germany.

⁸These applicants account for a smaller share of total patenting (about 18%), as compared to firms they usually only hold one or at most a few patents per applicant.

⁹Previously this relationship was not observable; firm size did not have effects on innovation

stress the necessity for investigating innovation effects for smaller and medium sized firms, but also outside of firms such as for suppliers or private entrepreneurs.

The results show that on average an increase in net trade exposure (defined as import- minus export exposure) causes an increase in patenting. This effect is purely driven by a positive link between import exposure and innovation, whereas export exposure does not influence innovation. Interestingly, this paper shows that effects are heterogeneous across exposure origins. 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 region (here Kreis), increases patenting by 0.333 patents per 100,000 inhabitants in that region. Increasing integration with China has no effects on innovation.

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

2 Data & Stylized Facts

For this paper, I combine crawled patent data 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).¹⁰ The Establishment History Panel is a detailed micro-level data set that covers all establishments in Germany from 1975 to 2010 (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 then allows for aggregating establishment level variables to the county level. I thus obtain local labor market information on education (employment shares

intensity. See for instance Cohen et al. (1987) and Cohen and Klepper (1996).

¹⁰For further information concerning the BHP see also Gruhl et al. (2012) (German version) or Hethey-Maier and Seth (2010) (English version).

by skill category), the industry structure (employment shares at the 3-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 an additional proxy for R&D intensity.

2.1 Patenting

The patent dataset in this paper is based on data that I crawled from the DPMARegister database of the German Patent and Trademark Office (DPMA) and covers the years 1980 to 2012. The data contain the entire universe of patent applications from German applicants. Applicants can be either natural (e.g. private entrepreneur) or legal persons (e.g. corporation). 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 sub-classification according to the International Patent Classification, “IPC”) and patent history (changes in ownership, different steps in the application process). Using a zip code-municipality cross walk provided by the German postal service (“Deutsche Post Direkt”), I use the zip code information of the applicants and inventors to create regional measures for patent intensity at the administrative level. The smallest administrative unit for which I calculate regional patenting intensity is the municipality level. For the empirical analysis, however, the data is aggregated to the county (“Kreis”) level to match the regional aggregation level of the trade exposures. The baseline index for regional innovation intensity is given as:

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

where the innovation activity IA in administrative region i at time t is the weighted sum of the patents that were filed in zip code area z , which (at least partly) has to be located inside the administrative region i . If the zip code area crosses county lines, each county accounts for fraction $\frac{1}{k^z}$ of the patent, where k is the number of

administrative regions that are part of the zip code area.¹¹ 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 is the number of inventors / applicants.¹² To obtain an innovation measure that takes county population into account, the absolute number of patenting (in the numerator) is divided by the population size of the county 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 coding corresponds to that of the Establishment History Panel and is necessary, since without territorial reallocation cases would arise, in which the county of the inventors or applicants changes without the inventors or applicants having actually moved.

Figure 1 shows the yearly numbers of patent applications in Germany (including Eastern Germany) both in total (right axis) and also broken down by subsections (left axis) from 1980 to 2012. In the 1980’s, yearly patenting¹³ increased continuously from around 25,000 in 1980 to slightly more than 40,000 in 1989 before a sharp drop around the time of the reunification. This trend is similar for all of the eight subsections. After 1991, patenting increased quickly in the 1990’s and the first half of the 2000’s to a peak of more than 60,000. Afterwards, in the second half of the 2000’s, 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 ca. 23%. “Textiles, Pa-

¹¹In Germany, zip codes are areas defined for service delivery which do not always adhere to geopolitical administrative boundaries. However, for around 80% 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 increases the number of cases, for which the zip code area corresponds to only one administrative region further.

¹²In 2012, the average number of inventor per patent was 2.3 and the average number of applicants was 1.1.

¹³“Patenting” here refers to the process of filing a patent application. The procedure until a patent is granted oftentimes takes several years such that patent applications rather than granted patents are the more feasible and immediate measure. The share of patents that eventually is granted remains constant over the years.

