Essays on International Trade, Regional Change and Structural Growth

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Contents

Preface

Economists (should) care about regions! On the one hand this is true because macroeconomic shocks have vastly different effects across regions. The pressing topics of robotization and artificial intelligence, Brexit, or U.S. tariffs will affect Würzburg differently than Berlin, implying varying interests among its population, firms and politicians. On the other hand, shocks in individual regions, such as inventions, bankruptcies or the attraction of a major plant can, through trade and input-output linkages, magnify to aggregate effects of macroeconomic importance. Yet, regional heterogeneities in Germany and the complicated network of linkages that connect regions are still not well documented nor understood. A fact that is especially true for local labor markets that are of core interest to regional policy makers and that also feature substantial heterogeneity.

The highest local unemployment rate in a German county in 2005, for example, was 6.4 times larger than the lowest one and this number has increased to 9.3 by 2017 despite a strong overall reduction in the average unemployment rate.[1] This thesis provides a thorough quantification of such heterogeneities and an in-depth analysis of the sources and mechanisms that drive these differences. In doing so it helps to understand why of the 10 counties with the highest unemployment rate in Germany in 2012 four have remained on this list in 2017 whereas six managed to substantially improve their ranking and thus, why some counties prosper in the same economic environment that is detrimental to others.

This thesis is therefore connected to the large line of empirical literature that analyses the responses of local labor markets to aggregate shocks. A seminal work in this regard is the study by Autor et al. (2013) who look at the effects of a rise in Chinese import competition on U.S. local labor markets. Dauth et al. (2014) provide a similar analysis for local labor markets in Germany and Acemoglu and Restrepo (2017) and Dauth et al. (2018) look at the effects of robotization in the United States and Germany, respectively. A common shortcoming of this branch of the literature is, however, that it can not deliver the full general equilibrium effects of the respective shocks. In particular, it does not capture the complex network of linkages between counties both in terms of trade and in terms of factor

[1] Source: Federal regional and statistical offices ("Statistische Ämter des Bundes und der Länder")

mobility. These linkages, however, are especially strong at the regional level and explain how effects in each labor market propagate through the regional network and spill over to other locations. Therefore, the essays in this thesis instead rely on a different branch of the literature that has developed (spatial) quantitative models that tightly connect theory with numbers and that can be used to derive full general equilibrium effects of shocks.

Specifically, this line of research incorporates an arbitrary number of locations with heterogeneous geography, productivities, amenities, and local factors, as well as trade and commuting costs into general equilibrium models. These models in turn build on the new economic geography (or isomorphic models) becoming applicable to quantification by restraining the agglomeration forces so that multiple equilibria can not emerge. The recent survey of this literature by Redding and Rossi-Hansberg (2017) shows how to construct these models relying on a menu of components including, for example, various possible trade models such as the Armington model (Anderson 1979; Anderson and Van Wincoop 2003), the monopolistic competition model with homogeneous firms (Krugman 1980; Helpman and Krugman 1985), or heterogeneous firms (Melitz 2003) and the multi-region Ricardo model (Eaton and Kortum 2002) as well as on different assumption about labor mobility (see Redding 2016, for an overview) and the existence of a fixed factor such as land as in Helpman (1998).

The essays in this thesis develop the necessary data to calibrate such models to capture effects in German regions. Using such spatial quantitative models they then contribute to the understanding of the two initially mentioned avenues, that is, the heterogeneity in responses of different locations to aggregate shocks as well as the consequences and spillovers of local shocks on the remaining economy. In this process, each essay provides an independent contribution that can be understood without further information. Yet, in the following I provide a short overview of the common thread connecting the essays that also serves as a guideline for the reader.

The first essay, *"How deep is your love? A quantitative spatial analysis of the transatlantic trade partnership"*, explores the quantitative effects of trade liberalization envisioned in a Transatlantic Trade and Investment Partnership (TTIP) between the United States and the European Union. In contrast to other works analyzing TTIP the quantitative trade model employed in this paper features consumptive and productive uses of land and allows for labor mobility and a spatial equilibrium. One of the difficulties in assessing the effects of TTIP was that, at the time of writing this paper, negotiations were still ongoing and their eventual outcome thus uncertain. Moreover, tariffs in E.U.-U.S. trade are already very low, so that TTIP or any future agreement will have a major impact only by eliminating non-tariff barriers. These are extremely hard to quantify, however, as abstract standards, rules and regulations need to be translated into cost creating barriers. In the paper these uncertainties are addressed by considering a corridor of trade-liberalization paths and by providing numerous robustness checks. The main result is that, even with ambitious liberalization, real income gains within a TTIP are only in the range of up to 0.46 percent for most countries and the effect on outside countries is typically negative, yet even smaller.

An important contribution of this essay is to take land and housing as fixed factors into account. It is shown that doing so scales down the welfare effects attributed to a TTIP strongly. Moreover, in analyzing the role of land and housing the paper also reveals that the share of land and housing in aggregate spending is much smaller than what is often assumed in the literature, a fact that is also central to the third essay of this thesis. Specifically, for Germany and the United States the value is about 10 percent and thus far from the common 25, 33 or even 40 percent assumed in other quantitative work. This discrepancy is discussed in detail in this thesis.

The paper also sets the groundwork for analysing regional effects in Germany that are an important part of all further essays. However, without appropriate data available it relies on simple proportionality assumptions to model the intra-national trade and production structure. This lack of interregional trade data is addressed in the second essay of this thesis. With respect to TTIP the surprising finding is that all German counties derive unambiguous welfare gains even though the model allows for negative terms-of-trade effects. Lastly, the paper shows that that in order to arrive at the same welfare gains as under a TTIP, a multilateral liberalization would have to be much more ambitious for the U.S. than for the E.U., a finding that provides quantitative evidence for the argument by Bhagwati (1994) that large economies profit from sequential bilateral bargaining over multilateral agreements.

The essay is a version of the paper by the same name, a joint work with Michael Pflüger, that is published in the Review of International Economics (2018, Volume 26, Issue 1) and that was adapted to the format and style of this thesis.

The lack of interregional trade data for Germany became apparent in the first essay and was circumvented by relying on the assumption that trade flows are proportional to output and demand levels in each county. However, the uncertainty about actual intra-national trade flows is a severe problem both for regional analysis of aggregate shocks such as trade agreements as well as for the analysis of network effects of regional policies and shocks. At the heart of my second essay, *"RIOTs in Germany - Constructing an interregional input-output table for Germany"*, was thus the fact that despite their importance, little is known about the spatial structure of trade and production networks within Germany and their connection to the international markets. The paper develops a unique data set to take an in-depth look at these networks at the county level. The analysis of sectoral specialization and agglomeration patterns in the paper relies on data from the regional statistical offices ("Statistische Ämter des Bundes und der Länder") and the institute for employment research

(IAB) and finds a strong heterogeneity across counties with a production network that differs substantially from patterns constructed based on simple proportionality assumptions.

The subsequent analyses of interregional trade networks relies on a unique data set of county level goods shipments by truck, train or ship for the year 2010. In contrast to the proportionality assumption, deriving county level trade flows based on this data set captures complex motives for trade between counties, such as the existence of subsidiaries, trusted long-term relationships or the availability of highly specialized parts and components. The paper then shows how to adapt recent advances in regionalization of input-output tables to derive an interregional input-output table for 402 German counties and 26 foreign partners for 17 sectors that is cell-by-cell compatible with the world input-output database (WIOD) tables with respect to national aggregates and can be used for impact analysis and CGE model calibration.

During the analysis of the German regional production structure and trade network it quickly became apparent that trade imbalances of counties were, relative to their economic sizes, much larger than international imbalances. At the national level a driving force of trade imbalances are differences in intertemporal saving and consumption that can not be captured by static models and are hence usually represented by exogenous monetary transfers between countries. Arguably, at the county level the "foreign" ownership of fixed factors and commuting play a much larger role for trade imbalances, as the income generated in one location is spend in another. This argument is also supported by the data which shows large trade surpluses in productive cities such as Munich or Wolfsburg and big trade deficits in surrounding, more rural counties from which workers commute to town.

To capture how important commuting is as a linkage in the German production network, the third essay, *"On the Road (Again): Commuting and Local Employment Elasticities in Germany"* constructs a quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting. The paper uses this model to address how local labor markets in Germany respond to labor demand shocks, focusing on the local employment elasticities, that is, the response of local employment to these shocks. An important result of this analysis is that that the network of local German labor markets functions much smoother than what is typically presumed. Specifically, the local employment elasticities in response to local productivity shocks turn out to be significantly larger than what is reported for the United States.

To be able to draw this comparison the methodology and calibration employed in the paper stay as close as possible to Monte et al. (2018) who perform a similar analysis for the United States. However, the authors of this article use a share of land and housing in total spending of 40 percent. In relation to the finding in the first essay, this value is hard to justify. A further contribution of the third essay of this thesis is, therefore, to perform a robustness check of the results with a much lower expenditure share devoted to housing. This turns out to have a striking effect on the size and heterogeneity of the resulting elasticities. Importantly, while a simple inverse measure of openness to commuting, that is, the share of residents who work in the county where they live, is a powerful ex-ante predictor for the resulting general equilibrium employment elasticities when the housing share is large, it becomes insignificant with the lower share. Intuitively, a lower spending share devoted to housing reduces the dispersive effect of housing congestion and increases the strength of general equilibrium effects that can not be predicted by ex-ante statistics.

This paper, a joint work with Michael Pflüger, was presented in 2018 at the annual conference of the Verein für Socialpolitik in Freiburg, at the Julius-Maximilians-University Würzburg and by Michael Pflüger at the annual conference of the "Ausschuss für Regionaltheorie und -politik".

As is common in the quantitative literature the analysis of German regional labor markets in the previous paper relied on a full employment model. In contrast, the final essay of this thesis, *"Shocking Germany - A spatial analysis of German regional labor markets"*, also quantifies the large heterogeneity of employment (and real income) effects across German counties in response to local productivity shocks, but explicitly models unemployment. In particular, it relies on a quantitative model with imperfect mobility and sector-specific labor market frictions. These assumptions imply two important additional channels that affect labor market outcomes. First, a population inflow is no longer equivalent to an increase in employment. Instead the paper shows that population mobility reduces the magnitude of local employment rate responses by a striking 70 percent on average as population inflows increase the number of potential workers and thus the strain on the local labor markets (cf. Harris and Todaro 1970). Second, changes in the sectoral composition of production shift workers between sectors with different matching frictions. Except for a few counties, however, this latter effect has a much weaker influence on employment elasticities than population mobility.

Regarding national effects of local productivity shocks, the paper finds that the German employment rate is less dependent on mobility effects with worker in- and outflows in individual counties leading to employment effects that partially cancel out. For productivity shocks that affect individual sectors across all counties, instead of all sectors within one county, the composition effect is substantially magnified and the mobility effect reduced. In line with recent real world observations the paper shows that real income and employment effects, while correlated, do not need to be of the same sign. A finding that can not occur in full employment models where a population inflow can only weaken positive real income effects.

Finally, the paper relies on the same outstanding data set of county level goods shipments used in the previous two essays to identify the sources of the heterogeneous responses in Germany's complex interregional linkages. It turns out that the spatial propagation of real income effects from local productivity shocks closely follows trade linkages whereas employment effects, driven by changes in productivity, mobility, and sectoral composition, are more complex to predict.

This paper was presented in 2016 at the European Trade Study Group (ETSG) conference in Helsinki, at the workshop "Internationale Wirtschaftsbeziehungen" in Göttingen and at the Julius-Maximilians-University Würzburg.

Each essay of this thesis provides an independent contribution that can be understood without further information and thus also has its own introduction, conclusion, bibliography and appendices, as well as its own numbering scheme for footnotes, figures, and tables. The list of references referred to in this preface and in the concluding remarks can be found at the end of the thesis.

Essay I

How deep is your love? A quantitative spatial analysis of the transatlantic trade partnership

How deep is your love? A quantitative spatial analysis of the transatlantic trade partnership*

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Abstract

This paper explores the quantitative effects of trade liberalization envisioned in a Transatlantic Trade and Investment Partnership (TTIP) between the United States and the European Union. We use a quantitative trade model that, in contrast to other works, features consumptive and productive uses of land and we allow for labor mobility and a spatial equilibrium. Our calibration draws mainly on the world input-output database (WIOD). The eventual outcome of the negotiations is uncertain. Tariffs in E.U.-U.S. trade are already very low, however, so that an agreement will have a major impact only by eliminating non-tariff barriers. These are extremely hard to quantify. We address these uncertainties by considering a corridor of trade-liberalization paths and by providing numerous robustness checks. Even with ambitious liberalization, real income gains within a TTIP are in the range of up to 0.46% for most countries. The effect on outside countries is typically negative, yet even smaller. Taking land into account scales down the welfare effects strongly. Interestingly, we find that all German counties derive unambiguous welfare gains even though the model allows for negative terms-of-trade effects. Our analysis also implies that in order to arrive at the same welfare gains as under a TTIP, a multilateral liberalization would have to be much more ambitious for the U.S. than for the E.U.

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1 Introduction

The prospect of a Transatlantic Trade and Investment Partnership (TTIP) between the United States and the European Union has sparked controversial debates since the negotiations started in the summer of 2013 (Bhagwati 2013). Progress at the negotiating table was limited even after 15 rounds of negotiations conducted until October 2016. The year 2016 saw rising resistance against a TTIP in a number of E.U. countries and opposition against trade deals from the contenders in the run-up for the American elections, notably so from the candidate elected to be the new president. Political observers conjectured already before these elections that a TTIP would not be concluded for years to come.[1]

Despite the uncertainties thrown up by these developments it is important to understand what is at stake in such a trade deal. A TTIP would be of paramount importance for the global economy as it involves economies accounting for almost one half of global value added and one third of world trade (Hamilton and Quinlan 2014). Moreover, proposals for a Free Trade Area spanning the Atlantic Ocean are recurring time and again ever since they were launched in the 1990s (see Langhammer et al. (2002)).

This paper explores the quantitative effects of transatlantic trade liberalization on welfare and its constituent parts (wages, prices and land rents) in the countries of the European Union, the United States and third countries. We also look at how regions in Germany would be affected. What distinguishes our analysis from other works addressing TTIP is the spatial perspective: we use a simple quantitative spatial trade model where land has both consumption and production value and where labor mobility is allowed for. More specifically, we complement the trade analysis with a scenario where labor is mobile between the countries of the EU and within Germany (between German counties). This regional approach ties up our analysis with current research on within-country effects of shifts in the global economy.[2]

The debate around TTIP involved several issues and it is important to clarify at the outset to which of these our analysis speaks and which of these are not addressed in this paper.

[1]See the coverage in the Economist April 30, 2016 ('Trading Places') and September 15, 2016 ('Why Germans are protesting free trade'), December 10, 2016, 'Dealing with Donald') and July 8, 2017 ('The German Problem'). President Trump's trade agenda is still not well-defined. He pulled his country out of the Trans-Pacific Partnership (TPP) with 11 countries around the Pacific Rim and he also reinforced his critique of the North-American Free Trade Agreement. Transatlantic trade has not been fraught with similar allegations of unfair competition from his part as those that he levied against China or Mexico, except for recent attacks concerning the German trade surplus. Industry organizations such as the German American Chamber of Commerce continue to lobby strongly for a TTIP and its leading members are reported to deem the prospect of a continuation of the TTIP-talks 'fairly optimistic' and the German Chancellor Angela Merkel has recently voiced calls to re-launch TTIP-negotiations (see Frankfurter Allgemeine Zeitung, December 7, 2016 and June 27, 2017).

[2]See, for example Autor et al. (2013) and Caliendo et al. (2015).

One issue is that such bilateral agreements may have negative effects on outsiders and undermine the global trading system (Bagwell et al. 2016; Bhagwati et al. 2014). Our quantitative analysis identifies locations that are potential winners or losers from transatlantic trade liberalization, but we have nothing to say concerning any broader systemic effects.

Another key issue concerns the fact that tariffs prevailing in E.U.-U.S. trade are already very low (on average less than 3 percent for manufactures and slightly more for agricultural products). Hence, any significant liberalization has to tackle non-tariff barriers, thus involving steps towards 'deep integration' (Lawrence 1996) in fields such as product and production standards, environmental regulation, health and safety, labor standards, cultural diversity and investor state dispute settlement procedures. Regulations in these fields reflect a variety of concerns that may range from pure protectionism to entirely legitimate nonprotectionist domestic policies which accord with WTO law if exerted nondiscriminatorily. We do not contribute to the analysis of the economic foundation and the trade and welfare effects of domestic policies and regulations that are chosen by the European Union or the United States for nonprotectionist motives such as market failures owing to externalities, market power, or asymmetric information.[3] Neither do we contribute to the extraordinary difficult quantification of such nontariff trade barriers.

We deal with the reduction of nontariff barriers by considering a wide range of conceivable trade liberalization scenarios. This strategy allows us to circumvent the quantification issue and also to cope with the fact that the specific provisions that a TTIP might eventually entail are highly uncertain.[4] We proceed by presuming that the trade frictions and regulations to be reduced and/or harmonized are quantitatively reflected in our corridor of trade liberalization paths. Technically, we make use of the 'exact hat algebra' developed by Dekle et al. (2007) to get rid of many exogenous parameters that will enter only indirectly through their effect on the observed ex-ante values of equilibrium variables (Costinot and Rodríguez-Clare 2014). Most importantly in the context of TTIP, we do not need the bilateral trade cost matrix and hence, we do not have to quantify tariff equivalents of the pre-existing nontariff barriers , a task that has led to widely differing results (cf. subsection 3.4). Instead, our strategy is to assume that these parameters rationalize the observed ex-ante trade flows so that the data are exactly generated by our model. Hence, the model's fit with the data is due to calibration and not an empirical "test" of the model.[5]

[3] We have contributed to this research elsewhere with analyses, for example, of the causes and effects of subsidies to market entry (Pflüger and Südekum 2013), the trade and welfare effects of environmental policies (Pflüger 2001) and the taxation of international trade (Haufler and Pflüger 2004, 2007).