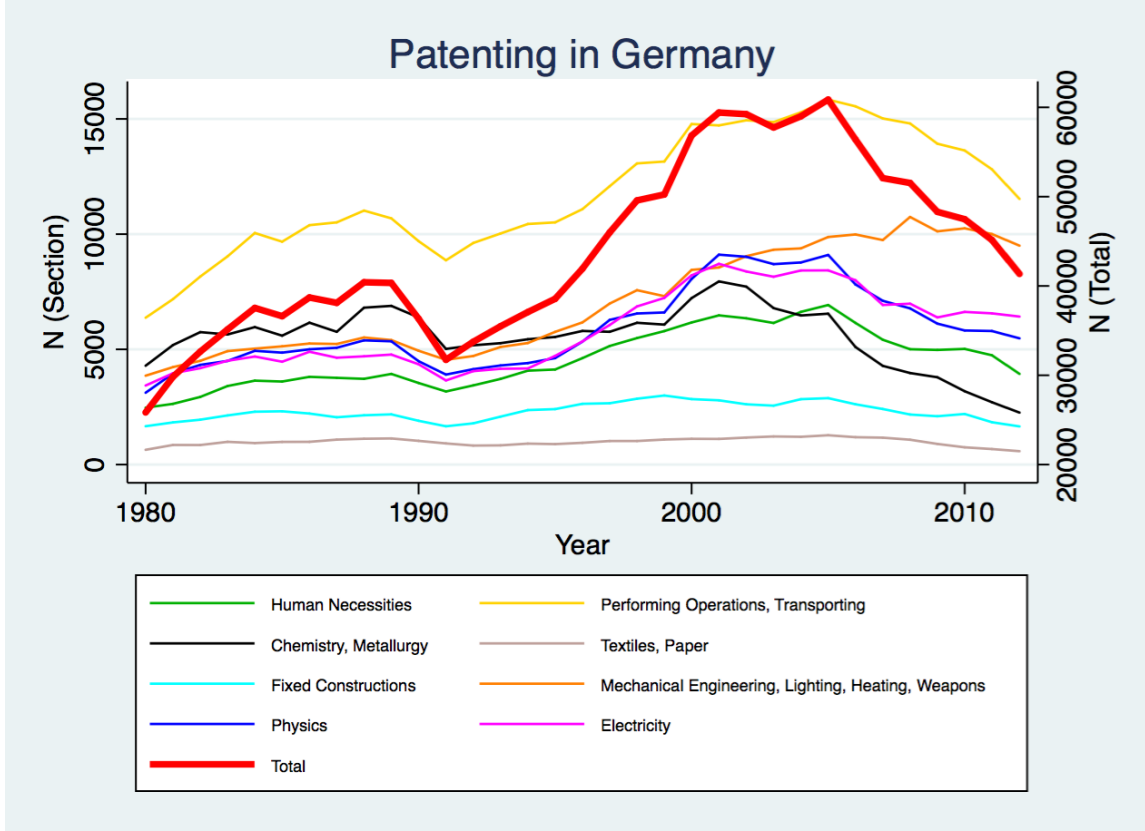


Figure 1: Patenting in Germany: Total Patenting and Subsections

per” (ca. 1%), “Fixed Constructions” (ca. 4%) and “Chemistry, Metallurgy” (ca. 6%) only play a minor role in patenting. Over time, patent growth within the subcategories roughly follows the growth pattern of total patenting described above. This means that subsection 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 (ca. 14.4% and 13.4%). Ever since, the share of “Mechanical Engineering, Lighting, Heating, Weapons” increased to about 23% and the one of “Chemistry, Metallurgy” decreased to only 5.5% in 2012. For all other sections shares remain within a 5 percentage points 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 location for every 1000 inhabitants at the municipality level using equation (1). The map shows both a distinct North-South- and West-East structure. In the Southern states of Baden-Wuerttemberg and Bavaria patent intensity is at much higher levels compared to states that are located further North. At the same time we can find much more innovation in Western Germany compared to the new Eastern states of Germany (including 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 Southern Germany a stretch reaching from Würzburg down to area of Lake Constance including the metropolitan regions of Nürnberg, Stuttgart and Munich is patent intensive. Consider that here the inventor rather than the applicant location is taken as the origin of innovation. Inventors may live in commuting distance from the firm (=applicant) 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 inventor location (see Figure 5 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 structure persists and per capita innovation is still relatively high in densely populated areas.

The picture changes slightly, when total patenting rather than per capita patenting is regarded (see Figure 6 in the Appendix). Now, also the largest German cities like Berlin, Hamburg or Dresden show high numbers of patent applications.

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

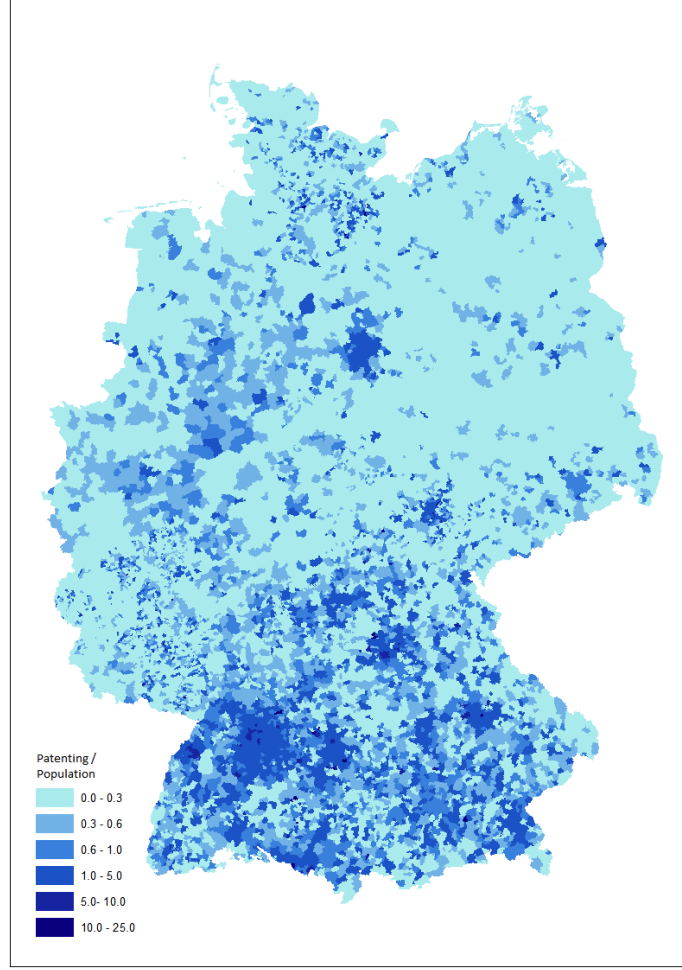


Figure 2: Patenting per 1000 inhabitants by Location of the Inventor

by the location of the inventor¹⁴ between the period averages of 1993 to 1995 and 2002 to 2004, $\bar{I\bar{A}}_i^{93-95} - \bar{I\bar{A}}_i^{02-04}$ (map on the left), as well as between the period averages of 2002 to 2004 and 2010 to 2012, $\bar{I\bar{A}}_i^{02-04} - \bar{I\bar{A}}_i^{10-12}$ (map on the right), for the German counties. One immediate observation is that regional growth of patenting differs considerably between the two periods. During the first period, patenting

¹⁴The 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 7 in the Appendix)