[4] The E.U. commission has started to publish summaries of the negotiation rounds in the fall of 2014 and has made its original proposal text available as well (see http://ec.europa.eu/trade/policy/in-focus/ttip/ for both). However, while the summary notes remain very general, the European Union's proposal does obviously not allow to infer the rules of the final text. The consolidated chapters remain confidential to the general public.

[5] See Redding and Rossi-Hansberg (2017) for a lucid discussion of the issue of connecting (quantitative

Our quantitative spatial trade model builds on Eaton and Kortum (2002), Redding (2014, 2016) and Caliendo and Parro (2015) - see section 2. For its calibration we draw predominantly on the world input-output database (WIOD) described in Timmer et al. (2015) and Timmer et al. (2016) - see section 3. The model is static, so that our estimates do not comprise effects associated with capital accumulation or dynamic growth effects. We deal with aggregate trade imbalances by assuming that these are kept at their initial levels.[6] The model does not feature multinational firms. Hence, our analysis does not embrace welfare effects associated with FDI.[7] The perspective of the proximity-concentration tradeoff (Brainard 1997) implies that a TTIP's focus on trade liberalization shifts the odds in favor of the trade channel, however. We abstract from tariff revenues on the grounds that if TTIP is to achieve significant liberalization it would primarily have to involve nontariff barriers but also because it allows us to avoid specifying how the loss in the budget of the E.U. induced by falling tariff incomes would affect individual member states. Our analysis thus captures the efficiency gains (the removal of production and consumption distortions) associated with the reduction of *both* nontariff and tariff barriers but neglects that tariff income falls with the elimination of the remaining tariff barriers.

We focus on symmetric trade liberalization. To prevent that trade is subsidized in any sector we estimate an upper threshold for the symmetric liberalization, which we calculate at 9.97 percent - see section 3.[8] To assume symmetric liberalization is arbitrary, of course. Our methodology allows us to address any liberalization scenario, however. We therefore also perform a large set of robustness checks that involve asymmetric liberalization paths in accordance with bottom-up and top-down estimates of the outcomes of the E.U.-U.S. trade talks found in the literature and we also consider possible spillovers of TTIP to other countries (cf. section 3.4).

We explore both a 'pure trade effect', which assumes that labor is immobile across locations and a 'labor-mobility regime' within Germany and across the member countries of the European Union. Our results can be summarized as follows.

First, starting with the pure trade effect, even with an extreme trade barrier reduction of 9.97 percent between the United States and the European Union, real income gains are in the range of up to 0.46 percent for most TTIP countries. Welfare effects in third countries such as China, Switzerland, Norway, Russia, Korea and Taiwan are negative, but typically

spatial) models with the data.

[6]An alternative is to assume that part of the income that derives from the use of land and structures is distributed to a national portfolio and distributed across regions to match regional trade imbalances (e.g., Caliendo et al. (2014)).

[7]An emergent literature introduces multinationals into quantitative trade models, see, for example, Ramondo and Rodríguez-Clare (2013), Arkolakis et al. (2014), Ramondo et al. (2014) and Alviarez (2015).

[8]We take such a scenario as extreme since we view many of the prevailing nontariff trade barriers in E.U.-U.S. trade as grounded in legitimate domestic concerns such as those we have already alluded to.

small. The strongest winners and losers exhibit the closest ex-ante connections with the United States or the European Union as measured by initial spending shares, which, even in our age of globalization, are small.

Second, the welfare gains associated with transatlantic trade liberalization are overestimated in the order of 10 percent if the consumptive use of land is not taken into account, since housing is intrinsically nontradable and of considerable quantitative importance in spending.

Third, industry effects (measured by production values) are small in most parts of the European Union and in the United States. In Germany, machinery, transport equipment and wholesale obtain a small boost, but telecommunications and transport activities shrink slightly. Ireland is an exception both in terms of the strong aggregate welfare gains and also in terms of the predicted industry effects, which imply that the financial sector, telecommunications, and chemical and pharmaceutical products obtain a strong boost. Robustness checks reveal that the Irish results largely hinge on liberalizing trade in services and the financial sector.

Fourth, despite their heterogeneity all German counties win even before allowing for labor mobility (which equalizes welfare). This also holds true for asymmetric liberalization scenarios and is remarkable, because our model allows for negative welfare effects associated with terms-of-trade movements, which work through wage adjustments across locations. The fear that TTIP might only benefit already rich German counties at the cost of poorer ones is thus not backed. Yet even in our ambitious scenario the potential gains are limited to between 0.31 percent and 0.71 percent of real income. With labor mobility within Germany, these welfare effects level out at 0.46 percent.

Fifth, a long-run scenario of perfect population mobility within the European Union predicts migration flows from Eastern Europe into Ireland, Luxemburg and, to a lesser extent, into Belgium, the Netherlands, Great Britain, and Malta. As a result of extreme trade liberalization, real income gains among European Union members would be at a joint level of 0.32 percent. The bulk of the adjustment to such a spatial equilibrium within the European Union would take place through the adjustment of land prices.

Finally, we find that a multilateral reduction of trade barriers in the range of 0.5 to 1 percent would be enough for the European Union to achieve the same welfare gains as in our most ambitious TTIP scenario. For the United States this would require a decrease in multilateral barriers of 2.5 to 3 percent, however. This finding points to the importance of Bhagwati's (1994) prediction that a 'hegemonic power' is likely to gain more by bargaining sequentially than simultaneously and it provides one explanation why the United States favors preferential liberalization.

Relation to the previous literature. Our analysis is related to the growing literature on new quantitative trade modelling that has provided momentous stimuli to the research pertaining to the quantification of the gains from trade and the consequences of the globalization, more generally - see Costinot and Rodríguez-Clare (2014) for a survey. These new models have solid, yet possibly different, micro-foundations (spanning from perfect competition to monopolistic competition), which give rise to common gravity-type macro-level predictions for bilateral trade flows as a function of bilateral trade costs. We build on the Ricardian tradition established by Eaton and Kortum (2002) and generalized by Redding (2016) to comprehend factor mobility and by Caliendo and Parro (2015) to comprise an arbitrary number of heterogeneous interlinked industries. These new quantitative models have been applied recently to trade policy issues. Important examples are Ossa (2014), addressing optimal tariffs in a worldwide trade war, Redding (2014), studying the trade integration between the United States and Canada, Costinot and Rodríguez-Clare (2014), providing estimates of trade integration for OECD countries, and Caliendo and Parro (2015), examining the trade integration between the United States and Mexico in the wake of the establishment of NAFTA. Our model bears close resemblance with the model developed in Caliendo et al. (2014) who, in studying labor elasticities across U.S. states, also allow for labor mobility. However, they abstract from all international economic interactions.[9] Moreover, in conspicuous contrast to both Caliendo et al. (2014) and Caliendo and Parro (2015), we take into account that land is not only used in production but also in consumption, a difference that has strong significance for the quantitative results.[10] We are the first to explore trade liberalization under a TTIP in a model which jointly considers input-output linkages, land for consumption and production and labor mobility.

Our paper also relates to the literature which has provided estimates of the economic effects of a transatlantic trade and investment partnership. Francois et al. (2013) set up a multiregion, multisector global computable general equilibrium (CGE) model that, in most sectors, assumes perfect competition, imposes the Armington assumption, and in some heavy manufacturing sectors allows for imperfect and monopolistic competition. In addition to looking at static effects, longer-run impacts of trade through investment effects on capital stocks are also considered. The data on nontariff barriers are drawn from Ecorys (2009). Fontagné et al. (2013) base their computations on MIRAGE, another computable general equilibrium model for the world economy developed by CEPII. This model differs in some choices from Francois et al. (2013) but it also features multiple industries and it also relies on the Armington assumption. Egger et al. (2015) complement the use of similar computational

[9] A minor difference is that in our model, contrary to Caliendo et al. (2014), the continuum of varieties produced in each sector enters consumer's utility rather than final goods production. Specifically, we extend the two sector framework (manufacturing and agriculture) of Michaels et al. (2012) to an arbitrary number of sectors.

[10] Pflüger and Tabuchi (2011) highlight the role of land for consumption and production from a new economic geography perspective building on Helpman (1998), see also Fujita and Thisse (2013).

methods with econometric techniques to establish a potential TTIP shock. The works by Felbermayr et al. (2015) and Felbermayr et al. (2013) and Aichele et al. (2016) are closest to our approach. Felbermayr et al. (2015) and Felbermayr et al. (2013) use a structurally estimated single-sector general equilibrium model in the tradition of Helpman and Krugman (1985). The strategy pursued in Felbermayr et al. (2015, 2013) differs from the computable general equilibrium tradition in that the parameters of the model are estimated on those data that the model has to replicate in the baseline equilibrium without drawing on the method established by Dekle et al. (2007). Aichele et al. (2016), in contrast, draw on this methodology, using a model in the tradition of Eaton and Kortum (2002), and Caliendo and Parro (2015). We revisit some of these analyses in our robustness checks. The key difference between these works and our analysis is that we include land both as a factor of production and as a consumption good (land for housing) and in that we take a regional perspective, allowing for labor mobility and a spatial equilibrium.

The structure of our paper is as follows. Section 2 sets up the model. Section 3 characterizes our empirical methodology and the data. Section 4 proceeds to our empirical analyses. Section 5 offers some final remarks.

2 The model

2.1 The setup

Our analysis builds on Redding's (2014; 2016) extension of Eaton and Kortum (2002), which features the use of land for consumption and labor mobility. We consider two production factors, labor and land. Final goods and intermediate goods are traded at a cost between all locations and labor is mobile between subgroups of all locations. We extend Redding's framework to comprise an arbitrary number of heterogeneous industries (sectors) similar to Caliendo and Parro (2015).

The economy consists of N locations, indexed by n, i or s. Each location is endowed with an exogenous quality-adjusted amount of land and structures H_n. The amount of labor L_n available at location n is either exogenously given or emerges endogenously in a subset of locations among which labor is mobile. Land and labor are used to produce a continuum of differentiated goods in each of K industries (sectors) indexed by k or j. All locations can trade with each other subject to iceberg trade costs so that $d_{nik} \geq 1$ units of a good produced in industry k in location i have to be shipped in order for one unit to arrive at location n. We assume that goods trade within a location is costless, $d_{nnk} = 1$. Workers are perfectly mobile between sectors at any location.

This framework flexibly allows for internal and external geographies at different levels. Subsets of locations, $N^m \subset N$, will be called countries and/or country groups and indexed by m. Such spatial entities are exogenously endowed with a measure of $\overline{L}^m$ workers who supply 1 unit of labor each and workers are assumed to be mobile (in the long-run) within such spatial entities but not across them. In a spatial equilibrium, real wages are equalized across locations of a spatial entity and $\overline{L}^m = \sum_{n \in m} L_n$.[11]

2.2 Preferences

Preferences of the representative consumer in location n are defined over the consumption of goods C_n and the residential use of land H_n^C and take the Cobb-Douglas form:

$$U_n = \left(\frac{C_n}{\alpha}\right)^{\alpha} \left(\frac{H_n^C}{1-\alpha}\right)^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{1}$$

The consumption aggregate C_n is defined over the consumption of the outputs of $k = 1, ..., K$ industries (C_{nk}) and is also assumed to be of Cobb-Douglas form

$$C_n = \prod_{k=1}^{K} C_{nk}^{\delta_{nC}^k}, \qquad 0 \leq \delta_{nC}^k \leq 1, \quad \sum_{k=1}^{K} \delta_{nC}^k = 1 \tag{2}$$

where δ_{nC}^k are the constant consumption shares on industries k. Each industry offers a continuum of varieties $\omega \in [0, 1]$ which enter preferences according to a constant elasticity of substitution function

$$C_{nk} = \left[\int_0^1 q_{nk}(\omega)^{\frac{\sigma_k - 1}{\sigma_k}} d\omega\right]^{\frac{\sigma_k}{\sigma_k - 1}}, \qquad \sigma_k > 1 \tag{3}$$

where $q_{nk}(\omega)$ is location n's consumption of variety ω produced in industry k and σ_k denotes the (constant) within-industry elasticity of substitution between any two varieties. The assumption of a continuum of varieties within each sector ensures that each individual good and producer are of zero weight within the economy.

[11] Land is important for the spatial equilibrium. An inflow of workers into a location bids up land prices and it also drives down the marginal product of labor and, hence, the wage. Clearly, in practice, there are further dispersion forces (e.g., consumptive or productive amenities) from which we abstract to keep the analysis simple.

2.3 Production

Production of each variety ω within any industry k and at any location n takes place with constant returns to scale and under perfect competition combining labor, land and all available varieties of outputs as intermediate inputs. Locations and industries differ in terms of their input mix and their productivities $z_{nk}(\omega)$, however. We follow Eaton and Kortum (2002) by assuming that productivities are drawn independently from location and industry-specific Fréchet distributions with cumulative density functions given by

$$F_{nk}(z_{nk}) = e^{-T_{nk}\ z_{nk}^{-\theta_k}} \tag{4}$$

where T_{nk} is a scale parameter that determines average productivity and the shape parameter θ_k controls the dispersion of productivities across goods within each sector k, with a bigger θ_k implying less variability. Taking iceberg costs $d_{nik} \geq 1$ into account, the cost to a consumer in location n of buying one unit of ω in sector k from a producer in location i is thus

$$p_{nik}(\omega) = \frac{d_{nik}c_{ik}}{z_{ik}(\omega)}, \tag{5}$$

where c_{ik} are the costs of an input bundle given by

$$c_{ik} = w_i^{\beta_{ik}} r_i^{\eta_{ik}} \rho_{ik}^{1-\beta_{ik}-\eta_{ik}}, \qquad 0 < \beta_{ik} < 1, \qquad 0 < \eta_{ik} < 1 \tag{6}$$

with w_i, r_i and ρ_{ik} being the wage rate, the rental rate of land, and the industry-specific index of intermediate input prices in i, respectively, and where β_{ik} and η_{ik} are the exogenous cost shares of labor and land.

2.4 Expenditure shares and price indices

Consumers and producers treat goods as homogeneous and consequentially source each good from the location that provides it at the lowest price. Hence,

$$p_{nk}(\omega) = min\left\{p_{nik}(\omega); i = 1, ..., N\right\} \qquad k = 1, ..., K \tag{7}$$

Using equilibrium prices and the properties of the Fréchet distribution as in Eaton and Kortum (2002), the share of expenditure of location n in industry k on varieties produced in i is

$$\pi_{nik} = \frac{T_{ik}(d_{nik}c_{ik})^{-\theta_k}}{\sum_{s=1}^{N} T_{sk}(d_{nsk}c_{sk})^{-\theta_k}} \tag{8}$$

where, by construction, $\sum_i \pi_{nik} = 1$. The implied perfect CES price index P_{nk} for industry aggregates (subutility) C_{nk} is

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} T_{ik}(d_{nik}c_{ik})^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \tag{9}$$

where $\gamma_k \equiv \left[\Gamma(\frac{\theta_k+1-\sigma_k}{\theta_k})\right]^{\frac{1}{1-\sigma_k}}$ and $\Gamma(\cdot)$ denotes the gamma function and where we assume that $1+\theta_k > \sigma_k$. The Cobb-Douglas price index for overall consumption is:

$$P_n = \prod_{k=1}^{K} P_{nk}^{\delta_{nC}^k} \tag{10}$$

Finally, we allow for the intermediate goods mix used by firms to differ from the mix used in consumption and to vary across industries and regions. Hence, the intermediate goods price index ρ_{nj} of industry j in location n can be written as

$$\rho_{nj} = \prod_{k=1}^{K} P_{nk}^{\delta_{nj}^k}, \quad 0 \leq \delta_{nj}^k \leq 1, \quad \sum_{k=1}^{K} \delta_{nj}^k = 1, \tag{11}$$

where δ_{nj}^k is the share of industry k in the input mix of industry j in location n.

2.5 Income and land rents

We follow Redding (2016) by assuming that a location's land rent is evenly distributed among that location's consumers. Hence, with v_n denoting expenditure per capita in n, that location's total expenditure is

$$v_n L_n = w_n L_n + (1-\alpha)v_n L_n + \sum_{k=1}^{K} \eta_{nk} R_{nk} + D_n \tag{12}$$

where R_{nk} is the total revenue of industry k firms in location n, and D_n is a fixed transfer accounting for the location's trade deficit (surplus if negative).[12] The first term on the right-hand side is labor income from production and the two following terms are the incomes from expenditures on residential land use and from commercial land use, respectively. Since labor costs are a constant share β_{nk} of revenue in each industry,

$$w_n L_n = \sum_{k=1}^{K} \beta_{nk} R_{nk}, \tag{13}$$

we can rewrite total expenditure as:

$$v_n L_n = \frac{\sum_{k=1}^{K} (\beta_{nk} + \eta_{nk}) R_{nk} + D_n}{\alpha} \tag{14}$$

Goods market clearing commands that the sum of spending from all locations on goods produced in location i and industry k must equal that industry's revenue. Using equation (14) this yields:

$$R_{ik} = \sum_{n=1}^{N} \pi_{nik} \left\{ \sum_{j=1}^{K} \left[\delta_{nC}^{k} (\beta_{nj} + \eta_{nj}) + \delta_{nj}^{k} (1 - \beta_{nj} - \eta_{nj}) \right] R_{nj} + \delta_{nC}^{k} D_n \right\} \tag{15}$$

where the term in parenthesis represents the combined consumption and intermediate demand of location n for industry k goods.

Land market clearing requires that for any location n total rent income must equal total spending on land:

$$r_n H_n = (1 - \alpha) v_n L_n + \sum_{k=1}^{K} \eta_{nk} R_{nk}$$

This together with equation (14) allows to write a location's rental rate of land in terms of its endogenously determined revenues, as well as its exogenously given trade deficit and supply of land:

$$r_n = \frac{\sum_{k=1}^{K} \left[(1 - \alpha) \beta_{nk} + \eta_{nk} \right] R_{nk} + (1 - \alpha) D_n}{\alpha H_n} \tag{16}$$

[12] Notice that while we keep the overall bilateral trade deficits exogenously fixed, the sectoral bilateral trade deficits are endogenously determined in the model.

2.6 Labor mobility

Corresponding to utility function (1), the welfare of a worker residing in location n, is given by her real income

$$V_n = \frac{v_n}{P_n^{\alpha} r_n^{1-\alpha}} \tag{17}$$

The mobility of labor across locations within a spatial entity m ensures that real incomes are equalized (whilst the immobility of workers *across* spatial entities implies that real incomes can differ across countries). Hence, there is a common utility level $\bar{V}^m$ that pertains across locations within spatial entity m. Using income per capita from equation (14) and the rental rate of land from equation (16) we can solve for the population in location n in terms of the endogenously determined revenues, price indices, and common utility level, as well as the exogenously given trade deficit and housing supply:

$$L_n = \frac{\sum_{k=1}^{K} (\beta_{nk} + \eta_{nk}) R_{nk} + D_n}{\alpha^{\alpha} P_n^{\alpha} \left[\frac{\sum_{k=1}^{K} ((1-\alpha)\beta_{nk} + \eta_{nk}) R_{nk} + (1-\alpha) D_n}{H_n} \right]^{1-\alpha} \bar{V}^m} \qquad \forall n \in N^m \tag{18}$$

2.7 General equilibrium

The general equilibrium of the model can be represented by the following system of four equations that jointly determines for all locations n the set of industry revenues R_{nk}, price indices P_{nk}, each location's sectoral trade shares π_{nik} and the population shares in each location, $\lambda_n^m \equiv L_n / \bar{L}^m$:

$$\pi_{nik} = \frac{T_{ik}(d_{nik} c_{ik})^{-\theta_k}}{\sum_{s=1}^{N} T_{sk}(d_{nsk} c_{sk})^{-\theta_k}}$$

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} T_{ik}(d_{nik} c_{ik})^{-\theta_k} \right]^{-\frac{1}{\theta_k}}$$

$$R_{ik} = \sum_{n=1}^{N} \pi_{nik} \left\{ \sum_{j=1}^{K} \left[\delta_{nC}^{k} (\beta_{nj} + \eta_{nj}) + \delta_{nj}^{k} (1 - \beta_{nj} - \eta_{nj}) \right] R_{nj} + \delta_{nC}^{k} D_n \right\}$$

$$\lambda_n^m = \frac{\frac{\sum_{k=1}^K (\beta_{nk}+\eta_{nk})R_{nk}+D_n}{P_n^\alpha \left(\frac{\sum_{k=1}^K ((1-\alpha)\beta_{nk}+\eta_{nk})R_{nk}+(1-\alpha)D_n}{H_n}\right)^{1-\alpha}}}{\sum_{i\in N^m}\left[\frac{\sum_{k=1}^K (\beta_{ik}+\eta_{ik})R_{ik}+D_i}{P_i^\alpha \left(\frac{\sum_{k=1}^K ((1-\alpha)\beta_{ik}+\eta_{ik})R_{ik}+(1-\alpha)D_i}{H_i}\right)^{1-\alpha}}\right]}, \tag{19}$$

where

$$c_{ik} = \left(\frac{\sum_{k=1}^K \beta_{ik}R_{ik}}{L_i}\right)^{\beta_{ik}} \left(\frac{\sum_{k=1}^K ((1-\alpha)\beta_{ik}+\eta_{ik})R_{ik}+(1-\alpha)D_i}{\alpha H_i}\right)^{\eta_{ik}} \left(\prod_{j=1}^K P_{ij}^{\delta_{ik}^j}\right)^{1-\beta_{ik}-\eta_{ik}} \tag{20}$$

This equation system involves the bilateral industry trade shares, equation (8), price indices, equation (9), and goods market clearing, equation (15). The shares of spatial entity m's population living in location n, equation (19), follow from applying $\lambda_n^m \equiv L_n/\bar{L}^m$ together with $\bar{L}^m = \sum_{n\in N^m} L_n$ to equation (18). Finally, the marginal costs c_{ik} are calculated by using the input price indices, equation (11), wages, equation (13), and rental rates of land, equation (16), to replace the corresponding values in equation (6).

3 Quantitative analysis

3.1 Counterfactual

We apply the method introduced by Dekle et al. (2007) to study the effects of a counterfactual change in trade costs, d_{nik}. We denote the value that an endogenous variable x takes in the counterfactual equilibrium with a prime (x') and its relative value in the counterfactual and initial equilibria by a hat $\hat{x} = x'/x$. Starting from the equilibrium system specified in the previous section and defining total expenditure $Y_n = v_n L_n$, and total wage income $W_n = w_n L_n$ the counterfactual equilibrium values must satisfy:

$$\pi'_{nik} = \frac{\pi_{nik}(\hat{d}_{nik}\hat{c}_{ik})^{-\theta_k}}{\sum_{s\in N} \pi_{nsk}(\hat{d}_{nsk}\hat{c}_{sk})^{-\theta_k}} \tag{21}$$

$$\hat{P}_{nk} = \left[\sum_{i=1}^N \pi_{nik}(\hat{d}_{nik}\hat{c}_{ik})^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \tag{22}$$

$$R'_{ik} = \sum_{n=1}^{N} \pi'_{nik} \left\{ \sum_{j=1}^{K} \left[\delta^k_{nC}(\beta_{nj} + \eta_{nj}) + \delta^k_{nj}(1 - \beta_{nj} - \eta_{nj}) \right] R'_{nj} + \delta^k_{nC} D_n \right\} \tag{23}$$

$$\lambda'^m_n = \frac{\lambda^m_n \left(\frac{\hat{Y}_n}{\hat{P}^\alpha_n \hat{r}^{1-\alpha}_n} \right)}{\sum_{i \in N^m} \lambda^m_i \left(\frac{\hat{Y}_i}{\hat{P}^\alpha_i \hat{r}^{1-\alpha}_i} \right)} \tag{24}$$

where

$$\hat{c}_{ik} = \left(\frac{\hat{W}_i}{\hat{\lambda}^m_i} \right)^{\beta_{ik}} \hat{r}^{\eta_{ik}}_i \left(\prod_{j=1}^{K} \hat{P}^{\delta^j_{ik}}_{ij} \right)^{1-\beta_{ik}-\eta_{ik}}, \quad \hat{r}_n = \frac{\sum_{k=1}^K [(1-\alpha)\beta_{nk} + \eta_{nk}] R'_{nk} + (1-\alpha) D_n}{\sum_{k=1}^K [(1-\alpha)\beta_{nk} + \eta_{nk}] R_{nk} + (1-\alpha) D_n},$$

$$\hat{W}_n = \frac{\sum_{k=1}^K \beta_{ik} R'_{ik}}{\sum_{k=1}^K \beta_{ik} R_{ik}} \quad \text{and} \quad \hat{Y}_n = \frac{\sum_{k=1}^K (\beta_{nk} + \eta_{nk}) R'_{nk} + D_n}{\sum_{k=1}^K (\beta_{nk} + \eta_{nk}) R_{nk} + D_n}$$

The implied change in real income ($\hat{V}_n = V'_n / V_n$) for a consumer living in location n is then, under labor mobility:

$$\hat{V}_n = \frac{\hat{Y}_n}{\hat{\lambda}_n \hat{r}^{1-\alpha}_n} \prod_k \hat{\pi}_{nnk}^{-\alpha \frac{\delta^k_{nC}}{\theta_k}} \hat{c}_{nk}^{-\alpha \delta^k_{nC}} \tag{25}$$

An inspection of the equation system characterizing the counterfactual, equations (21) to (24) and of the implied change in the real income (25) reveals the parsimony of our method. In order to numerically solve this equation system we only need information concerning a small number of exogenous variables, the share of goods in consumption (α), the cost shares of labor and land (or intermediates), (β_{nk}, η_{nk} or $1 - \beta_{nk} - \eta_{nk}$), sectoral expenditure and cost shares ($\delta^k_{nC}, \delta^k_{nj}$) for which data are readily available, and estimates for the sectoral productivity dispersion (θ_k). Neither does our method require information concerning the elasticity of substitution (σ_k), nor on the location- and sector specific scale parameters of technology (T_{nk}) or the factor supplies (except for population shares of locations within spatial entities). Most importantly, however, no information is needed concerning the multidimensional matrix of trade frictions (d_{nik}), the key advantage of this method established by Dekle et al. (2007).

Notice that a regime of pure trade but without factor mobility among a subset of locations is simply represented by imposing $\hat{\lambda}^m_n = \lambda'^m_n / \lambda^m_n = 1$ in the above system. We will make use of this in our ensuing empirical analysis in order to identify and distinguish the (medium-run) pure trade effects from the longer-run effects of labor mobility within the European Union, in one scenario, and among the counties of Germany, in another scenario.

3.2 Calibration

Input-output structure. In addition to the data requirements concerning the exogenous parameters of our model ($\alpha, \beta_{nk}, \eta_{nk}, \delta_{nC}^k, \delta_{nj}^k, \theta_k$) we need a matrix of bilateral industry trade shares π_{nik} that includes own-trade. We use the world input-output database (WIOD) as our main data source. This data set provides a time series of world input-output tables compiled on the basis of officially published input-output tables in combination with national accounts and international trade statistics. We take the data for the year 2014 as it is the most current year available in the database at the time of writing. The world input-output table for this year covers data from 56 industries in 44 countries, including one artificial "rest of the world" (ROW) country.

Because of differences in sector classifications across countries, some countries have zero output and consumption in some of these sectors. To avoid the problems associated with zero output and consumption we aggregate the data to 35 industries according to table A.1 in the appendix and we drop real estate services for reasons spelled out below. The countries include all current members of the European Union, as well as the United States and all major trading partners of the European Union and the United States. The complete list is provided in table A.2 in the appendix. We use the resulting input-output table to derive the consumption and intermediate good shares (δ_{nC}^k and δ_{nj}^k), the share of value added ($\beta_{nk} + \eta_{nk}$) and the bilateral industry trade shares (π_{nik}). Section A of the appendix explains this derivation and details how we handle inventory changes and zeros in bilateral trade flows.

Land. To implement Redding's (2014; 2016) new quantitative spatial model we also need parameter values for the consumption share of land $(1 - \alpha)$ and the cost shares of land in all industries (η_{ik}). One might suspect that the WIOD along with complementary databases is the best choice for that purpose. After all, the world input-output table (WIOT) features a sector 'real estate services' whose output is an intermediate for the other sectors and also enters final demand. Moreover, the WIOT also provides information on the value added of all industries at the national level, which the Socio-Economic Accounts (SEAs) of the WIOD then split into the compensation of labor and capital, with the latter being further decomposed in the E.U.-KLEMS-database into a list of asset categories that includes residential and nonresidential structures and that is also meant to include a separate category 'land' (see Erumban et al. (2012) on the SEA's and Van Ark (2005) on E.U.-KLEMS). Serious data problems make such an approach impossible, however.[13] To start, the total share of capital in value added is calculated only residually in input-output tables and

[13] We are very grateful for conversations with Gaaitzen de Vries and with Martin Gornig who shared their expertise with us on these issues.

national accounts. More severe, even though the E.U.-KLEMS Database is intended to include 'land' and even though there are suggested ways to arrive at estimates of its use, data on land are lacking, as yet (Van Ark (2005); O'Mahony and Timmer (2009)). This implies that the share $(1-\alpha)$ would have to be conjectured from the categories residential and nonresidential structures alone. The problem with these asset categories is that there are also serious deficiencies in how they are recorded. To take one example, whereas the category 'residential structures' contains imputations for the use of self-owned housing, no similar imputation is made for 'nonresidential structures'. This leads to a crass underestimation of the use of 'nonresidential structures'. For example, nonresidential structures contribute nearly nothing to the value added in the sector 'real estate activities' in many countries in the E.U.-KLEMS.[14] An inspection of the E.U.-KLEMS data also reveals national idiosyncracies in recording these data.[15]

Since these data problems are severe and abounding we base our parameter estimates for the consumption share of land and the cost shares of land in intermediates on other sources. In order not to overestimate the impact of land but still to be able to use the WIOT as our backbone for all other calculations, we eliminate the real estate sector from the WIOT. We explain in A in the appendix how we arrive at an internally consistent refined world input-output table. Our parameter for the consumption share of land is based on the entry for housing in the use tables of the U.S. Bureau of Economic Analysis and census data for housing from the German Statistical Office (Destatis). Relating those to the respective values for total final expenditure, including government spending and investments, and averaging we arrive at a value of $(1-\alpha) = 0.08642$. To split value added between labor and land and structures, we borrow from Valentinyi and Herrendorf (2008), who calculate the income shares of land and structures for different U.S. sectors. In particular we set the share of land in value added at 32 percent, 15 percent, 9 percent, and 21 percent in agricultural, manufacturing, construction and service sectors, respectively.

Labor force. For data on the labor force we rely on the International Labor Associations' estimates of the labor force from ILOSTAT for 2014.

[14]A further issue is that the intermediate input of 'real estate activities' for other industries has high entries in the WIOT despite consisting mainly of 'residential structures'.

[15]For instance, in Germany the asset category 'residential structures' is used in the real estate services sector only, whilst in Spain, the Netherlands and Finland, to take three examples, 'residential structures' enter the value added of further sectors.

3.3 Estimating technological dispersion

We estimate the technological dispersion parameters θ_k based on the 'gravity' relationship implied by our model as we explain below. Using these estimates we calculate the Head-Ries Index (Head and Mayer 2014) as detailed in section B of the appendix. This is important because it gives us an estimate of the upper threshold for the feasible trade liberalization corridor.[16]

Using equation (8) and the definition of the bilateral trade share $\pi_{nik} = X_{nik}/E_{nk}$, where X_{nik} is the value of the trade flow for industry k between exporting country i and destination country n, and where $E_{nk} = \delta^k_{nC}\alpha v_n L_n + \sum_{j=1}^{K} \delta^k_{nj}(1 - \beta_{nj} - \eta_{nj})R_{nj}$ is country n's total spending in industry k, we obtain, after rearranging,

$$X_{nik} = M_{nk} S_{ik} d_{nik}^{-\theta_k} \tag{26}$$

where $M_{nk} \equiv \frac{E_{nk}}{\sum_{s=1}^{N} T_{sk}(d_{nsk}c_{sk})^{-\theta_k}}$ and $S_{ik} \equiv T_{ik}c_{ik}^{-\theta_k}$ are country-industry-specific effects of the importer and the exporter, respectively. M_{nk} comprises all those features of the market for k in the destination location n that promote shipments from all other locations and S_{ik} comprises features of the supplier location i that are relevant for all destination regions. The transportation cost term $d_{nik}^{-\theta_k}$ is the only factor that is specific to the bilateral relation between exporter i and the importer n.

The standard gravity literature estimates equation (26) or a version thereof in log-linear form with importer and exporter fixed effects and by proxying log barriers with a sum of log distance, log tariffs and a range of binary indicator variables for contiguity, common language, common colonial past and so on. However, recent research has shown that this leads to biased results since the multilateral resistance terms in M_{nk} and S_{ik} are then based on estimated instead of true bilateral trade costs (Egger and Nigai 2015). A second issue is the potential endogeneity of trade policy (Baier and Bergstrand 2007). Further problems for this standard approach are zero trade flows (which have to be dropped) and potential heteroscedasticity. As a solution to these problems recent literature suggests to rely on panel data, include a time-invariant asymmetric bilateral fixed effect (D_{nik}) and employ a Poisson pseudo-maximum likelihood (PPML) estimation on the following transformed regression equation

$$X_{nikt} = M_{nkt} S_{ikt} e^{(D_{nik} + RTA_{nit} - \theta_k log(1+\tau_{nikt}))} \tag{27}$$

[16]Moving beyond this threshold implies negative trade barriers, that is, subsidies.

where τ_{nikt} denotes tariffs and where RTA_{nit} is a dummy that is equal to 1 if countries n and i are members of a common regional trade agreement at time t (Egger and Nigai 2015; Piermartini and Yotov 2016; Santos Silva and Tenreyro 2006, 2011; Yotov et al. 2016).

We obtain tariff data from the WITS/UNCTAD TRAINS database. Unfortunately, tariff data is not available aggregated to the ISIC Rev. 4/CPA 2008 level used in the WIOD's 2016 release. Therefore, we rely on data reported according to the HS 2007 or HS 2012 classification, for which a precise (many-to-one) matching to the 2-digit CPA 2008 classification is possible with concordance tables from Eurostat.[17] To ensure consistency between the matching and aggregation process of our trade and tariff data we rely on Comtrade data from WITS, given in the same original HS classification as tariffs and we extend our country sample to all countries for which tariff and trade data is available.[18] In accordance with the mentioned literature we use only every third year, allowing for the adjustment of fixed effects over time. Data for RTA's are from Mario Larch's Regional Trade Agreements Database.[19]

Table 1 sums up key results (appendix table A.3 provides the full results). The θ_k's are in the range of expected values and significant across industries with the exception of the textiles industry which is only significantat the 15 percent level. As expected, industries that are likely to produce more homogeneous goods, such as mining, utilities (including gas, electricity and water) and basic metals tend to have higher θ_k's implying stronger reactions of flows to changes in trade costs. In contrast, more differentiated sectors such as food, beverages and tobacco, transport equipment or crop and animal production exhibit lower values.

[17]There are 32 6-digit HS codes for which the corresponding 2 digit CPA sector is ambiguous. We assign these codes to one of the potential sectors based on their description.

[18]In aggregating tariff data from the product to the industry level we rely on import weighted averages and use total imports as weights in case of zero bilateral industry flows.

[19]The database can be acceded at http://www.ewf.uni-bayreuth.de/en/research/RTA-data/index.html.