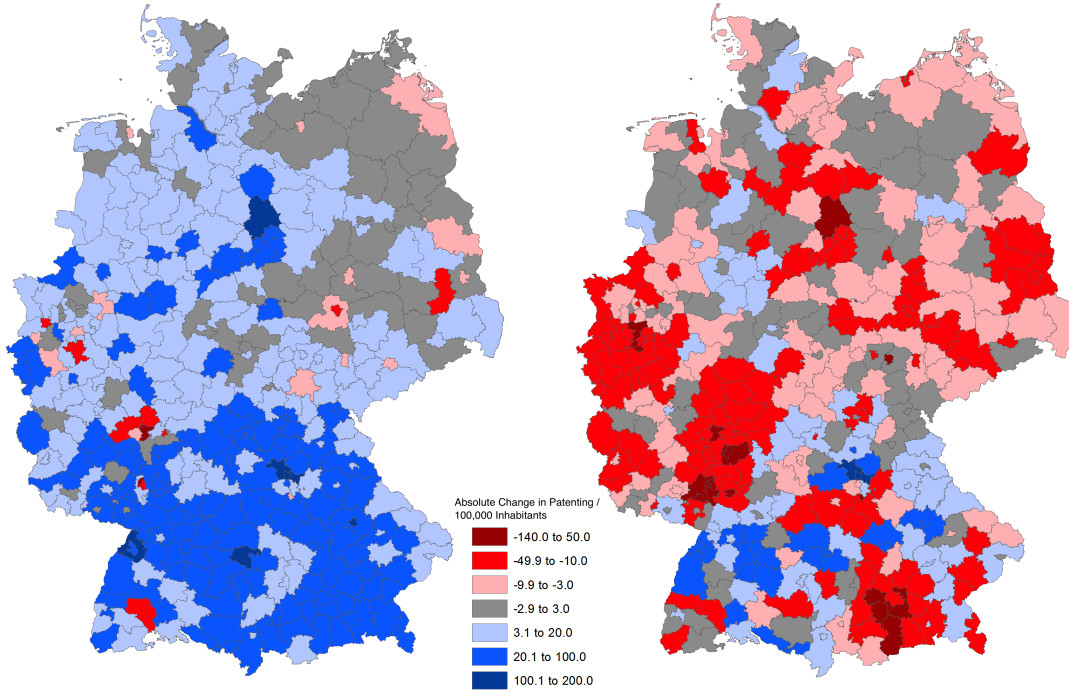


Figure 3: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Inventor; $\bar{I\bar{A}}_i^{93-95} - \bar{I\bar{A}}_i^{02-04}$ (Left) and $\bar{I\bar{A}}_i^{02-04} - \bar{I\bar{A}}_i^{10-12}$ (Right)

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: In about 60% of the counties patenting decreases, whereas approximately the same share of remaining counties indicate increasing and stable numbers of patenting. Again, most of the regions with increased patenting are located in the South, whereas the Eastern German regions face a decrease in patenting. Regional and periodical differences 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 industries. This will result in dispersed patterns of regional innovation, as certain industries tend to be regionally concentrated. For instance, in the second period patenting decreases sharply in the Ruhr area - a

region characterized by traditional manufacturing industries such as "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 considerably dispersed. Patenting intensities also vary considerably at the county level within a state, making Kreise a suitable aggregation level for the empirical analysis.

2.2 Trade Exposure

The fall of the Iron Curtain and the opening of China, increased import competition for Germany, but at the same time this development created opportunities to tap new export markets. The full data cover the years 1993 to 2012 for Germany as a whole and from 1980 to 2013 for Western Germany. Over the time span, German trade relations are marked by strong intensification of trade with China and Eastern Europe. Figure 4 shows the increase in exporting and importing (measured in billion US-dollars) for both Eastern Europe (left) and China (right). During the 1980's and early 1990's, trade with either of the two regions was almost non existent.¹⁵ After the fall of the Iron Curtain in the early 1990's trade with Eastern Europe picked up pace. Also trade with China started to increase slowly. However, it was not until its WTO accession in 2001 that the trade increase with China became eminent. Accordingly, the import and export exposure in the 1990's primarily originated from trade with Eastern Europe, whereas it was both, Eastern Europe and China, that contributed to increasing exposures in the 2000's. Overall, German imports and exports from and to Eastern Europe and China increased by more than factor 15 and 18 respectively from the early 1990's until 2012.

To compute regional trade exposures, I use two different methods: First, I fol-

¹⁵This observation supports the previous claim that the industry structure in the late 1980s and early 1990s is well suited to allocate trade flows, as it will be unaffected by Eastern trade at that point in time.



Figure 4: German trade with Eastern Europe and China

low the approach of Autor, Dorn and Hanson (2013) and exploit the cross-regional variation in the German industry structure to regionally allocate trade flows.¹⁶ To do so, I obtain trade flows between Germany and Eastern Europe, as well as China at the 4-digit product level from the UN Comtrade database. 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, Eastern Germany and Slovakia¹⁷ as well as China (combined flows from both regions from now on referred to as “East”). Using a product-industry crosswalk, the trade flows are converted into the industry classifications of the Establishment History Panel. To obtain the change in regional import exposure $\Delta Imp_{jt}^{Ger-East}$ in region i at time t from trade with the East, the following expression is calculated:

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

where the change in imports ΔImp of industry j is allocated to county i according

¹⁶For Germany, this identification strategy was for instance used by Dauth, Findeisen and Südekum (2014) or by Dippel, Gold and Heblich (2015), who measure the effect of trade exposure on voting behavior.

¹⁷To 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

to the share of total employment in industry j that can be found in county i , $\frac{E_{ijt}}{E_{it}}$. 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. Summing over all industries then yields the regional import exposure. Likewise, the change in regional export exposure $\Delta Imp_{jt}^{Ger-East}$ in region i at time t is calculated as:

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

In this paper, the change in the net exposure is defined as $\Delta Imp_{it}^{East} - \Delta Exp_{it}^{East}$. To overcome concerns that shocks that affect both German trade and regional innovation might drive results, I follow Autor, Dorn and Hanson (2013) and instrument for the trade flows $\Delta Imp_{jt}^{Ger-East}$ and $\Delta Exp_{jt}^{Ger-East}$ in equation (3) and (4) respectively 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 contestability. The selection of the instrument group for the baseline estimations follows Dauth, Findeisen and Südekum (2014) and includes Australia, Canada, Japan, New Zealand, Norway, Singapore, Sweden and the UK.¹⁸

As a robustness check, I use regional trade exposures from a spatial CGE model for the German economy computed by Bröcker and Meier (2018).¹⁹ Calibrated to the economy in 2010, the model reproduces national input-output, final demand, imports and exports as well as regional factor prices and the regional distribution of labor. The model is then shocked with good-specific German import and export values and all endogenous variables adjust such that regional labor market effect will entirely be reflected by wage changes. The CGE exposure measure covers the time period from 1993 to 2012 as well.

¹⁸The rationale for the selection of this instrument group in particular is well described in their paper. As a robustness check, I additionally alter the instrument group by adding other countries and conducting the regressions with various composition of the instrument group. Results remain unaffected by the choice of the instrument group.

¹⁹Results for the CGE exposures are pending and thus not included in this version of the paper.