Table 1: Estimates of the technological dispersion parameter

Industry	θ_k	z-ratio	N	Pseudo R^2
Crop and Animal Production	1.121**	2.088	22907	0.9947
Forestry	4.204**	2.090	8642	0.9973
Fishing	3.824*	1.703	8715	0.9926
Mininig	22.683***	2.956	14628	0.9906
Food, Beverages, Tobacco	1.128***	3.148	27721	0.9914
Textiles, Leather	1.023[a]	1.587	29976	0.9959
Wood	2.648***	3.970	18641	0.9977
Paper, Printing	2.955***	5.123	20544	0.9979
Chemicals, Pharmaceutical	2.151**	2.120	29244	0.9924
Plastics	1.410***	3.669	26631	0.9983
Non-Metallic Minerals	3.651***	6.410	22096	0.9945
Basic Metals	4.150***	3.068	20233	0.9805
Fabricated Metals	2.269***	3.584	26966	0.9970
Computer	3.273**	2.058	30452	0.9974
Electrical	2.770***	4.827	28250	0.9986
Machinery n.e.c	3.309***	3.917	29691	0.9982
Transport Equipment	1.011**	2.527	25764	0.9980
Other Manufacturing	2.597***	3.795	27356	0.9985
Utilities	14.30***	6.235	13095	0.9904

Note: [a]p<0.15; *p<0.1; **p<0.05; ***p<0.01; Pseudo R^2 is the square of correlation between fitted values and data. High correlation is due to the use of bilateral fixed effects. In the construction and service sectors no reliable tariff data is available. We follow Costinot and Rodríguez-Clare (2014) by setting the dispersion paramter in these sectors equal to 5.

3.4 Quantifying the TTIP shock

While the parsimony of our model and method allow us to avoid the quantification of the level of nontariff barriers (NTBs), we still need to be concerned with the *relative change* of NTBs implied by the introduction of TTIP. Even after many rounds of negotiations between the European Union and the United States it is impossible to know how ‘deep’ a final trade agreement might eventually be and how the various sectors could be affected. However, even if we knew the final outcome (e.g., the harmonization of standards in the car industry or agreements on the testing of pharmaceutical or medical products), there is no simple way to translate these (reductions of) barriers into tariff equivalents. Previous research has dealt with this issue in two different ways. One line has followed a 'bottom-up' approach and has indeed tried to figure out tariff equivalents of the prevailing NTBs. Given the derived tariff equivalents these studies then proceeded to specific reduction scenarios based on experts' and practitioners' assumptions about the potential of TTIP and the share of negotiable vs. nonnegotiable barriers (e.g., different languages or geographical distance). This methodology has led to widely differing results, however. Table 2 lists the tariff equivalents that two of the most influential studies have obtained, Ecorys (2009) on which the study of Francois et al. (2013) for the E.U. commission is based, and Fontagné et al. (2013). The numbers are confined to the three broad sectors agriculture, manufacturing and services. In view of these problems and discrepancies, Felbermayr et al. (2013) go so far to argue that no consistent and reliable quantification is possible for NTBs on the sectoral level.

Table 2: Estimated tariff equivalents

	Ecorys (2009)		Fontagné et al. (2013)	
	US $\rightarrow$ EU	EU $\rightarrow$ US	US $\rightarrow$ EU	EU $\rightarrow$ US
ariculture	56.8	73.3	48.2	51.3
manufacturing	19.3	23.4	42.8	32.3
services	8.5	8.9	32.0	47.3

Egger et al. (2015), Felbermayr et al. (2013, 2015) and Aichele et al. (2016) use an alternative 'top down approach' whereby estimates of the effects of *existing* trade agreements on bilateral trade volumes in different industries are used to calibrate the TTIP shock to result in these volume changes. Compared with the often considered symmetric barrier cuts in the 'bottom-up' approaches this has the advantage that it allows for shocks to vary across industries, which opens a further channel for welfare effects. As a downside, however, their predictions can only be as good as TTIP is an "average" trade agreement as compared to previous RTAs.[20]

We adopt a different strategy to tackle the uncertainties concerning the outcome of the trade negotiations and the inherent difficulties in deriving tariff equivalents for nontariff barriers. We consider the range of *conceivable* symmetric reductions of nontariff barriers between the Europoean Union and the US. We take great care to avoid that our symmetric reductions of NTBs would lead to subsidizing trade in any sector. To achieve this, we construct a Head and Ries index (see, e.g., Head and Mayer (2014)). We use this index along with our estimates of the θ_k-parameters to derive an upper threshold for the potential relative reduction of trade

[20]Not uncommonly, results for our sectoral RTA estimates supplied in table A.3 in the appendix are mixed and include several negative values, though only positive values are significant. This reinforces our ambition to provide a range of possible outcomes of a TTIP instead of assuming effects to mimic average previous RTAs.

barriers. This procedure, explained in detail in section B of the appendix, leads to an estimate of a threshold of 9.97 percent for the most ambitious symmetric liberalization scenario.[21] The assumption of symmetric liberalization is arbitrary, of course. We therefore complement our analysis with robustness checks involving the sectorally asymmetric liberalization paths considered by Francois et al. (2013), Fontagné et al. (2013) and Aichele et al. (2016).

Two issues have figured prominently in the scholarly debate on TTIP, liberalization in the service sector and possible spillover effects on third countries. Concerning the former, the experience from previous trade agreements shows that nontariff barriers in the area of services are far more difficult to tackle and far less likely to be considerably reduced compared to those in the manufacturing sector. However, liberalization in the service sector is one of the major declared goals of the TTIP partners, and the European Single Market shows that such liberalization is possible, in principle. Concerning the latter, it has been argued that a TTIP may have positive spillover effects on third countries as a result of regulatory convergence, that is, exporters form third countries save on adaptation costs in serving E.U.- and U.S.-markets when the regulatory standards of the European Union and the United States converge. Moreover, apart from this direct effect there could be an indirect spillover if TTIP manages to set global standards and thereby also reduces the trade barriers between third countries. The evidence for such spillovers is weak and little can be said about their actual size, however (see Felbermayr et al. (2015)). Because of the mentioned issues, our baseline estimate abstracts from spillover effects and from a specific provisions concerning service trade. We carry out detailed robustness checks for both, however.

4 The liberalization of transatlantic trade

4.1 Pure Trade Effects

Real income changes - pure trade. Figure 1 reports our findings for the change in real incomes, $\hat{V}_n \equiv V'_n/V_n$ from equation (25) for the pure trade scenario, $\hat{\lambda}^j_n = {\lambda'}^j_n/\lambda^j_n = 1$ (no labor mobility in Europe). Real income gains within a TTIP are in a range of up to 0.46 percent for most countries even in the most ambitious scenario of trade barrier reductions of 9.97 percent. The United States and Germany derive real income gains at around 0.32 percent and 0.37 percent, respectively. Similar or slightly lower findings obtain, as shown, for France, as well as for Finland, Sweden, Denmark, and Hungary (not shown - see table A.4 in the appendix for a full list of results). The real income gains of Belgium, the

[21]Note that tariff equivalent barriers are given by $d_{nik} - 1$ and thus fall by more than 9.97 percent when d_{nik} is reduced by that amount, with the exact percentage change depending on the initial level of the barrier.

Netherlands, United Kingdom and Malta are slightly higher. Ireland and Luxemburg (not shown) are outliers which would experience considerably higher welfare gains in this baseline simulations, with real income gains of 3.03 percent and 1.85 percent, respectively. For the rest of the countries the quantitative effects are much smaller, even in this most ambitious scenario, with countries in the North-East and South of Europe such as Spain, Italy, Poland, Lithuania, or Romania gaining only between 0.08 percent and 0.16 percent.

Figure 1 also shows that there are negative third-country effects owing to trade diversion: China, Switzerland and Norway experience such negative welfare effects. Trade diversion is similarly strong for Russia, Korea and Taiwan as these countries are tightly integrated with the United States and the European Union respectively but would not be involved in transatlantic trade liberalization. Negative effects on other third countries are negligible and there are even slight gains for Canada and the ROW.

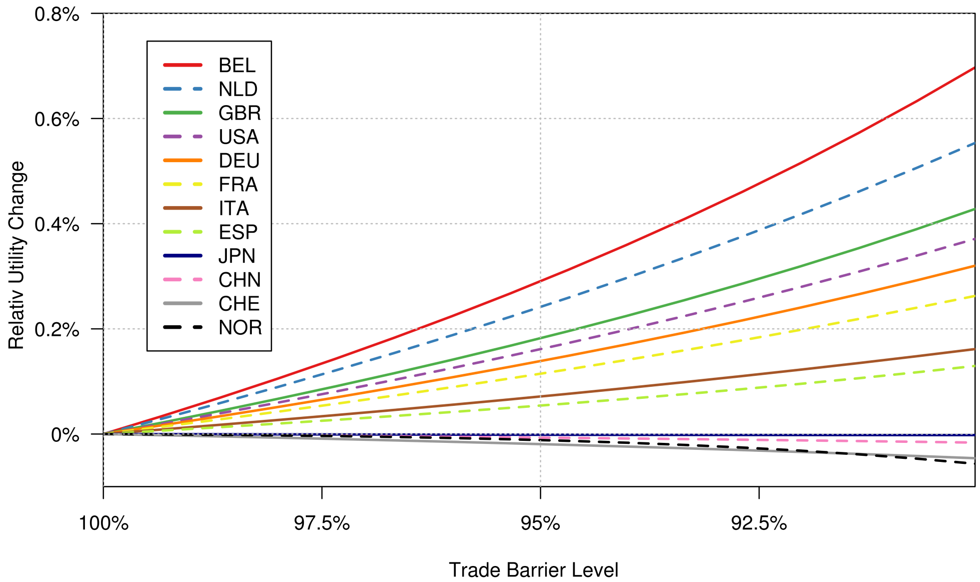


Figure 1: Welfare effects of trade barrier reduction; pure trade regime

In Figure 2 we have ordered E.U. countries according to their real income gains. It becomes apparent that the level of gains is closely related to the ex-ante spending share on US goods and services. Figure 2 reveals in addition that the limited overall welfare results that we have diagnosed stem from the small share that U.S. goods have in overall spending in most countries. For the strongest winners Luxemburg and Ireland spending shares are in the range of 11 percent to 14 percent and for Belgium and the Netherlands at around 3 percent. However, for the remaining E.U. members they are well below 2 percent.

Figure 3 provides a detailed look into the fabrics of the real income changes. As is clear from equation (17), real income is composed of nominal income, goods prices, and land prices. A breakdown of the overall welfare change into the changes in goods prices, incomes and land rents is provided in that figure. The numbers reported are for the most ambitious trade liberalization scenario. It is interesting to note that the overall welfare effects have very heterogeneous roots. For the United States and United Kindom, the overall welfare gain is due to a strong increase in wages that overcompensates rising goods and land prices. For Ireland, the Benelux countries, and the large economies of Germany, France, Italy, and Spain both rising wages and falling prices drive welfare effects. Finally, the majority of Eastern and Southern European countries experience falling wages but benefit in real terms as goods and land prices fall. Finally, falling prices for both goods and land also buffer the negative effects of trade diversion in third party countries, resulting in only minimal welfare losses. In the cases of Canada, ROW, and Brazil, falling prices even lead to (marginal) real income gains despite reduced wages. Overall, our results suggest that economically more powerful countries in Europe can strengthen their nominal value added whereas weaker economies are hit by the increased competition and benefit only through falling prices.

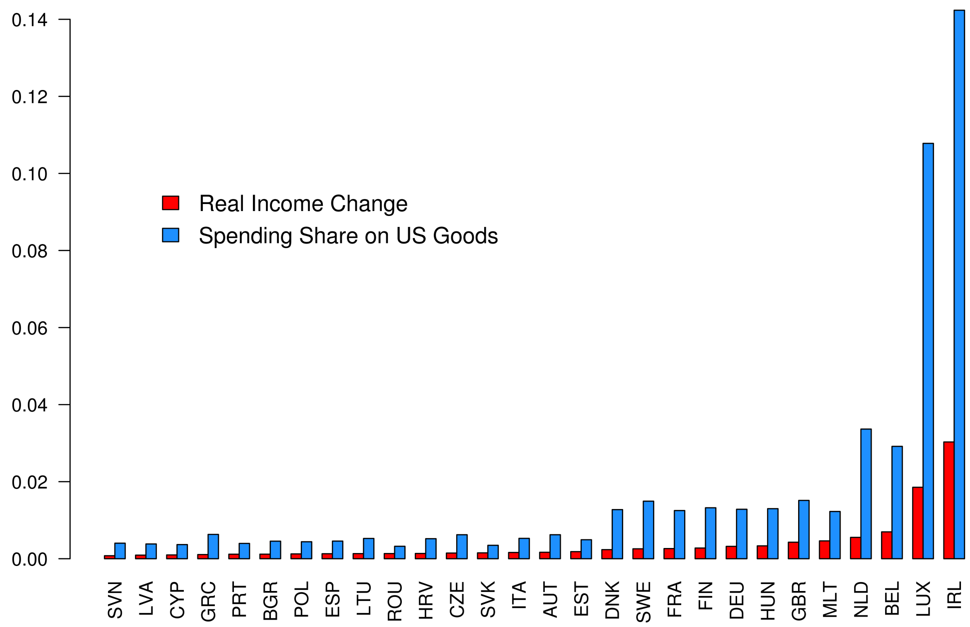


Figure 2: Welfare effects and initial spending shares with maximal liberalization

Industry effects. We have also looked at the changes in the industry mix (measured by production values) that are implied by transatlantic trade liberalization. Figure 4 reports the results on industry mix, again under the assumption of the most ambitious liberalization path. Germany is representative of many other countries in that there is only very little, if any, effect on the industry mix. The strongest changes occur in machinery, transport equipment, and wholesale, which would expand under transatlantic trade liberalization, while telecommunications and transport activities shrink. Ireland, which would be the overall winner in welfare terms, experiences strong effects, in some industries, however. Financial and insurance, telecommunications, chemical and pharmaceutical products, as well as the food and the construction sector would all experience a strong boost.

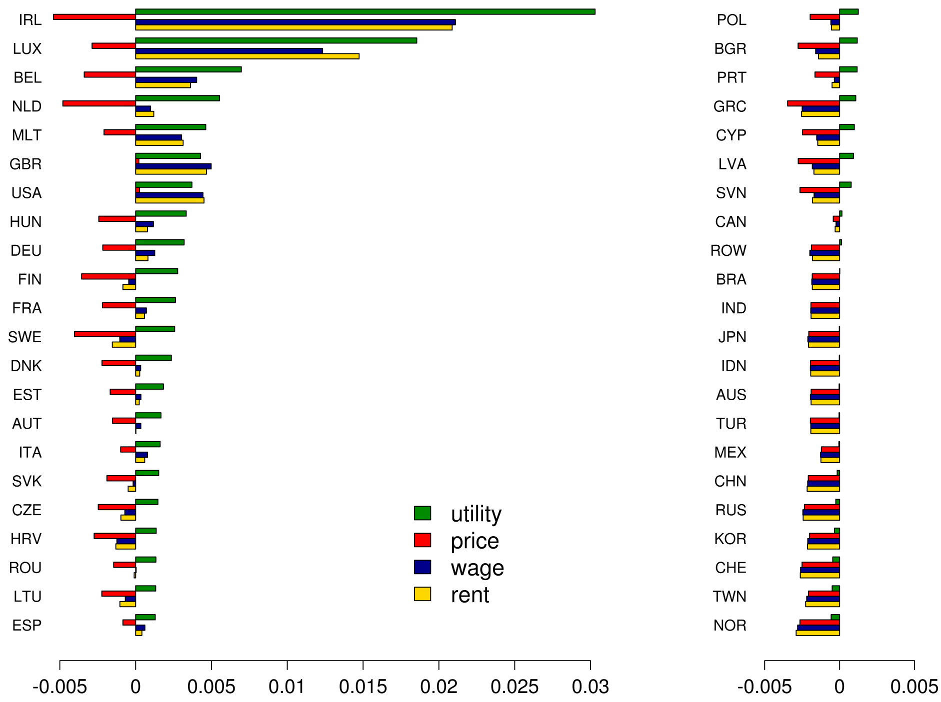


Figure 3: The components of welfare changes with maximal liberalization

The role of land. A key innovation of our analysis in relation to previous studies of transatlantic trade liberalization is that we integrate land, notably as a consumption good, but also as a production factor. This has straightforward but very important consequences. This becomes clear from the following theoretical thought experiment. Suppose that land is only used for housing purposes, but not as an input in production ($\eta_{nk} = 0$). It then follows from our model that $r_n H_n = (1-\alpha) v_n L_n$ so that $\hat{r}_n = \hat{v}_n$ and $\hat{V}_n = (\hat{v}_n / \hat{P}_n)^{\alpha}$. Ignoring land in consumption ($\alpha = 1$) would thus lead to an overestimation of the welfare effects of the magnitude $(1-\alpha)/\alpha$. For a value of the share of land in consumption of $1/10$, disregarding land in consumption hence implies an overestimation of real income effects in the range of 11.1 percent.

Turning to the full model with land used as a consumption good and as an input in production, our numerical analyses suggest that real income effects of plausible TTIP scenarios would be overestimated by about 9.49 percent for the United States and 9.36 percent percent for Germany, for example (see table A.5 in the appendix). These simulations also reveal that the effects of disregarding land in production are by several magnitudes smaller compared with omitting land for housing.[22]

The upshot of this section is that a disregard of land leads to overestimates of the static real income effects of transatlantic trade liberalization. This is a key reason why we find

[22]The effects become more pronounced, however, in the regime with population mobility, but are still small compared to the effects derived omitting land in consumption.