3 Results

The result section is organized as follows: The next subsection presents the baseline estimations for the effects of trade on innovation. First, the effect of net exposure on innovation is estimated. Then this effect is further broken down into import and export exposure. Finally coefficients are estimated separately depending on the origin of the exposure (Eastern Europe and China). Section 3.2. presents and discusses several robustness checks.

3.1 Baseline Estimations

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:

$$\Delta \overline{IA}_{it} = \alpha + \beta_1 \Delta \overline{NetX}_{it}^{East} + \overline{X}_{it}' + \sigma_i + \kappa_t + u_{it}, \text{ with} \quad (4)$$

$$\Delta \overline{NetX}_{it}^{East} = \Delta \overline{Imp}_{it}^{East} - \Delta \overline{Exp}_{it}^{East} \quad (5)$$

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 averages of net trade exposure. The change in net trade exposure is defined as the difference between the change in three year averages of import exposure $\Delta \overline{Imp}_{it}^{East}$ and the change in three year averages of export exposure $\Delta \overline{Exp}_{it}^{East}$ (cf. equation (3) and (4)). \overline{X}_{it}' is a vector of regional control variables. Region fixed effects σ_i are implemented at the county, state or regional level (South, North, East and West).²⁰ κ_t are time fixed effects. The standard error u_{it} is clustered at the level of 263 commuting zones.

I then disentangle the net exposure effect and separately include changes in three-year averages of regional import and export exposure:

²⁰The regional fixed effects specification follows Dauth, Findeisen and Südekum (2014); region North covers the states of Schleswig-Holstein, Hamburg, Bremen and Lower Saxony. Region West includes Rhineland-Palatinate, Hesse and Saarland. South contains Bavaria and Baden-Wuerttemberg and East is the new eastern states of Germany plus Berlin.

$$\Delta \overline{IA}_{it} = \alpha + \beta_1 \Delta \overline{Exp}_{it}^{East} + \gamma \Delta \overline{Imp}_{it}^{East} + \overline{X}_{it}' + \sigma_i + \kappa_t + u_{it}, \quad (6)$$

I estimate differences between periods that consist of three year averages. Patenting is comparatively volatile, contrary for instance to labor market outcomes such as manufacturing employment (e.g. Autor, Dorn and Hanson (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.

In the baseline scenario, 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). The choice of periods is primarily driven by the data availability. The BHP only contains sufficient observations for Eastern Germany from 1993 onwards and the patent data ends in 2012. However, this time framing also 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 they years of period two. The following years from period two to period three are then marked by a steady decline in patenting.

Patenting per 100,000 inhabitants based on the home address of the inventor is the preferred baseline measure of regional innovation. This measure is frequently used in the innovation literature and has been proven to reliably determine the regional origin of innovation. Since inventors will most likely live in close proximity to their workplace, which is the regional origin of trade exposure, a geographic link between innovation and trade exposure can be established. Alternative innovation measures are less suited to build this link. For instance, using patenting based on the location of the applicant would imply the risk that not the location of the inventive part of the patenting process, but the location of the admanistrative part (e.g. headquarter) is used to determine the regional origin of innovation.

Table 1 presents the baseline results from equation (4). Every two columns include one specification. The first column of the pairs always contains the OLS estimates and the second one the IV results, where I instrument for net exposure with trade exposures from other similar countries as discussed previously. The least conservative

specification in the first two columns only includes basic labor market controls such as the start-of period employment shares of skilled worker, foreigners, women and workers performing routine tasks. Additionally, I control for the start-of period manufacturing share. On the one hand, the share of manufacturing drives the trade exposures, and on the other hand, manufacturing accounts for approximately 75% of total 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. The preferred and most conservative 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. In 2012, the 10 largest inventors account for almost 30% of total patenting in Germany. Primarily, these firms are part of the automobile (6 out of 10 of these firms) or chemical industry. Accordingly, I add controls for the start-of period employment share in these three-digit industries. Additionally, I add a control for the start-of share of the largest industry in a region.

Table 1 around here.

The effect of net exposure on innovation is insignificant for the estimations with only basic labor market controls, but turns significant and is positive when adding fixed effects and industry information. OLS estimates are similar to the IV results. As the change in net exposure is defined in units of \$1000 per worker, the coefficient of 0.0127 in the preferred 2SLS estimation implies that a \$1000 increase in the net exposure per worker in a region (here Kreis) increases patenting by 0.0127 patents per 100,000 inhabitants in that region.²¹ 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. The first stage estimations are displayed at the bottom of the table and indicate fitting instruments; the F-tests show that the hypotheses that instruments are excluded can be rejected.

²¹These results might seem small in magnitude at a first glance, but it has to be considered that the figures for average patenting per Kreis 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 400 Kreise in Germany, average yearly patenting per Kreis amounts to a number of around 120.

To identify whether the positive coefficient is either explained by positive effects from changes in import exposures or negative effects from changes in export exposures, estimation (4) disentangles both effects. The results are displayed in table 2. As before, the three specifications “baseline labor market”, “fixed effects” and “industry controls” are applied. Again, the first column for every specification shows the OLS estimate, whereas the last two columns show the IV results. I now conduct the IV regression for both Germany as a whole (middle column) and for Western Germany only (third column) to rule out that the inclusion of the new eastern states of Germany drives the results.

Table 2 around here.

The results show that the positive effect on innovation from increasing net exposure is completely driven by import exposure effects. $\Delta \overline{Exp}_{it}^{East}$ is insignificant for all specifications, whereas $\Delta \overline{Imp}_{it}^{East}$ is significant and positive. The coefficients for Western Germany only are slightly larger than for Germany as a whole, which could be explained by the fact that especially after reunification the manufacturing sector in Eastern Germany (and thus exposure) was on the decline. Again first stage estimations displayed at the bottom of the table show generally strong instruments.²²

To further disentangle the findings, equation (4) is now separately estimated for both Eastern European and Chinese exposure. This distinction is well justified, as exposures from Eastern Europe and China are rather diverse. First, exposure from Eastern Europe was kicking in much earlier after the fall of the Iron Curtain in the early 1990’s, whereas China’s exposure increase primarily began after its WTO accession in 2001. Second, exposure from the East is much higher compared to China. Both imports from and exports to Eastern Europe are approximately 10 times larger in the 1990’s and still twice as high in 2012.