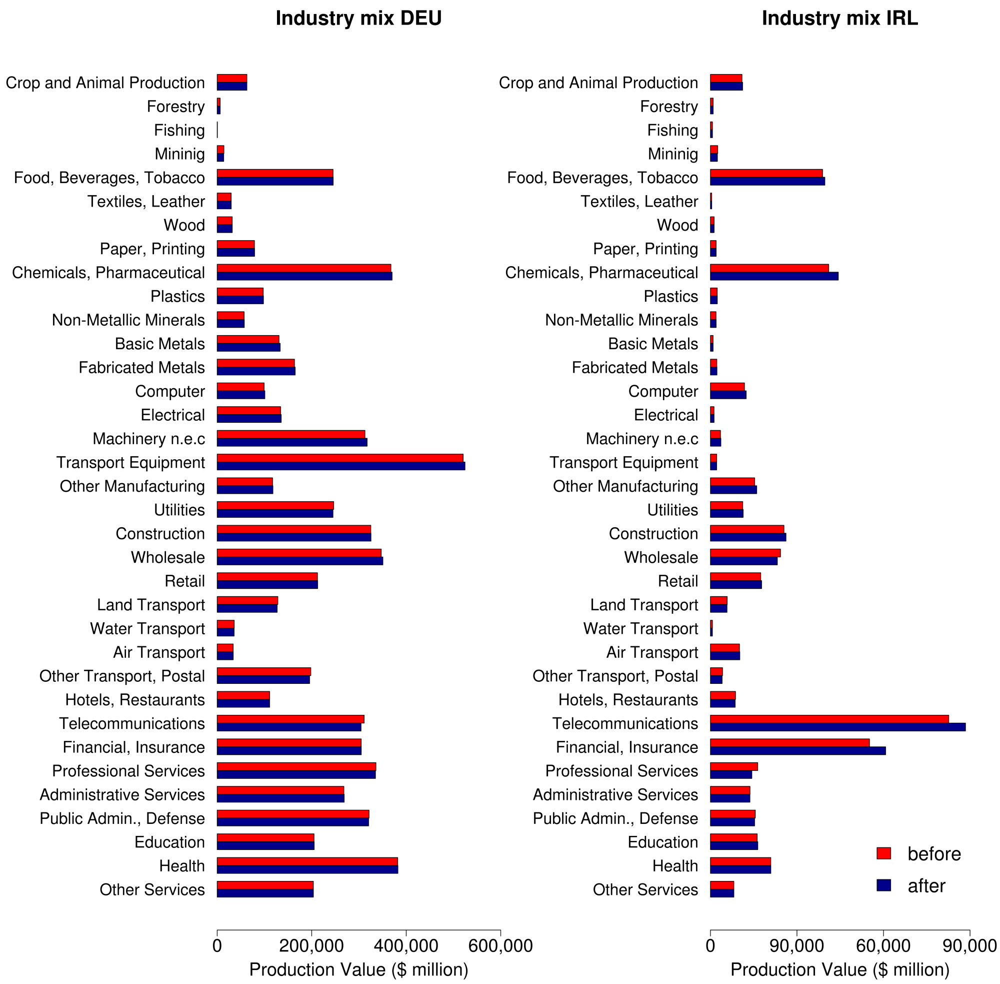


Figure 4: Effects on the industry mix: Germany vs. Ireland with maximal liberalization

more limited effects than previous analyses of a TTIP. It should also be pointed out that, by highlighting the role of land, our analysis contributes to the more general discussion of the sensitivity of the new quantitative trade models to auxiliary assumptions (see Costinot and Rodríguez-Clare (2014), section 5).

4.2 The local perspective: German Counties

Awareness of the local labor market consequences of shifts in the global economy has been growing recently both in public and among academics (e.g., Autor et al. 2013; Caliendo et al. 2015). Public concern over transatlantic trade liberalization is similarly strong, in particular in Europe. It is therefore important to explore how local labor markets within countries are affected by a transatlantic deal. We take Germany as a case in point and trace the effects of trade liberalization down to the local level.

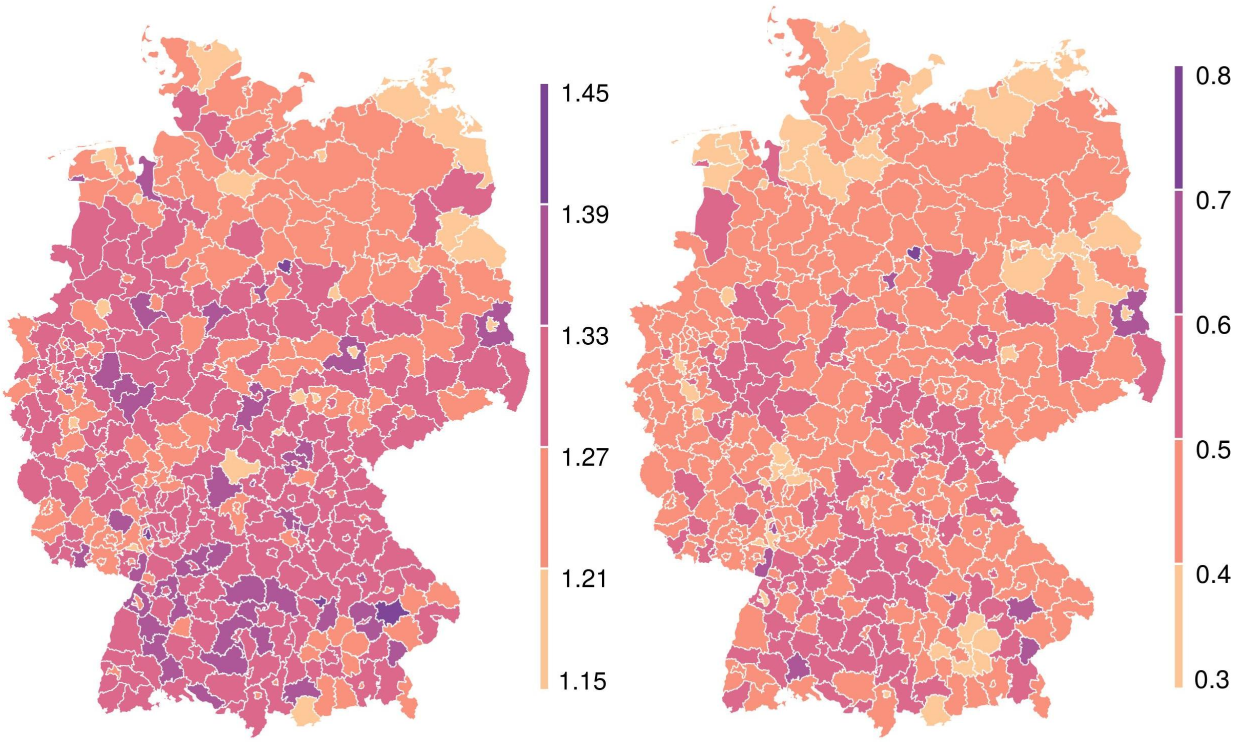
Data. For this purpose we use value added data from national accounts, which is available at the regional level from the German federal and state statistical offices ("Regionaldatenbank der Statistischen Ämter des Bundes und der Länder"). This data is available for all 402 regions ("Kreise") disaggregated into six groups of NACE/ISIC industries that match directly with WIOD industries as can be seen in section C of the appendix. We label these sectors "Agriculture", "Manufacturing", which includes mining and raw materials, "Construction", "Trade", which includes transportation and tourism, "Financial" and "Government", which includes health and education. Assuming that the German input-output structure holds for all German regions we use production data to calculate intermediate demand and regional population data to spread consumption allowing us to rewrite the world input-output table in terms of our new six sectors and including 402 German regions instead of the country as a whole. This method is explained in detail in section C of the appendix.

Descriptive evidence. The initial heterogeneity in the industry mix across locations is portrayed in Figure A.1 in the appendix. Regions in the Northwest and in the Northeast of Germany have the strongest focus on agriculture, though no region produces much more than 8.5 percent of its value added in this sector. Manufacturing, in contrast, is of greater importance for locations in the South of Germany and especially for regions in which the three major car manufacturers (VW, BMW and Mercedes) are active. In these locations it can be responsible for more than 80 percent of value added. The trade sector, which includes transportation, is most important for those regions that are close to the two major German airports (Frankfurt and Munich) or have large ports, like Hamburg.[23] In and around Frankfurt where several important German banks, the largest German stock market and the German central bank are located, the financial sector plays a crucial role, being responsible for up to 35 percent of total value added in these regions. The share of government tasks, including health and education, in value added is strongest in regions that consist of only one large city, and, in general, in the Northeast of Germany.

We also look at how important regions are for Germany as a whole. Figure A.2 in the appendix gives the share of a region's value added in a specific industry relative to Germany's value added in the industry. The largest agricultural producers are found in the Northwestern regions. All other sectors are, with some exceptions, dominated by the highly populated regions Berlin, Hamburg, Munich, "Region Hannover", and Cologne (all above one million inhabitants).

[23] The outlier in the Northwest of Germany is „Landkreis Leer", which has the second largest concentration of shipping companies after Hamburg.

Transatlantic trade liberalization. We begin by calculating the effects of our maximum liberalization scenario between the United States and all E.U. members without population mobility in order to show the heterogeneity of expected real income changes. The initial spending shares on U.S. goods and the real income effects from the policy experiment on regions are shown in Figure 5. It is clear to see, that the initial share of a country's total spending on U.S. goods (both final and intermediate) is again a very good indicator for its real income changes owing to the barrier reduction. A key finding of our calculations is that despite their heterogeneity all regions win. This is remarkable, because our model, in principle, allows for negative welfare effects through terms of trade movements that work through wage adjustments across locations. The fear that TTIP might benefit only the already-rich German locations at the cost of the poor ones is not supported by our analysis. Yet even in our ambitious scenario the potential gains are limited to between 0.31 percent and 0.71 percent of real income (Figure A.3 in the appendix provides a disaggregation of the real income effects).



(a) US Spending Shares

(b) Real Income Changes

Figure 5: Initial US Spending Shares and Real Income Changes with maximal liberalization

Labor mobility. We show more detailed results for the case with population mobility among German regions (i.e., only in Germany - not between other E.U. members) in Figure 6 below. Population losses are strongest in the North of Germany and population gains strongest in Southern Germany. As a result of the low real income effects observed under population immobility the incentive to move is limited. The forecast effects on population are consequently only in the range of -0.39 percent to 0.62 percent, despite our assumption of perfect mobility. The fear that individual German regions could experience strong population losses owing to a restructuring thus also seems unwarranted.

The maps that depict population shifts and the evolution of rents provide a fairly similar picture. Intuitively, the (Northern) parts of Germany that shrink in population experience a fall in rents and the expanding (Southern) parts see rising rents. The predicted price increases for goods and services in the shrinking regions in the North reflect both higher wages (the marginal product of labor for the remaining population rises) and also higher trade costs, since a higher share of goods and services have to be imported from other counties. Price increases in expanding Southern counties can be rationalized by higher wages that are needed to compensate for higher rents. However, the predicted effects for both prices and wages are very low, in general.

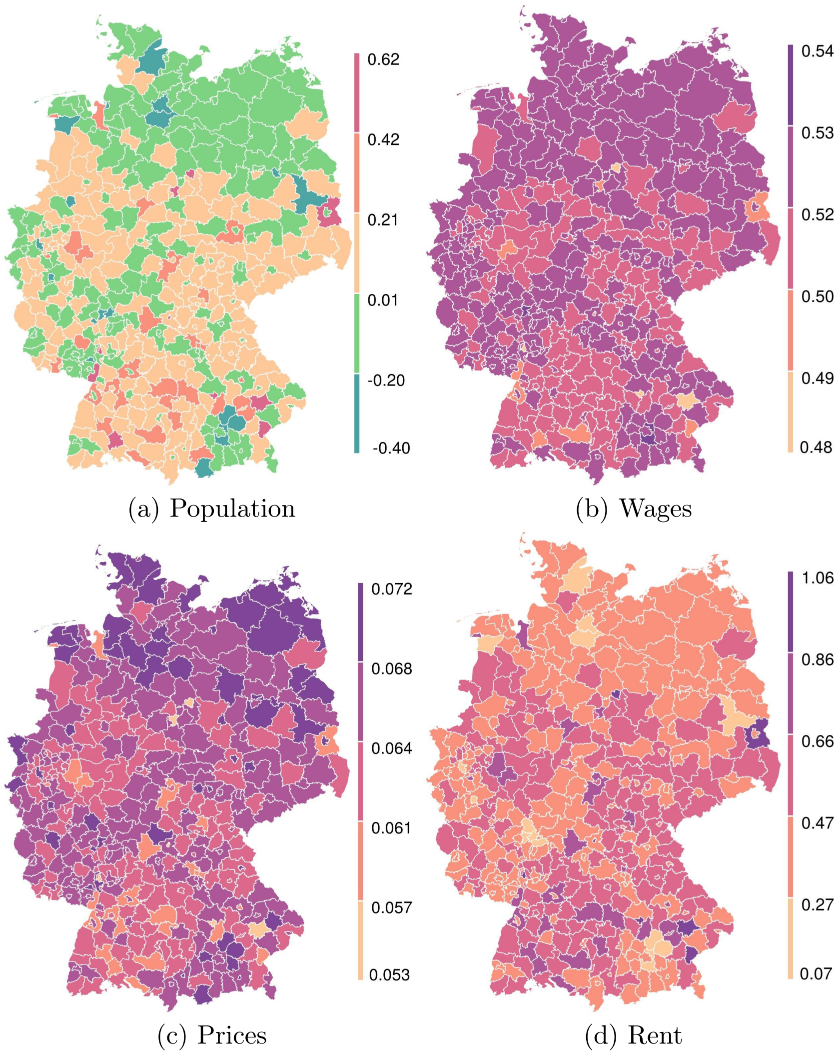


Figure 6: Effects in the extreme scenario with population mobility and maximal liberalization

4.3 Labor mobility in Europe

Figure 7 portrays our findings under the assumption of full labor mobility in the European Union. It should be noted that our model captures only one dispersion force, scarce land, and hence land prices. Clearly, there are further forces which reduce labor mobility in Europe, in particular heterogeneous location preferences and a plethora of mobility costs which exceed those that prevail between German counties by far. The results in this section should therefore be seen as an extreme scenario, just as the no mobility case (depicted in Figure 1) goes to the other extreme. The establishment of a spatial equilibrium in the mentioned extreme case would level income gains at 0.32 percent in all E.U. members. Ireland and Luxemburg would experience a strong inflow of labor followed, with an already much weaker inflow, by Belgium, the Netherlands, United Kingdom, and Malta. The inflows immensely reduces wages in these countries, but thereby also lower production costs and consequently lead to much lower price increases as compared to the no-mobility case in Figure 3. A close inspection of Figure 7 reveals that the bulk of the adjustment to the spatial equilibrium within the European Union takes place through the adjustment of land prices.

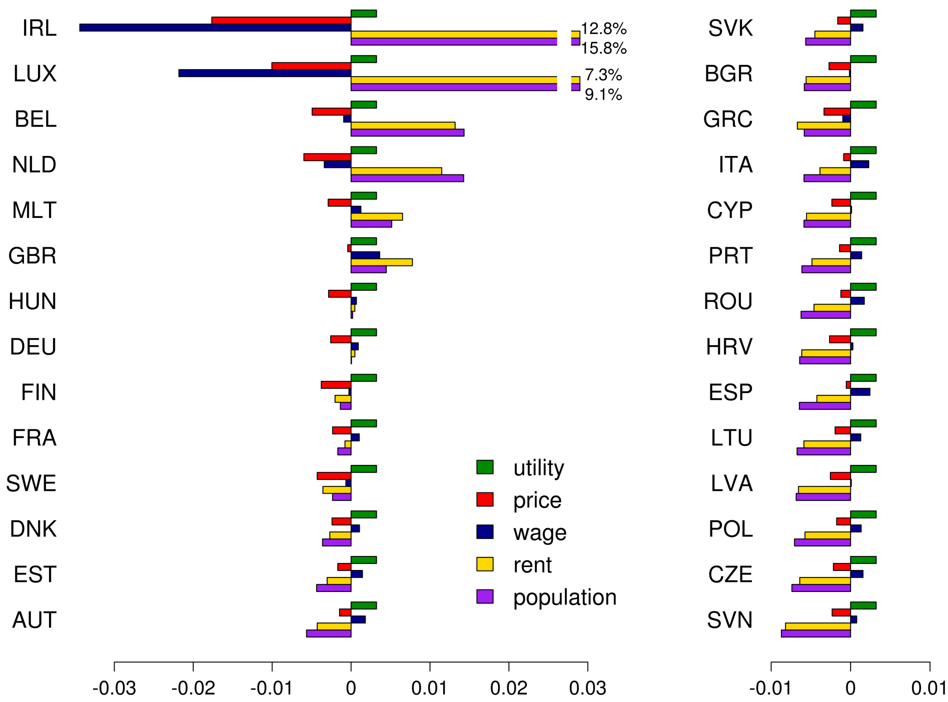


Figure 7: Welfare effects in European countries, with labor mobility maximal liberalization

4.4 TTIP versus multilateral trade liberalization

An important concern regarding TTIP is that it may undermine the global trading system (Bagwell et al. 2016; Bhagwati et al. 2014). Our analysis has in fact identified countries that lose owing to trade diversion. An alternative to regional engagements would be to bring in more effort into the trade talks at the multilateral level, which are stalling. What level of multilateral trade liberalization would have to be achieved in order to match the real income effects that the European Union and the United States derive from a transatlantic deal? Redoing our calculations for a multilateral trade barrier reduction we find that the answer differs considerably between the two locations.[24]. A multilateral reduction of trade barriers in the range of 0.5 to 1 percent would be enough for Europe to achieve the same welfare gains as in our most ambitious TTIP scenario.[25] For the United States, however, this would require a decrease in multilateral barriers of 2.5 to 3 percent. Consequently, the United States appears to gain more from TTIP in comparison to a multilateral agreement, while the same does not necessarily hold true for the European Union. This finding points to the importance of Bhagwati's (1994) prediction that a 'hegemonic power' is likely to gain more by bargaining sequentially than simultaneously. Hence, TTIP might indeed harm the multilateral trading system by diverting the political energy of one of its key players, the United States, away from WTO negotiations.

4.5 Discussion: How deep ... ?

Both our model and our empirical strategy differ from earlier studies of the transatlantic trade partnership. This section puts our results in perspective to previous research. In this section we also perform a variety of robustness checks including the effects of trade liberalization scenarios envisioned in these other studies within our model.

Comparison with previous studies. Our estimated welfare effects are within the range of two major CGE based studies. For maximal liberalization, we obtain similar effects of TTIP to those projected in Francois et al. (2013) and Fontagné et al. (2013), all methodological differences notwithstanding. Our results are lower than those reported in Egger et al. (2015) and similar to the lower end of their 95 percent confidence interval, except for Ireland and Luxemburg which are in the range of their projected real income gains. The one-sector new quantitative trade study by Felbermayr et al. (2015) reports significantly

[24] See tables A.6 and A.7 in the appendix for detailed results.

[25] In the case without population mobility this value, of course, varies across E.U. member states. However, as can be seen in table A.6 in the appendix it remains in the range of 2 percent to 3 percent for most, including Germany.

higher welfare effects than we do. They find that the E.U. 28 would achieve a welfare gain of 3.9 percent and the United States of 4.9 percent while the welfare loss that they compute for the rest of the world is -0.9 percent. Aichele et al. (2016), drawing on a nonspatial Ricardian multi-industry model, also forecast higher welfare gains than we do.

Felbermayr et al. (2015) report that the member states at the E.U. periphery benefit most. This corresponds to our finding with respect to Ireland. However, we also find that a country at the geographic center, Luxemburg, would derive extremely strong benefits and that E.U. members in the Eastern periphery benefit less. Furthermore, Felbermayr et al. (2015) find that Spain would derive strong gains in the range of 5.6 percent, which is strongly at odds with our findings and which is also hard to understand given the small share of spending that Spain devotes to U.S. goods and services (cf. Figure 2).

What explains these different results? Clearly, part is due to the fact that the estimates are based on different models that differ along several choices. Our analysis points to the importance of land in consumption and production and suggests that a disregard of land may imply an overestimation of the real income gains in the range of 10 percent. Indeed, simply applying this margin to the average E.U. and U.S. welfare outcomes of Aichele et al. (2016), that is, 0.43 percent and 0.49 percent, pushes their results remarkably close to the level of welfare effects that we derive (0.32 percent and 0.37 percent). The real income gains projected by Felbermayr et al. (2015) would be reduced considerably but still remain higher than our findings.[26] The welfare results of Egger et al. (2015) would also remain slightly higher than our effects. The second important reason for the divergence of results is due to the fact that different liberalization scenarios are considered. We address this issue in our robustness checks.

Robustness checks. We begin our robustness checks by discussing the results that we obtain with our model and method for the liberalization paths considered in Aichele et al. (2016), Francois et al. (2013), and Fontagné et al. (2013). To do so we extract the relative barrier changes implied by their reference scenarios and we perform a rough matching of sectors to our model. We report the welfare results of these exercises in table A.8 in the appendix.[27]

Start with the top-down approach pursued by Aichele et al. (2016). Their estimate of previous trade agreements implies that TTIP would result in very large barrier reductions for basic metals (with *relative* changes in barriers by more than 40 percent), as well as mining

[26]Felbermayr et al. (2015) assume that goods production represents all of an economy's activity. This assumption biases up results, as Egger et al. (2012) have shown (see the discussion in Egger et al. (2015), p.567).

[27]A supplementary appendix available online on the homepage of the Review of International Economics shows the sectoral matching for these scenarios.

and electrical equipment (both about 30 percent) but have lower effects in the remaining industries and especially low effects in service industries (4.8 percent to 9.2 percent). After matching their industry classification to ours we find the following. First, effects, both positive and negative, become more pronounced for most countries. In fact, the magnitude of welfare results is in the range of Egger et al. (2015) who rely on a similar method to establish their NTB reduction scenario. Second, we find that the large gains that Aichele et al. (2016) deduce for Croatia and which are absent in our symmetric approach now also appear and, thus, hinge critically on the assumed scenario. In contrast, the strong gains in Ireland, Luxemburg, Belgium and the Netherland remain stable across scenarios. Third, the average long-term effect for the European Union with population mobility would be a real income gain of 1.28 percent and thus much higher than for our upper bound estimate of our across the board reduction (0.32 percent). Our main result that effects are low except for some industries in some countries, remains intact, however.

Similar to our study, both Francois et al. (2013) and Fontagné et al. (2013) consider a symmetric scenario. However, since they approximate initial trade barriers, the symmetric reduction of these barriers implies an asymmetric *relative* reduction. The implied relative reductions are much smaller than in the case of Aichele et al. (2016) and more in line with our projected range, that is, between 0.6 percent and 10.6 percent (unweighted average 2.7 percent) for Francois et al. (2013) and between 0.1 percent and 14.9 percent (unweighted average 4.8 percent) for Fontagné et al. (2013). Consequently, when comparing the results of our extreme scenario with their liberalization paths the latter lead to smaller effects (0.2 percent and 0.14 percent, respectively, compared with 0.32 percent in the mobile case). It is reassuring to see that throughout all ambitious liberalization scenarios considered by these previous works, the welfare effects for Ireland and Luxemburg remain the highest and second highest, leading with similar margins over other countries.

We turn next to the effects of regulatory spillovers, a potential source of additional welfare gains as discussed in section 3.4. Since little can be said about the economic importance of such spillovers we adopt the standard approach (as in Francois et al. 2013; Felbermayr et al. 2015; Egger et al. 2015) by assuming that for every 1 percent trade barrier reduction between TTIP partners the barriers for third country exporters to the European Union or the United States are reduced by 0.2 percent. In a separate scenario we additionally consider indirect spillovers that reduce trade barriers between and to third countries by 0.1 percent for every 1 percent reduction between TTIP partners. We report the welfare consequences of these scenarios with our maximal liberalization in Table A.9 in the appendix. As can be seen, the effects on all members of TTIP of both direct and indirect spillovers are positive but generally small. Furthermore, the negative consequences of the TTIP shock for third countries are eliminated. However, positive effects are of noticeable magnitude across the board only under the extreme assumption that both direct and indirect spillovers prevail. As a further robustness check we consider the effects of asymmetric liberalization in the service and manufacturing sectors as discussed in subsection 3.4. Table A.10 in the appendix reports the welfare results for our maximal liberalization scenario keeping trade barriers in either the finance sector or all service sectors at their original level. Taking only the finance sector out of the liberalization has little effect on the welfare gains of most countries. However, in line with the role of this sector in Luxemburg, the welfare gains in this country are reduced to one sixth from 1.85 percent to 0.32 percent. While Ireland remains the strongest beneficiary its gains are also brought down considerably from 3.03 percent to 2.57 percent. Taking the complete service sector out of the liberalization reduces the benefits for all members, driving welfare gains in Europe under population mobility from 0.32 percent to 0.17 percent. Again, the most heavily affected countries are Ireland and Luxemburg. However, even in this scenario Ireland remains the strongest winner from TTIP with a gain in real income of 0.52 percent, a result that we attribute to the observed very close ties of the Irish and U.S. economies (cf. Figure 2).

Finally, we repeat these robustness checks to see how German counties are affected by the alternative liberalization paths. Table A.11 in the appendix lists the range, mean and coefficient of variation for the “no service sector” liberalization and a spillover scenario as in Francois et al. (2013). As can be seen, similar to our country results above, the different liberalization paths lead to lower welfare gains from TTIP.

5 Conclusion

This paper uses a static Ricardian new quantitative trade model to evaluate the quantitative consequences of the liberalization of transatlantic trade associated with the envisioned E.U.-U.S. trade and investment partnership. The key aspect that distinguishes our analysis from other works addressing TTIP is our spatial perspective, the use of a spatial trade model where land has both consumption and production value and where labor mobility is allowed for.

We employ the method of Dekle et al. (2007) to arrive at our counterfactual results. The advantage of this approach is that we do not need information on the initial trade cost matrix to perform the numerical analysis. Trade costs are extremely hard to quantify since the most important outstanding trade barriers are of non-tariff nature. Previous analyses have obtained widely differing results for the tariff equivalents of these barriers and, hence, exhibit considerable uncertainties. Our approach allows us to circumvent this problem since these parameters are already embedded in the baseline specification. With our method it is easy to establish the real income effects for a whole range of trade cost reductions. Our extensive robustness checks reveal that, all detailed numbers notwithstanding, the qualitative effects associated with liberalization paths studied in previous works are very similar.

Our results have to be seen against the background of three important caveats. First, our analysis sheds only light on the static gains from trade liberalization but not on the likely follow-up effects associated with induced capital accumulation and dynamic growth effects. The neglect of dynamic effects implies that we underestimate the full effects of trade liberalization. Second, for Europe we study a scenario both with no labor mobility and one with labor mobility hindered only by changing land prices. Both these scenarios are to be thought of as the extreme limiting cases. Third, our approach, like previous analyses of the transatlantic partnership, does not embrace the additional welfare effects associated with FDI. Embedding multinationals into our quantitative trade models and taking the effects of FDI on the European Union, United States and other countries into account is one avenue for future research.

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Appendix: How deep is your love? A quantitative spatial analysis of the transatlantic trade partnership

Tables

Figures

Table A.1: List of Sectors

WIOD		This Paper	
#	Label	#	Label
1	Crop and animal production, hunting and related service activities	1	Crop, Animal Production
2	Forestry and logging	2	Forestry
3	Fishing and aquaculture	3	Fishing
4	Mining and quarrying	4	Mininig
5	Food products, beverages and tobacco products	5	Food, Beverages, Tobacco
6	Textiles, wearing apparel and leather products	6	Textiles, Leather
7	Wood, cork, except furniture; articles of straw and plaiting materials	7	Wood
8	Paper and paper products	8	Paper, Printing
9	Printing and reproduction of recorded media		
10	Coke and refined petroleum products	9	Chemicals, Pharmaceuticals
11	Chemicals and chemical products		
12	Basic pharmaceutical products and pharmaceutical preparations		
13	Rubber and plastic products	10	Plastics
14	Other non-metallic mineral products	11	Non-Metallic Minerals
15	Basic metals	12	Basic Metals
16	Fabricated metal products, except machinery and equipment	13	Fabricated Metals
17	Computer, electronic and optical products	14	Computer
18	Electrical equipment	15	Electrical
19	Machinery and equipment n.e.c.	16	Machinery n.e.c
20	Motor vehicles, trailers and semi-trailers	17	Transport Equipment
21	Other transport equipment		
22	Furniture; other manufacturing	18	Other Manufacturin
23	Repair and installation of machinery and equipment		
24	Electricity, gas, steam and air conditioning supply	19	Utilities
25	Water collection, treatment and supply		
26	Sewerage; waste collection, treatment and disposal activities		
27	Construction	20	Construction
28	Wholesale, retail trade and repair of motor vehicles and motorcycles	21	Wholesale
29	Wholesale trade, except of motor vehicles and motorcycles		
30	Retail trade, except of motor vehicles and motorcycles	22	Retail
31	Land transport and transport via pipelines	23	Land transport
32	Water transport	24	Water transport
33	Air transport	25	Air transport
34	Warehousing and support activities for transportation	26	Other transport, postal
35	Postal and courier activities		
36	Accommodation and food service activities	27	Hotels, Restaurants
37	Publishing activities	28	Telecommunications
38	Motion picture, video and television programme production, sound recording and music publishing activities; broadcasting activities		
39	Telecommunications		
40	Computer programming, consultancy; information service activities		
41	Financial service activities, except insurance and pension funding	29	Financial, Insurance
42	Insurance, pension funding, except compulsory social security		
43	Activities auxiliary to financial services and insurance activities		
44	Legal, accounting activities; head offices; management consultancy	30	Professional services
45	Architectural and engineering activities; technical testing and analysis		
46	Scientific research and development		
47	Advertising and market research		
48	Other professional, scientific, technical activities; veterinary activities		
49	Administrative and support service activities	31	Administrative services
50	Public administration and defence; compulsory social security	32	Public Admin., Defense
51	Education	33	Education
52	Human health and social work activities	34	Health
53	Other service activities	35	Other services
54	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		
55	Activities of extraterritorial organizations and bodies		

Source: WIOD Database

Table A.2: Country Sample

Code	Country
AUS	Australia
AUT	Austria
BEL	Belgium
BGR	Bulgaria
BRA	Brazil
CAN	Canada
CHE	Switzerland
CHN	China
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland

Source: WIOD Database

Code	Country
FRA	France
GBR	Great Britain
GRC	Greece
HRV	Croatia
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ITA	Italy
JPN	Japan
KOR	Korea
LTU	Lithuania
LUX	Luxemburg
LVA	Latvia
MEX	Mexico

Code	Country
MLT	Malta
NLD	Netherlands
NOR	Norway
POL	Poland
PRT	Portugal
ROU	Romania
RUS	Russia
SVK	Slovakia
SVN	Slovenia
SWE	Sweden
TUR	Turkey
TWN	Taiwan
USA	United States of America
ROW	Rest of World

Table A.3: Estimation of θ_k - Full results

Industry	θ_k	z-ratio	RTA	z-ratio	N	Pseudo R^2
Crop and Animal Production	1.121**	2.088	-0.053	-0.637	22907	0.9947
Forestry	4.204**	2.090	-0.484	-1.631	8642	0.9973
Fishing	3.824*	1.703	-0.123	-0.597	8715	0.9926
Mininig	22.683***	2.956	-0.072	-0.443	14628	0.9906
Food, Beverages, Tobacco	1.128***	3.148	-0.023	-0.387	27721	0.9914
Textiles, Leather	1.023	1.587	0.437**	1.992	29976	0.9959
Wood	2.648***	3.970	0.228***	2.732	18641	0.9977
Paper, Printing	2.955***	5.123	0.065	1.471	20544	0.9979
Chemicals, Pharmaceutical	2.151**	2.120	0.069	0.747	29244	0.9924
Plastics	1.410***	3.669	-0.078	-1.470	26631	0.9983
Non-Metallic Minerals	3.651***	6.410	-0.076	-1.125	22096	0.9945
Basic Metals	4.150***	3.068	0.347***	3.278	20233	0.9805
Fabricated Metals	2.269***	3.584	0.174***	3.404	26966	0.9970
Computer	3.273**	2.058	0.100	0.861	30452	0.9974
Electrical	2.770***	4.827	0.094*	1.663	28250	0.9986
Machinery n.e.c	3.309***	3.917	0.124*	1.694	29691	0.9982
Transport Equipment	1.011**	2.527	0.298***	3.490	25764	0.9980
Other Manufacturing	2.597***	3.795	0.383**	2.052	27356	0.9985
Utilities	14.30***	6.235	0.029	0.116	13095	0.9904

*p $<$ 0.1; **p $<$ 0.05; ***p$<$0.01; Pseudo R^2 is the square of correlation between fitted values and data.

Table A.4: Detailed effects in the extreme scenario

	Real Income		Prices		Wages		Rents		Population
	immobile	mobile	immobile	mobile	immobile	mobile	immobile	mobile	
AUS	0,00 %	0,00 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	0,00 %
AUT	0,17 %	0,32 %	-0,15 %	-0,15 %	0,03 %	0,18 %	0,00 %	-0,43 %	-0,56 %
BEL	0,70 %	0,32 %	-0,34 %	-0,49 %	0,40 %	-0,09 %	0,36 %	1,32 %	1,43 %
BGR	0,12 %	0,32 %	-0,28 %	-0,27 %	-0,16 %	-0,01 %	-0,14 %	-0,56 %	-0,58 %
BRA	0,00 %	0,00 %	-0,18 %	-0,22 %	-0,19 %	-0,22 %	-0,18 %	-0,22 %	0,00 %
CAN	0,02 %	0,02 %	-0,04 %	-0,07 %	-0,02 %	-0,05 %	-0,03 %	-0,06 %	0,00 %
CHE	-0,05 %	-0,03 %	-0,25 %	-0,30 %	-0,26 %	-0,29 %	-0,26 %	-0,29 %	0,00 %
CHN	-0,02 %	-0,02 %	-0,21 %	-0,25 %	-0,21 %	-0,25 %	-0,22 %	-0,25 %	0,00 %
CYP	0,10 %	0,32 %	-0,25 %	-0,24 %	-0,15 %	0,01 %	-0,15 %	-0,55 %	-0,59 %
CZE	0,15 %	0,32 %	-0,25 %	-0,22 %	-0,07 %	0,16 %	-0,10 %	-0,64 %	-0,74 %
DEU	0,32 %	0,32 %	-0,22 %	-0,26 %	0,13 %	0,09 %	0,08 %	0,05 %	0,00 %
DNK	0,24 %	0,32 %	-0,22 %	-0,24 %	0,03 %	0,11 %	0,03 %	-0,27 %	-0,36 %
ESP	0,13 %	0,32 %	-0,08 %	-0,05 %	0,06 %	0,24 %	0,04 %	-0,42 %	-0,64 %
EST	0,18 %	0,32 %	-0,17 %	-0,17 %	0,03 %	0,14 %	0,02 %	-0,30 %	-0,44 %
FIN	0,28 %	0,32 %	-0,36 %	-0,38 %	-0,05 %	-0,03 %	-0,08 %	-0,20 %	-0,14 %
FRA	0,26 %	0,32 %	-0,22 %	-0,23 %	0,07 %	0,10 %	0,06 %	-0,08 %	-0,17 %
GBR	0,43 %	0,32 %	0,02 %	-0,04 %	0,50 %	0,36 %	0,47 %	0,78 %	0,45 %
GRC	0,11 %	0,32 %	-0,35 %	-0,33 %	-0,25 %	-0,10 %	-0,25 %	-0,67 %	-0,58 %
HRV	0,14 %	0,32 %	-0,27 %	-0,26 %	-0,12 %	0,03 %	-0,13 %	-0,62 %	-0,64 %
HUN	0,33 %	0,32 %	-0,24 %	-0,29 %	0,12 %	0,07 %	0,08 %	0,05 %	0,02 %
IDN	0,00 %	0,00 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	0,00 %
IND	0,00 %	0,00 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	-0,19 %	-0,23 %	0,00 %
IRL	3,03 %	0,32 %	-0,54 %	-1,76 %	2,11 %	-3,44 %	2,09 %	12,78 %	15,82 %
ITA	0,16 %	0,32 %	-0,10 %	-0,09 %	0,08 %	0,23 %	0,06 %	-0,39 %	-0,59 %
JPN	0,00 %	0,00 %	-0,21 %	-0,24 %	-0,21 %	-0,24 %	-0,21 %	-0,24 %	0,00 %
KOR	-0,03 %	-0,04 %	-0,20 %	-0,24 %	-0,21 %	-0,25 %	-0,21 %	-0,25 %	0,00 %
LTU	0,13 %	0,32 %	-0,22 %	-0,20 %	-0,07 %	0,13 %	-0,10 %	-0,59 %	-0,67 %
LUX	1,85 %	0,32 %	-0,29 %	-1,00 %	1,23 %	-2,18 %	1,47 %	7,32 %	9,05 %
LVA	0,09 %	0,32 %	-0,28 %	-0,25 %	-0,18 %	0,01 %	-0,17 %	-0,66 %	-0,69 %
MEX	0,00 %	0,00 %	-0,12 %	-0,15 %	-0,13 %	-0,15 %	-0,12 %	-0,15 %	0,00 %
MLT	0,46 %	0,32 %	-0,21 %	-0,29 %	0,30 %	0,12 %	0,31 %	0,65 %	0,52 %
NLD	0,55 %	0,32 %	-0,48 %	-0,60 %	0,10 %	-0,34 %	0,12 %	1,15 %	1,43 %
NOR	-0,06 %	-0,06 %	-0,26 %	-0,31 %	-0,28 %	-0,33 %	-0,29 %	-0,34 %	0,00 %
POL	0,12 %	0,32 %	-0,20 %	-0,18 %	-0,06 %	0,13 %	-0,05 %	-0,57 %	-0,71 %
PRT	0,12 %	0,32 %	-0,16 %	-0,14 %	-0,03 %	0,14 %	-0,05 %	-0,49 %	-0,61 %
ROU	0,13 %	0,32 %	-0,15 %	-0,12 %	0,00 %	0,17 %	-0,01 %	-0,46 %	-0,62 %
RUS	-0,03 %	-0,03 %	-0,23 %	-0,27 %	-0,25 %	-0,28 %	-0,24 %	-0,28 %	0,00 %
SVK	0,15 %	0,32 %	-0,19 %	-0,16 %	-0,02 %	0,16 %	-0,05 %	-0,45 %	-0,57 %
SVN	0,08 %	0,32 %	-0,26 %	-0,23 %	-0,17 %	0,08 %	-0,18 %	-0,82 %	-0,87 %
SWE	0,26 %	0,32 %	-0,40 %	-0,43 %	-0,10 %	-0,07 %	-0,15 %	-0,36 %	-0,23 %
TUR	0,00 %	0,00 %	-0,19 %	-0,23 %	-0,19 %	-0,22 %	-0,19 %	-0,23 %	0,00 %
TWN	-0,05 %	-0,05 %	-0,21 %	-0,25 %	-0,22 %	-0,26 %	-0,23 %	-0,27 %	0,00 %
USA	0,37 %	0,38 %	0,03 %	0,01 %	0,44 %	0,43 %	0,45 %	0,44 %	0,00 %
ROW	0,01 %	0,03 %	-0,19 %	-0,23 %	-0,20 %	-0,23 %	-0,18 %	-0,21 %	0,00 %