Table 3 around here.

Table 3 shows the IV estimations for both Eastern Europe and China using again the three specifications from above. Not surprisingly, changes in export exposure

²²Results indicate that instruments are fitting for the import exposure and export exposure when only Western Germany is regarded. One possible explanation why instruments for export exposure are weaker for Germany as a whole is that exporting, especially for Eastern Germany in the early 1990’s, was much lower to the East compared to exports to the instrument countries.

remain insignificant for both Eastern Europe and China. Interestingly however, the results show that the import exposure effect is purely driven by exposure from Eastern Europe: For all specifications the effect is positive and significant, whereas exposure from China is insignificant. The coefficient of 0.333 in the preferred 2SLS estimation implies that a \$1000 increase in Eastern European import exposure per worker in a region (here Kreis), increases patenting by 0.333 patents per 100,000 inhabitants in that region. The heterogeneity in the effects across exposure origin also explains why the combined effect in table 2 is smaller in size. The results are well in line with the observed trend in patenting (cf. Figure 1). During the time of increasing import exposure from Eastern Europe in the 1990's, patenting in Germany increases tremendously. However, during the second wave of import exposure during the 2000's, now primarily from China, 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 influx of patenting. When China, almost a decade later, entered the world market (at the beginning with low quality goods similar to the Eastern European product mix), Germany did not face immediate competition anymore as it already had adjusted.

3.2 Robustness

After identifying Eastern Europe as the driver behind positive exposure effects on innovation in Germany, I now validate the robustness of the results by conducting a wide range of sensitivity checks. The following robustness checks all refer to the estimations (hereafter referred to as “baseline estimation”) for table 3 that uncover heterogeneous effects across exposure origin. Note that most results of the robustness check are not published in this paper, but are available upon request.

3.2.1 Instrument Group

As a robustness check, I first alter the instrument group by adding other countries and conducting the regressions with various compositions of the instrument group. In

particular, I follow the approach of Dauth, Findeisen and Südekum (2014) and drop the UK from the instrument group. Additionally, I also add the US and afterwards several neighboring countries to the instrument group. Second-stage results and also the validity of instruments remain widely unaffected by the choice of the instrument group.

3.2.2 Time Framing

I then change the time framing of the estimations. First, I do not use value changes between three year averages, but conduct estimations based on single year data instead. I use all 27 year-year-year combinations from the years that are covered in the baseline scenario.²³ Results remain qualitatively unchanged and are not driven by the choice of the years.

Next, I alter the periods and repeat the estimation twice, once for decennial changes (where period one includes the years 1990, 1991, 1992, period two includes 2000, 2001, 2002 and period three includes 2010, 2011, 2012) and once for thirteen-year changes (1984, 1985, 1986 to 1997, 1998, 1999 to 2010, 2011, 2012). As data is only available for Eastern Germany from 1993 onwards, the new period choice implies that only Western German regions are included in the first period. Using data from the 1980's reinforces the claim that regional innovation could not have been affected by trade with China or Eastern Europe in the start-of period, as the existence of the Iron Curtain and the closeness of China prevented Eastern trade. Results for decennial and thirteen-year changes are qualitatively identical.

Time framing 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 (cf. equation (2) and (3)). Even though Eastern trade is still very limited during the first period, I additionally use the industry

²³In 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

composition ten years prior to the start-of period to compute regional exposures. 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. Thus concerns about reverse causality should be overcome. However, it is also a well established fact that changes in trade exposure effect the regional industry structure (see for instance Dauth, Findeisen and Südekum (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.

Finally, I also use of time varying regional controls X'_{it} instead of start-of period regional controls in the baseline scenario. The use of time varying regional controls does not change the results qualitatively.

3.2.3 Regional sensitivity

Here I discuss the regional robustness of the results. As a first check, I only include Western German counties in the estimation. This restriction rules out that reunification effects from Eastern Germany influence results and accounts for the fact that large fractions of the patent intensive manufacturing sector are located in Western Germany, whereas manufacturing in the East is comparatively scarce. Dropping Eastern Germany yields very similar results, but increases the effect size.

The choice of the regional aggregation level is crucial, especially in the 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 Kreise are too small to capture this link. The smaller the geographic entities, the higher the chance that inventors commute across Kreis borders. Accordingly, I additionally repeat the estimation at the level of 150 labor market regions (in German: “Arbeitsmarktregionen”). Labor market regions cover the center of functional labor markets and its surroundings. The regional units are (with a few exceptions) Kreis-sharp and are formed under the condition that commuting flows across regions

are minimized. Regression results at the labor market level do not differ qualitatively from the results at the Kreis level. The same holds true for the results, when re-estimating the regression at the level of 97 regional planning regions (in German: “Raumordnungsregionen”).

As an additional robustness check, I also change the aggregation-level of the regional fixed effects. Instead of fixed effects for the four regions, I include fixed effects at the state and even Kreis level. Still the results indicate positive innovation effects from Eastern European import exposure, whereas Chinese exposure does not show any (significant) effects. The findings even persists, when adding state-time and Kreis-time interactions.

In summary, the robustness checks show that neither the choice of instruments, nor the time framing, nor regional units and controls influence the results. These findings reinforce the observation that Eastern Europe is the driver behind exposure based innovation.

4 Conclusion

So far, we have little systematic evidence, especially empirical evidence, on the effect of increasing trade integration on innovation in high-wage countries. 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. To do so, I create a regional measure of innovation activity by crawling online patent data and apply different regional trade exposure measures. The results show that on average an increase in the change of net trade exposure (defined as import minus export exposure) causes an increase in the change of innovation. Disentangling the effect further, I find that it 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 effects on innovation. The effects are robust for a wide range of

sensitivity checks and remain widely unchanged by the choice of instruments, the time framing, and the choice of regional units and controls.