Table A.5: The significance of land

	Maximal liberalization - No mobility - Change in real income					
	(1) No Land	(2) Full Land	(3) Housing only in consumption	[(1)-(2)]/(2) Full effect	[(1)-(3)]/(2) Consumption effect	[(2)-(3)]/(2) Production effect
AUS	0,00 %	0,00 %	0,00 %	8,32 %	9,36 %	-1,04%
AUT	0,18 %	0,17 %	0,17 %	9,43 %	9,46 %	-0,03%
BEL	0,76 %	0,70 %	0,70 %	9,44 %	9,49 %	-0,05%
BGR	0,13 %	0,12 %	0,12 %	9,59 %	9,48 %	0,11%
BRA	0,00 %	0,00 %	0,00 %	10,45 %	9,55 %	0,91%
CAN	0,02 %	0,02 %	0,02 %	9,61 %	9,47 %	0,13%
CHE	-0,05 %	-0,05 %	-0,05 %	8,70 %	9,39 %	-0,69%
CHN	-0,02 %	-0,02 %	-0,02 %	9,20 %	9,44 %	-0,23%
CYP	0,11 %	0,10 %	0,10 %	9,53 %	9,47 %	0,06%
CZE	0,16 %	0,15 %	0,15 %	9,53 %	9,47 %	0,06%
DEU	0,35 %	0,32 %	0,32 %	9,36 %	9,47 %	-0,11%
DNK	0,26 %	0,24 %	0,24 %	9,52 %	9,48 %	0,05%
ESP	0,14 %	0,13 %	0,13 %	9,47 %	9,47 %	-0,00%
EST	0,20 %	0,18 %	0,18 %	9,53 %	9,47 %	0,06%
FIN	0,30 %	0,28 %	0,28 %	9,44 %	9,47 %	-0,03%
FRA	0,29 %	0,26 %	0,26 %	9,49 %	9,47 %	0,02%
GBR	0,47 %	0,43 %	0,43 %	9,50 %	9,48 %	0,02%
GRC	0,12 %	0,11 %	0,11 %	9,45 %	9,46 %	-0,02%
HRV	0,15 %	0,14 %	0,14 %	9,55 %	9,47 %	0,08%
HUN	0,37 %	0,33 %	0,33 %	9,39 %	9,47 %	-0,08%
IDN	0,00 %	0,00 %	0,00 %	7,93 %	9,33 %	-1,40%
IND	0,00 %	0,00 %	0,00 %	9,23 %	9,44 %	-0,21%
IRL	3,31 %	3,03 %	3,02 %	9,34 %	9,59 %	-0,25%
ITA	0,18 %	0,16 %	0,16 %	9,46 %	9,47 %	-0,01%
JPN	0,00 %	0,00 %	0,00 %	9,84 %	9,49 %	0,35%
KOR	-0,04 %	-0,03 %	-0,03 %	9,12 %	9,43 %	-0,30%
LTU	0,14 %	0,13 %	0,13 %	9,35 %	9,46 %	-0,10%
LUX	2,03 %	1,85 %	1,85 %	9,34 %	9,54 %	-0,19%
LVA	0,10 %	0,09 %	0,09 %	9,65 %	9,48 %	0,17%
MEX	-0,01 %	0,00 %	0,00 %	9,26 %	9,44 %	-0,19%
MLT	0,51 %	0,46 %	0,46 %	9,62 %	9,50 %	0,12%
NLD	0,61 %	0,55 %	0,55 %	9,53 %	9,49 %	0,04%
NOR	-0,06 %	-0,06 %	-0,06 %	9,07 %	9,42 %	-0,35%
POL	0,14 %	0,12 %	0,13 %	9,66 %	9,48 %	0,18%
PRT	0,13 %	0,12 %	0,12 %	9,49 %	9,47 %	0,02%
ROU	0,15 %	0,13 %	0,13 %	9,54 %	9,47 %	0,07%
RUS	-0,03 %	-0,03 %	-0,03 %	8,92 %	9,41 %	-0,49%
SVK	0,17 %	0,15 %	0,15 %	9,38 %	9,46 %	-0,08%
SVN	0,08 %	0,08 %	0,08 %	9,62 %	9,48 %	0,14%
SWE	0,28 %	0,26 %	0,26 %	9,42 %	9,47 %	-0,05%
TUR	0,00 %	0,00 %	0,00 %	6,09 %	9,17 %	-3,08%
TWN	-0,05 %	-0,05 %	-0,05 %	9,10 %	9,43 %	-0,32%
USA	0,41 %	0,37 %	0,37 %	9,49 %	9,48 %	0,01%
ROW	0,01 %	0,01 %	0,01 %	9,51 %	9,46 %	0,04%

Table A.6: Multilateral Liberalization - No Mobility

	Real income effects for multilateral trade barrier reductions by					
	0.5%	1%	1.5%	2%	2.5%	3%
AUS	0,14 %	0,29 %	0,44 %	0,60 %	0,76 %	0,92 %
AUT	0,24 %	0,49 %	0,74 %	1,00 %	1,26 %	1,53 %
BEL	0,35 %	0,70 %	1,06 %	1,43 %	1,81 %	2,20 %
BGR	0,32 %	0,65 %	0,99 %	1,34 %	1,70 %	2,07 %
BRA	0,08 %	0,16 %	0,24 %	0,32 %	0,41 %	0,50 %
CAN	0,21 %	0,41 %	0,63 %	0,84 %	1,06 %	1,29 %
CHE	0,23 %	0,47 %	0,72 %	0,97 %	1,22 %	1,48 %
CHN	0,05 %	0,11 %	0,17 %	0,22 %	0,28 %	0,34 %
CYP	0,28 %	0,56 %	0,85 %	1,14 %	1,44 %	1,75 %
CZE	0,33 %	0,67 %	1,02 %	1,37 %	1,73 %	2,10 %
DEU	0,19 %	0,39 %	0,58 %	0,79 %	0,99 %	1,20 %
DNK	0,24 %	0,47 %	0,72 %	0,96 %	1,21 %	1,47 %
ESP	0,15 %	0,30 %	0,45 %	0,61 %	0,77 %	0,93 %
EST	0,37 %	0,74 %	1,12 %	1,50 %	1,90 %	2,30 %
FIN	0,18 %	0,36 %	0,54 %	0,73 %	0,92 %	1,11 %
FRA	0,15 %	0,31 %	0,47 %	0,63 %	0,79 %	0,96 %
GBR	0,16 %	0,33 %	0,50 %	0,68 %	0,86 %	1,04 %
GRC	0,15 %	0,30 %	0,45 %	0,60 %	0,76 %	0,92 %
HRV	0,27 %	0,54 %	0,82 %	1,11 %	1,40 %	1,71 %
HUN	0,37 %	0,75 %	1,14 %	1,53 %	1,94 %	2,35 %
IDN	0,14 %	0,27 %	0,42 %	0,56 %	0,71 %	0,86 %
IND	0,08 %	0,15 %	0,24 %	0,32 %	0,41 %	0,51 %
IRL	0,57 %	1,15 %	1,74 %	2,35 %	2,97 %	3,60 %
ITA	0,12 %	0,24 %	0,36 %	0,49 %	0,61 %	0,74 %
JPN	0,10 %	0,19 %	0,29 %	0,39 %	0,50 %	0,60 %
KOR	0,18 %	0,37 %	0,56 %	0,75 %	0,95 %	1,16 %
LTU	0,31 %	0,63 %	0,95 %	1,28 %	1,62 %	1,96 %
LUX	1,06 %	2,15 %	3,27 %	4,41 %	5,57 %	6,77 %
LVA	0,29 %	0,59 %	0,89 %	1,20 %	1,51 %	1,83 %
MEX	0,15 %	0,29 %	0,44 %	0,59 %	0,74 %	0,90 %
MLT	0,61 %	1,24 %	1,88 %	2,53 %	3,20 %	3,89 %
NLD	0,36 %	0,72 %	1,09 %	1,47 %	1,85 %	2,24 %
NOR	0,22 %	0,44 %	0,67 %	0,89 %	1,12 %	1,35 %
POL	0,24 %	0,49 %	0,74 %	1,00 %	1,26 %	1,53 %
PRT	0,19 %	0,39 %	0,59 %	0,80 %	1,00 %	1,22 %
ROU	0,23 %	0,46 %	0,69 %	0,94 %	1,19 %	1,45 %
RUS	0,20 %	0,40 %	0,60 %	0,81 %	1,02 %	1,23 %
SVK	0,34 %	0,69 %	1,05 %	1,41 %	1,78 %	2,15 %
SVN	0,31 %	0,62 %	0,94 %	1,26 %	1,60 %	1,94 %
SWE	0,21 %	0,42 %	0,63 %	0,85 %	1,08 %	1,31 %
TUR	0,17 %	0,35 %	0,53 %	0,71 %	0,89 %	1,07 %
TWN	0,28 %	0,57 %	0,86 %	1,16 %	1,46 %	1,76 %
USA	0,07 %	0,14 %	0,21 %	0,28 %	0,35 %	0,43 %
ROW	0,21 %	0,42 %	0,64 %	0,87 %	1,09 %	1,33 %

Table A.7: Multilateral Liberalization – mobility within the EU

	Real income effects for multilateral trade barrier reductions by					
	0.5%	1%	1.5%	2%	2.5%	3%
AUS	0,14 %	0,29 %	0,44 %	0,60 %	0,76 %	0,92 %
AUT	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
BEL	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
BGR	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
BRA	0,08 %	0,16 %	0,24 %	0,32 %	0,41 %	0,50 %
CAN	0,21 %	0,41 %	0,63 %	0,84 %	1,06 %	1,29 %
CHE	0,24 %	0,48 %	0,73 %	0,98 %	1,24 %	1,50 %
CHN	0,05 %	0,11 %	0,17 %	0,22 %	0,28 %	0,34 %
CYP	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
CZE	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
DEU	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
DNK	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
ESP	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
EST	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
FIN	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
FRA	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
GBR	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
GRC	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
HRV	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
HUN	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
IDN	0,14 %	0,27 %	0,42 %	0,56 %	0,71 %	0,86 %
IND	0,08 %	0,15 %	0,24 %	0,32 %	0,41 %	0,51 %
IRL	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
ITA	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
JPN	0,10 %	0,19 %	0,29 %	0,39 %	0,50 %	0,60 %
KOR	0,18 %	0,37 %	0,56 %	0,76 %	0,96 %	1,16 %
LTU	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
LUX	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
LVA	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
MEX	0,15 %	0,29 %	0,44 %	0,59 %	0,74 %	0,90 %
MLT	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
NLD	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
NOR	0,22 %	0,44 %	0,66 %	0,89 %	1,12 %	1,34 %
POL	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
PRT	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
ROU	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
RUS	0,20 %	0,40 %	0,60 %	0,81 %	1,01 %	1,22 %
SVK	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
SVN	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
SWE	0,21 %	0,43 %	0,66 %	0,88 %	1,11 %	1,35 %
TUR	0,17 %	0,35 %	0,52 %	0,70 %	0,89 %	1,07 %
TWN	0,28 %	0,57 %	0,86 %	1,16 %	1,46 %	1,76 %
USA	0,07 %	0,14 %	0,21 %	0,28 %	0,36 %	0,43 %
ROW	0,21 %	0,43 %	0,65 %	0,87 %	1,10 %	1,34 %

Table A.8: Real income effects of alternative scenarios

	Aichele et al.		Francois et al.		Fontagné et al.		Fontagné averages	
	immobile	mobile	immobile	mobile	immobile	mobile	immobile	mobile
AUS	-0,08 %	-0,08 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
AUT	0,78 %	1,28 %	0,05 %	0,09 %	0,06 %	0,14 %	0,11 %	0,20 %
BEL	1,45 %	1,28 %	0,16 %	0,09 %	0,29 %	0,14 %	0,44 %	0,20 %
BGR	0,83 %	1,28 %	0,03 %	0,09 %	0,07 %	0,14 %	0,07 %	0,20 %
BRA	-0,02 %	-0,02 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
CAN	-0,48 %	-0,49 %	0,01 %	0,01 %	0,01 %	0,01 %	0,01 %	0,01 %
CHE	-0,12 %	-0,12 %	-0,01 %	-0,01 %	-0,02 %	-0,01 %	-0,03 %	-0,02 %
CHN	-0,08 %	-0,08 %	0,00 %	0,00 %	-0,01 %	-0,01 %	-0,01 %	-0,01 %
CYP	0,27 %	1,28 %	0,02 %	0,09 %	0,07 %	0,14 %	0,07 %	0,20 %
CZE	0,97 %	1,28 %	0,05 %	0,09 %	0,03 %	0,14 %	0,09 %	0,20 %
DEU	1,03 %	1,28 %	0,10 %	0,09 %	0,13 %	0,14 %	0,20 %	0,20 %
DNK	0,18 %	1,28 %	0,06 %	0,09 %	0,08 %	0,14 %	0,15 %	0,20 %
ESP	1,17 %	1,28 %	0,03 %	0,09 %	0,05 %	0,14 %	0,08 %	0,20 %
EST	0,66 %	1,28 %	0,05 %	0,09 %	0,07 %	0,14 %	0,11 %	0,20 %
FIN	1,37 %	1,28 %	0,07 %	0,09 %	0,12 %	0,14 %	0,17 %	0,20 %
FRA	0,76 %	1,28 %	0,07 %	0,09 %	0,12 %	0,14 %	0,18 %	0,20 %
GBR	2,30 %	1,28 %	0,12 %	0,09 %	0,22 %	0,14 %	0,28 %	0,20 %
GRC	0,48 %	1,28 %	0,02 %	0,09 %	0,03 %	0,14 %	0,06 %	0,20 %
HRV	2,86 %	1,28 %	0,02 %	0,09 %	0,07 %	0,14 %	0,08 %	0,20 %
HUN	1,58 %	1,28 %	0,07 %	0,09 %	0,11 %	0,14 %	0,21 %	0,20 %
IDN	-0,05 %	-0,05 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
IND	0,01 %	0,01 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
IRL	4,59 %	1,28 %	0,66 %	0,09 %	1,40 %	0,14 %	1,86 %	0,20 %
ITA	0,91 %	1,28 %	0,05 %	0,09 %	0,06 %	0,14 %	0,10 %	0,20 %
JPN	0,02 %	0,02 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
KOR	-0,10 %	-0,10 %	-0,01 %	-0,01 %	-0,01 %	-0,01 %	-0,02 %	-0,02 %
LTU	0,79 %	1,28 %	0,05 %	0,09 %	0,02 %	0,14 %	0,08 %	0,20 %
LUX	1,58 %	1,28 %	0,38 %	0,09 %	0,81 %	0,14 %	1,04 %	0,20 %
LVA	0,93 %	1,28 %	0,03 %	0,09 %	0,04 %	0,14 %	0,06 %	0,20 %
MEX	-0,31 %	-0,31 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
MLT	1,22 %	1,28 %	0,11 %	0,09 %	0,24 %	0,14 %	0,29 %	0,20 %
NLD	2,11 %	1,28 %	0,13 %	0,09 %	0,18 %	0,14 %	0,37 %	0,20 %
NOR	-1,64 %	-1,65 %	0,01 %	0,01 %	-0,03 %	-0,03 %	-0,03 %	-0,04 %
POL	0,95 %	1,28 %	0,04 %	0,09 %	0,06 %	0,14 %	0,08 %	0,20 %
PRT	0,86 %	1,28 %	0,02 %	0,09 %	0,06 %	0,14 %	0,07 %	0,20 %
ROU	1,28 %	1,28 %	0,03 %	0,09 %	0,07 %	0,14 %	0,08 %	0,20 %
RUS	-0,45 %	-0,45 %	0,00 %	0,00 %	-0,01 %	-0,01 %	-0,01 %	-0,02 %
SVK	1,77 %	1,28 %	0,02 %	0,09 %	0,07 %	0,14 %	0,09 %	0,20 %
SVN	0,64 %	1,28 %	0,03 %	0,09 %	0,01 %	0,14 %	0,04 %	0,20 %
SWE	0,93 %	1,28 %	0,06 %	0,09 %	0,10 %	0,14 %	0,16 %	0,20 %
TUR	-0,01 %	-0,01 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
TWN	-0,14 %	-0,15 %	-0,02 %	-0,02 %	-0,02 %	-0,02 %	-0,03 %	-0,03 %
USA	0,98 %	0,99 %	0,11 %	0,12 %	0,13 %	0,14 %	0,23 %	0,23 %
ROW	-0,19 %	-0,18 %	0,00 %	0,01 %	0,01 %	0,01 %	0,01 %	0,01 %

The last two columns rely on the average barriers for agriculture, manufacturing and services directly reported in Fontagné et al. (2013) instead of the disaggregated values (columns 5 and 6) which we obtain from following their described method as closely as possible.