The findings shed light on the relation between trade and innovation and also bear 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 during the first exposure wave in the 1990's, Germany adapted its product mix to avoid competition with low-wage countries in Eastern Europe resulting in an influx of patenting. When China, almost a decade later, entered the world market (at the beginning with low quality goods similar to the Eastern European product mix), Germany did not face immediate competition anymore as it already had adjusted. Second, and more general, the results show that arguments that trade with low wage countries is bad for innovation and calls for increased trade protection 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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5 Tables

Table 1: Effect of periodic changes in regional net trade exposures on periodic change in patenting per 100,000 inhabitants

Estimation	Baseline Labor Market		+Region / Time FE		+Industry Information	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
$\Delta NetExposure$	0.0082 (0.0096)	0.0047 (0.0058)	0.0137** (0.0067)	0.0122* (0.0070)	0.0156** (0.0078)	0.0127** (0.0062)
% Manufacturing	97.1193*** (29.9266)	96.7920*** (28.6787)	31.1097* (16.6310)	31.0476 (15.9101)	41.8652*** (14.2464)	41.7369*** (13.6272)
% Skill	-311.3309*** (32.1493)	-312.0315*** (31.4143)	39.8675 (87.0176)	39.3372 (83.6319)	46.1117 (92.5629)	45.1640 (88.9468)
% Foreigner	-51.9621 (35.9767)	-51.9858 (34.7057)	112.1615** (51.1338)	112.2742** (49.3586)	123.1595** (51.2381)	123.3264** (49.3072)
% Women	212.3559*** (62.9411)	212.6606*** (61.0583)	-22.4741 (61.1151)	-22.4656 (98.7464)	-24.9956 (55.5355)	-29.0473 (53.2023)
% Routine	-198.7751*** (59.7115)	-198.5546*** (57.485)	-9.4786 (23.9740)	9-.5922 (23.1355)	-27.5687 (26.3345)	-27.6948 (25.3548)
% Chemistry					-70.4553 (54.9475)	-70.3521 (52.7466)
% Automobile					25.9389 (63.2201)	25.6738 (60.6262)
% Largest Industry					7.5930 (61.7981)	7.5895 (59.3071)
Region FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
2SLS First Stage Estimates, Dependent Variable: Net Exposure						
$\Delta NetExposure$		0.7630***		0.7630***		0.7646***
(Other Countries)		(0.2639)		(0.2600)		(0.2620)
F-Test excl. Instr.		8.36		8.61		8.51

Note: N=735; Clustered standard errors (by industries) 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 2: Effect of periodic changes in regional export and import exposures on periodic change in patenting per 100,000 inhabitants

Estimation	Baseline Labor Market			+Region / Time FE			+Industry Information		
	OLS	2SLS	2SLS	OLS	2SLS	2SLS	OLS	2SLS	2SLS
$\Delta Import Exposure$	0.0030 (0.0052)	-0.0027 (0.0061)	-0.0092 (0.0370)	0.0122** (0.0050)	0.0122** (0.0048)	0.0328** (0.0177)	0.0128** (0.0055)	0.0122*** (0.0043)	0.0326** (0.0130)
$\Delta Export Exposure$	-0.2084 (0.0882)	-0.1396 (0.1012)	-0.1090 (0.0842)	-0.0352 (0.0610)	0.0850 (0.1209)	0.0116 (0.0689)	-0.0218 (0.0730)	0.0831 (0.1351)	0.0163 (0.0796)
% Manufacturing	97.1106*** (27.9364)	95.7674*** (26.6859)	66.3216** (25.6827)	31.4162* (16.7212)	28.1130* (16.2459)	9.2433 (12.0990)	37.0548*** (13.8142)	33.6815** (13.6037)	20.1480 (12.5832)
% Skill	-248.2285*** (37.6493)	-267.8529*** (45.4226)	-158.4576 (109.1106)	34.8014 (78.8386)	15.0443 (75.7545)	91.8530 (97.3179)	38.0110 (85.6721)	25.2831 (80.2555)	94.3054 (96.7506)
% Foreigner	-36.2490 (32.9044)	-40.4646 (31.5434)	-82.8200** (41.4388)	111.5347** (54.6128)	117.1778** (52.9151)	123.044** (61.8801)	123.1051** (54.7726)	123.5768** (51.8794)	148.3094*** (55.5860)
% Women	174.3069*** (63.5504)	180.7306*** (62.3040)	250.5783*** (66.6727)	-33.4393 (57.5976)	-32.8572 (58.5073)	-83.7676 (60.2509)	-29.7825 (59.1667)	-39.4961 (60.6792)	-89.0070 (55.5119)
% Routine	-197.2168*** (53.6659)	-201.8671*** (52.3154)	-113.539*** (40.5822)	-20.6739 (21.5689)	-21.1392 (20.5643)	16.4783 (12.0827)	-34.8868 (22.2611)	-26.9330 (21.3718)	-8.5529 (19.3963)
% Chemistry							-47.8588 (41.8890)	-46.7938*** (38.5046)	-83.8812** (38.7276)
% Automobile							45.6661 (78.6465)	15.3644 (77.6525)	13.6926 (67.9025)
% Largest Industry							0.0567*** (15.0953)	1.1738 (59.9304)	43.4007 (57.2471)
Only Western GER Region FE Time FE	No No No	No No No	Yes No No	No Yes Yes	No Yes Yes	Yes Yes Yes	No Yes Yes	No Yes Yes	Yes Yes Yes
2SLS First Stage Estimates, Dependent Variable: Import Exposure									
$\Delta Import Exposure$ (Other Countries) F-Test excl. Instr.	0.8575*** (0.0916) 49.12	0.5801*** (0.1453) 43.65	0.8592*** (0.0919) (48.41)	0.5821*** (0.1434) (43.19)			0.8614*** (0.091) (50.06)	0.5827*** (0.1423) (34.48)	
2SLS First Stage Estimates, Dependent Variable: Export Exposure									
$\Delta Export Exposure$ (Other Countries) F-Test excl. Instr.	0.1413 (0.1094) 1.60	0.5413*** (0.1282) 9.66	0.1313 (0.1050) (1.27)	0.5183 (0.1314) (8.17)			0.1144 (0.0923) (1.21)	0.4681*** (0.1245) (7.45)	

Note: N=737 for full sample, N=606 for West Germany only; Clustered standard errors (by industries) 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 3: Heterogeneous Exposure Effects for Eastern Europe and China

Estimation	Baseline Labor Market		+Region / Time FE		+Industry Information	
	Eastern Europe	China	Eastern Europe	China	Eastern Europe	China
$\Delta Import Exposure$	0.0240** (0.0109)	-0.1428 (0.1129)	0.0288*** (0.0074)	0.0247 (0.0646)	0.3333*** (0.0105)	0.0125 (0.0577)
$\Delta Export Exposure$	-0.1636 (0.1877)	-0.5901* (0.3271)	0.0899 (0.1888)	0.1894 (0.3500)	-0.1021 (0.2274)	0.2815 (0.3669)
% Manufacturing	90.5999*** (28.2124)	96.0836*** (27.7672)	26.3973* (14.2996)	26.3900 (16.3197)	34.8843*** (10.8396)	36.3145*** (13.3303)
% Skill	-284.3697*** (48.5085)	-208.1218*** (69.4430)	31.9108 (100.6374)	40.1733 (92.0187)	43.7905 (105.7505)	61.1540 (82.5399)
% Foreigner	-39.5933 (33.2150)	-38.3784 (37.3225)	121.5363** (57.2416)	131.3174** (57.9184)	126.0112** (56.6713)	136.9262*** (50.9724)
% Women	179.4387*** (68.2121)	161.0553** (67.8300)	-17.9387 (57.2198)	-30.5599 (65.6525)	-18.6790 (56.0026)	-45.9425 (61.8154)
% Routine	-199.2905*** (46.5364)	-177.7226*** (51.2111)	-11.7291 (24.1432)	-0.9236 (22.2869)	-27.2853 (27.9696)	-4.0047 (21.8430)
% Chemistry					-36.8038 (32.6244)	-54.9407 (40.5791)
% Automobile					54.1951 (53.4480)	-4.8106 (65.7111)
% Largest Industry					-21.8019 (39.8059)	-3.3023 (56.2747)
Region FE	No	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
2SLS First Stage Estimates, Dependent Variable: Import Exposure						
$\Delta Import Exposure$ (Other Countries)	0.9674*** (0.0065)	0.3196*** (0.0236)	0.9646*** (0.0074)	0.3178*** (0.0246)	0.9748*** (0.0083)	0.3189*** (0.0250)
F-Test excl. Instr.	15296.64	93.88	11130.23	84.61	8695.30	83.31
2SLS First Stage Estimates, Dependent Variable: Export Exposure						
$\Delta Export Exposure$ (Other Countries)	0.5794*** (0.1652)	0.0531 (0.0450)	0.5560*** (0.1600)	0.0480 (0.0425)	0.4707*** (0.1717)	0.0447 (0.0396)
F-Test excl. Instr.	6.52	0.89	6.60	0.77	3.82	0.88

Note: N=732 for Eastern Europe, N=727 for China; Clustered standard errors (by industries) 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.

Appendices

A Regional Patenting structure in Germany

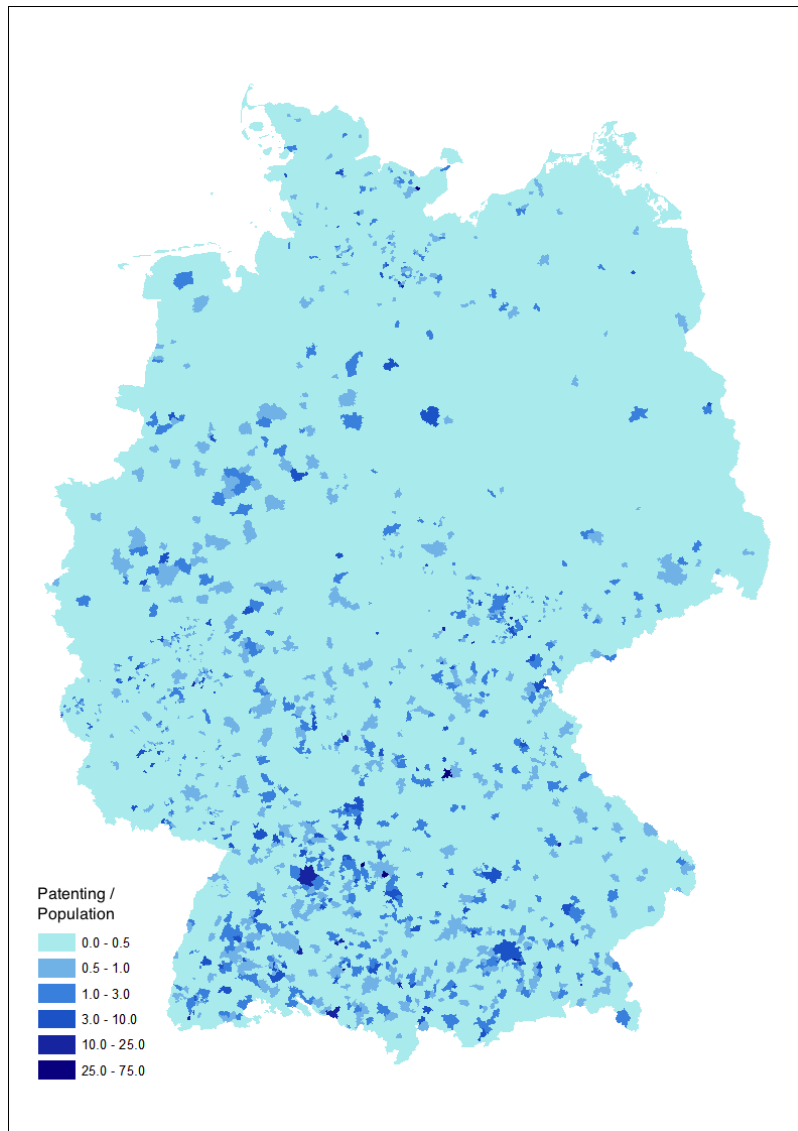


Figure 5: Patenting per 1000 inhabitants by Location of the Applicant

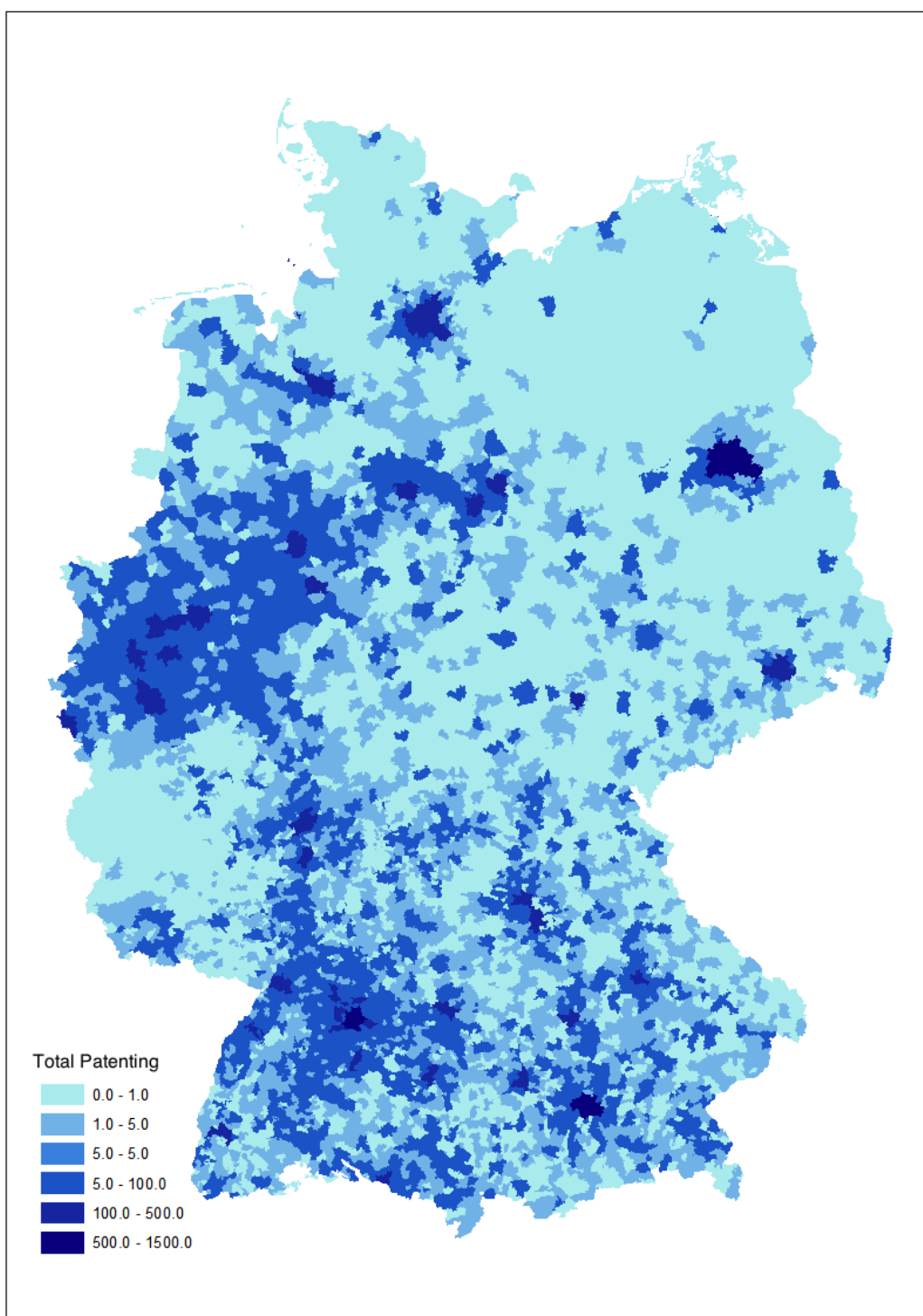


Figure 6: Total Patenting by Location of the Applicant

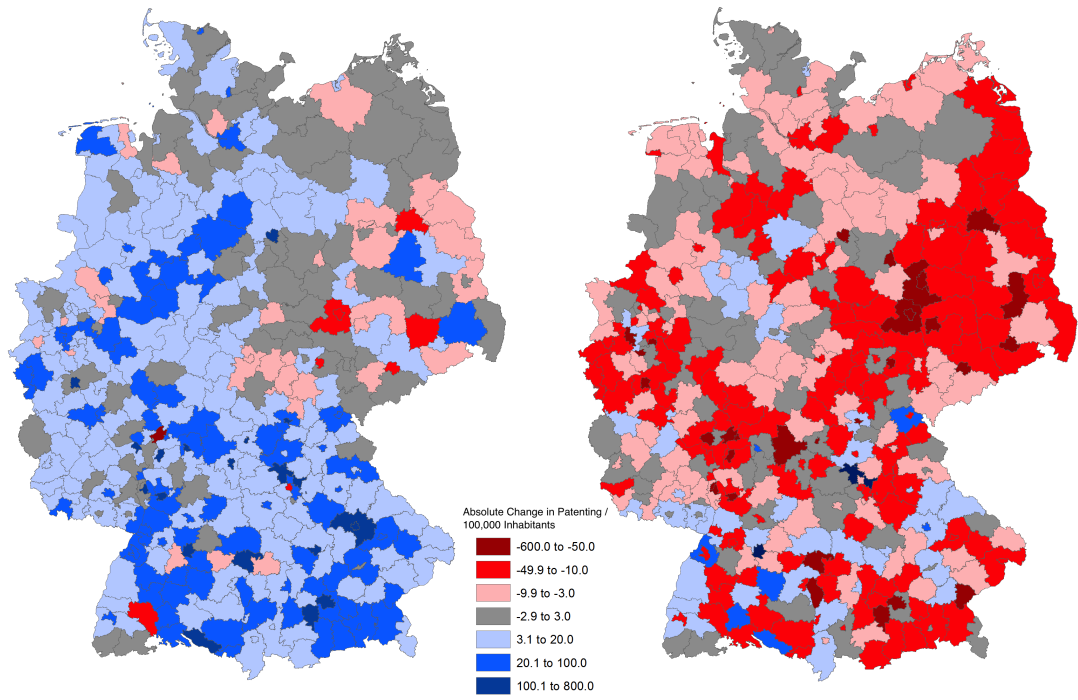


Figure 7: Absolute Change of Patenting per 100.000 Inhabitants by Location of the Inventor; $\bar{I\bar{A}}_i^{93-95} - \bar{I\bar{A}}_i^{02-04}$ (Left) and $\bar{I\bar{A}}_i^{02-04} - \bar{I\bar{A}}_i^{10-12}$ (Right)