Table A.9: Real income effects and spillovers (maximal liberalization)

	Immobile			Mobile		
Spillovers:	no	direct	indirect	no	direct	indirect
AUS	0,00 %	0,05 %	0,32 %	0,00 %	0,05 %	0,32 %
AUT	0,17 %	0,28 %	0,34 %	0,32 %	0,46 %	0,53 %
BEL	0,70 %	0,91 %	1,03 %	0,32 %	0,46 %	0,53 %
BGR	0,12 %	0,45 %	0,57 %	0,32 %	0,46 %	0,53 %
BRA	0,00 %	0,03 %	0,17 %	0,00 %	0,04 %	0,17 %
CAN	0,02 %	0,29 %	0,57 %	0,02 %	0,29 %	0,57 %
CHE	-0,05 %	0,28 %	0,60 %	-0,03 %	0,29 %	0,62 %
CHN	-0,02 %	0,03 %	0,12 %	-0,02 %	0,03 %	0,12 %
CYP	0,10 %	0,40 %	0,50 %	0,32 %	0,46 %	0,53 %
CZE	0,15 %	0,23 %	0,31 %	0,32 %	0,46 %	0,53 %
DEU	0,32 %	0,43 %	0,51 %	0,32 %	0,46 %	0,53 %
DNK	0,24 %	0,36 %	0,45 %	0,32 %	0,46 %	0,53 %
ESP	0,13 %	0,28 %	0,34 %	0,32 %	0,46 %	0,53 %
EST	0,18 %	0,45 %	0,56 %	0,32 %	0,46 %	0,53 %
FIN	0,28 %	0,41 %	0,46 %	0,32 %	0,46 %	0,53 %
FRA	0,26 %	0,39 %	0,44 %	0,32 %	0,46 %	0,53 %
GBR	0,43 %	0,57 %	0,64 %	0,32 %	0,46 %	0,53 %
GRC	0,11 %	0,33 %	0,38 %	0,32 %	0,46 %	0,53 %
HRV	0,14 %	0,36 %	0,48 %	0,32 %	0,46 %	0,53 %
HUN	0,33 %	0,49 %	0,59 %	0,32 %	0,46 %	0,53 %
IDN	0,00 %	0,02 %	0,29 %	0,00 %	0,02 %	0,29 %
IND	0,00 %	0,02 %	0,16 %	0,00 %	0,02 %	0,16 %
IRL	3,03 %	3,40 %	3,66 %	0,32 %	0,46 %	0,53 %
ITA	0,16 %	0,25 %	0,29 %	0,32 %	0,46 %	0,53 %
JPN	0,00 %	0,01 %	0,20 %	0,00 %	0,01 %	0,20 %
KOR	-0,03 %	0,04 %	0,39 %	-0,04 %	0,04 %	0,38 %
LTU	0,13 %	0,47 %	0,60 %	0,32 %	0,46 %	0,53 %
LUX	1,85 %	2,51 %	2,97 %	0,32 %	0,46 %	0,53 %
LVA	0,09 %	0,35 %	0,43 %	0,32 %	0,46 %	0,53 %
MEX	0,00 %	0,17 %	0,38 %	0,00 %	0,18 %	0,38 %
MLT	0,46 %	0,85 %	1,01 %	0,32 %	0,46 %	0,53 %
NLD	0,55 %	0,66 %	0,81 %	0,32 %	0,46 %	0,53 %
NOR	-0,06 %	0,26 %	0,57 %	-0,06 %	0,26 %	0,56 %
POL	0,12 %	0,23 %	0,30 %	0,32 %	0,46 %	0,53 %
PRT	0,12 %	0,30 %	0,35 %	0,32 %	0,46 %	0,53 %
ROU	0,13 %	0,29 %	0,35 %	0,32 %	0,46 %	0,53 %
RUS	-0,03 %	0,11 %	0,44 %	-0,03 %	0,10 %	0,44 %
SVK	0,15 %	0,37 %	0,47 %	0,32 %	0,46 %	0,53 %
SVN	0,08 %	0,26 %	0,36 %	0,32 %	0,46 %	0,53 %
SWE	0,26 %	0,39 %	0,47 %	0,32 %	0,46 %	0,53 %
TUR	0,00 %	0,14 %	0,42 %	0,00 %	0,14 %	0,42 %
TWN	-0,05 %	0,06 %	0,59 %	-0,05 %	0,05 %	0,58 %
USA	0,37 %	0,49 %	0,54 %	0,38 %	0,50 %	0,54 %
ROW	0,01 %	0,14 %	0,50 %	0,03 %	0,15 %	0,51 %

Real income effects for maximal liberalization with and without population mobility and with no spillovers, only 20% direct spillovers or 20% direct and 10% indirect spillovers.

Table A.10: Real income effects and service trade (maximal liberalization)

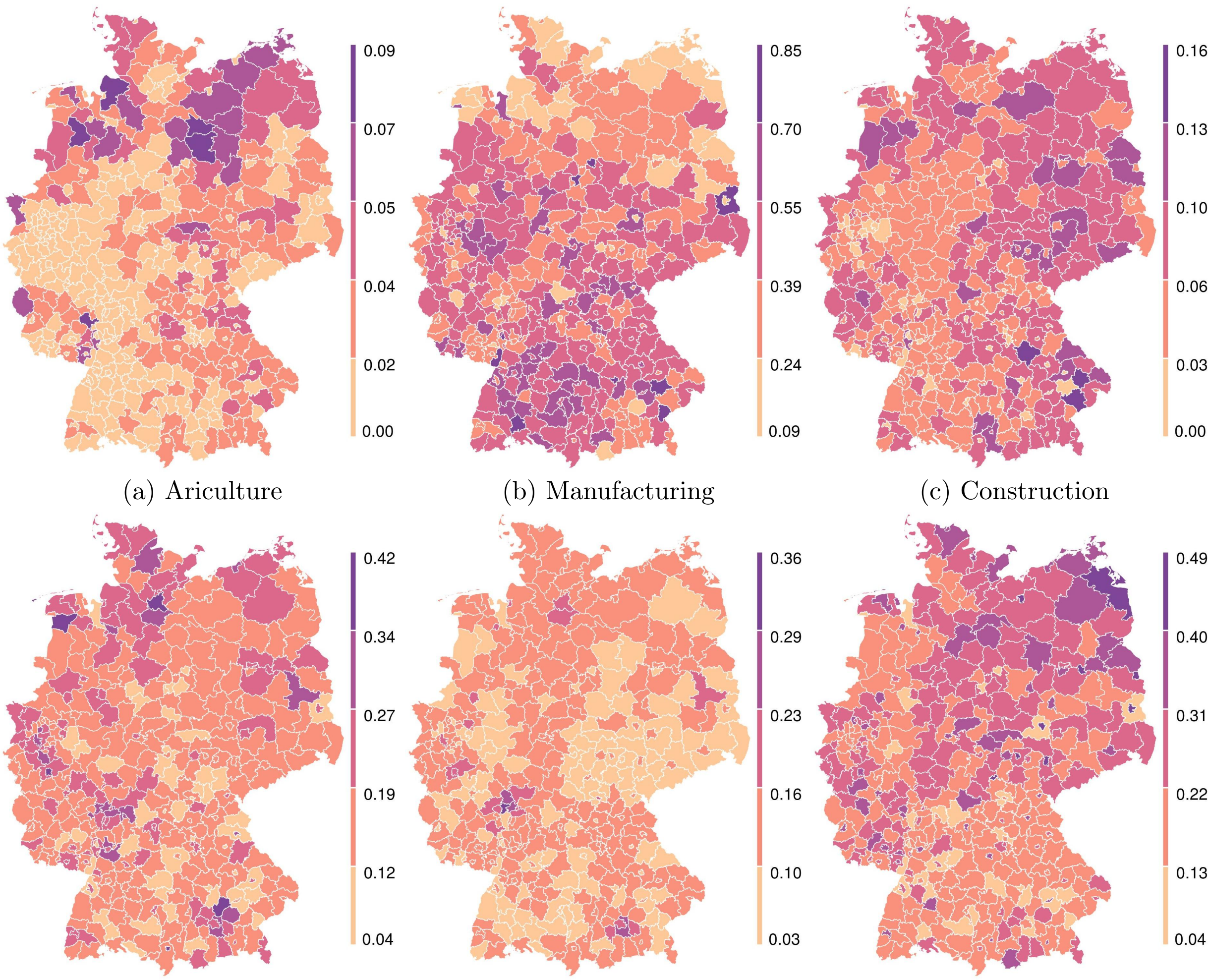
	Immobile			Mobile		
	full liberalization	no service liberalization	no finance liberalization	full liberalization	no service liberalization	no finance liberalization
AUS	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
AUT	0,17 %	0,11 %	0,17 %	0,32 %	0,17 %	0,31 %
BEL	0,70 %	0,34 %	0,69 %	0,32 %	0,17 %	0,31 %
BGR	0,12 %	0,05 %	0,12 %	0,32 %	0,17 %	0,31 %
BRA	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
CAN	0,02 %	0,01 %	0,02 %	0,02 %	0,01 %	0,02 %
CHE	-0,05 %	-0,03 %	-0,03 %	-0,03 %	-0,03 %	-0,02 %
CHN	-0,02 %	-0,01 %	-0,02 %	-0,02 %	-0,01 %	-0,02 %
CYP	0,10 %	0,04 %	0,08 %	0,32 %	0,17 %	0,31 %
CZE	0,15 %	0,10 %	0,15 %	0,32 %	0,17 %	0,31 %
DEU	0,32 %	0,22 %	0,32 %	0,32 %	0,17 %	0,31 %
DNK	0,24 %	0,08 %	0,24 %	0,32 %	0,17 %	0,31 %
ESP	0,13 %	0,11 %	0,13 %	0,32 %	0,17 %	0,31 %
EST	0,18 %	0,13 %	0,18 %	0,32 %	0,17 %	0,31 %
FIN	0,28 %	0,14 %	0,28 %	0,32 %	0,17 %	0,31 %
FRA	0,26 %	0,14 %	0,26 %	0,32 %	0,17 %	0,31 %
GBR	0,43 %	0,27 %	0,41 %	0,32 %	0,17 %	0,31 %
GRC	0,11 %	0,03 %	0,10 %	0,32 %	0,17 %	0,31 %
HRV	0,14 %	0,11 %	0,13 %	0,32 %	0,17 %	0,31 %
HUN	0,33 %	0,17 %	0,33 %	0,32 %	0,17 %	0,31 %
IDN	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
IND	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
IRL	3,03 %	0,52 %	2,57 %	0,32 %	0,17 %	0,31 %
ITA	0,16 %	0,11 %	0,16 %	0,32 %	0,17 %	0,31 %
JPN	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
KOR	-0,03 %	-0,02 %	-0,03 %	-0,04 %	-0,03 %	-0,04 %
LTU	0,13 %	0,13 %	0,13 %	0,32 %	0,17 %	0,31 %
LUX	1,85 %	0,05 %	0,32 %	0,32 %	0,17 %	0,31 %
LVA	0,09 %	0,06 %	0,09 %	0,32 %	0,17 %	0,31 %
MEX	0,00 %	-0,01 %	0,00 %	0,00 %	-0,01 %	0,00 %
MLT	0,46 %	0,16 %	0,27 %	0,32 %	0,17 %	0,31 %
NLD	0,55 %	0,22 %	0,54 %	0,32 %	0,17 %	0,31 %
NOR	-0,06 %	-0,07 %	-0,06 %	-0,06 %	-0,07 %	-0,06 %
POL	0,12 %	0,07 %	0,12 %	0,32 %	0,17 %	0,31 %
PRT	0,12 %	0,06 %	0,11 %	0,32 %	0,17 %	0,31 %
ROU	0,13 %	0,09 %	0,13 %	0,32 %	0,17 %	0,31 %
RUS	-0,03 %	-0,03 %	-0,02 %	-0,03 %	-0,03 %	-0,03 %
SVK	0,15 %	0,16 %	0,15 %	0,32 %	0,17 %	0,31 %
SVN	0,08 %	0,06 %	0,08 %	0,32 %	0,17 %	0,31 %
SWE	0,26 %	0,10 %	0,26 %	0,32 %	0,17 %	0,31 %
TUR	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
TWN	-0,05 %	-0,03 %	-0,05 %	-0,05 %	-0,03 %	-0,05 %
USA	0,37 %	0,23 %	0,36 %	0,38 %	0,24 %	0,36 %
ROW	0,01 %	-0,01 %	0,01 %	0,03 %	0,00 %	0,02 %

Real income effects for maximal liberalization with and without population mobility and with liberalization across all sectors, all sectors except services (19-35), and all sectors except finance (29).

Table A.11: Summary of German regional effects

	Maximal liberalization		Maximal liberalization (No service liberalization)		Francois et al. (2013) scenario	
	immobile	mobile	immobile	mobile	immobile	mobile
Minimum	0.31 %	0.46 %	0.24 %	0.34 %	0,03 %	0,03 %
Maximum	0.71 %	0.46 %	0.49 %	0.34 %	0,04 %	0,03 %
Mean	0.47 %	0.46 %	0.35 %	0.34 %	0,03 %	0,03 %
Coeff. of variation	0.127		0.102		0,748	

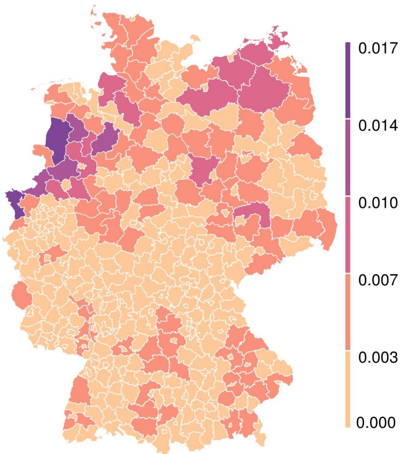
Range and mean of real income effects across German counties for different liberalization scenarios with and without population mobility. For all cases with population immobility coefficients of variation are reported in the last row. Full results across all German regions are available in a supplementary appendix.



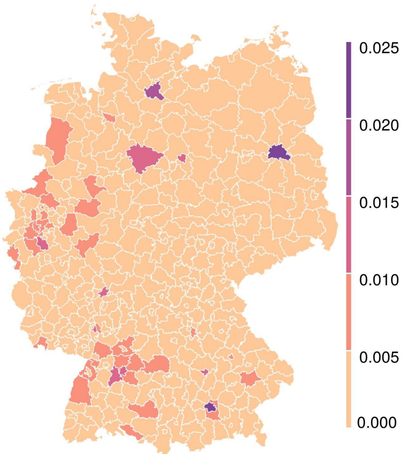
(a) Ariculture (b) Manufacturing (c) Construction

(d) Trade, Communication (e) Financial and Business (f) Gov., Health, Education

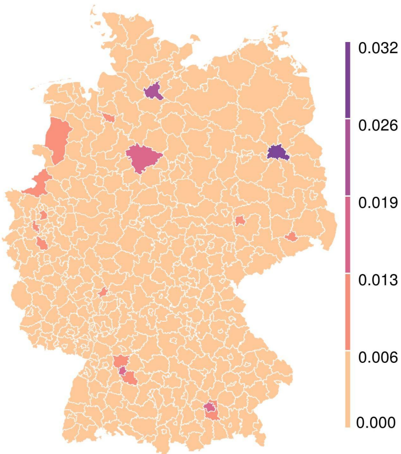
Figure A.1: Shares of different industries in the region's total production



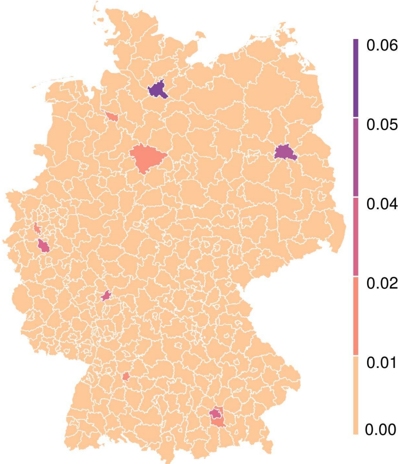
(a) Ariculture



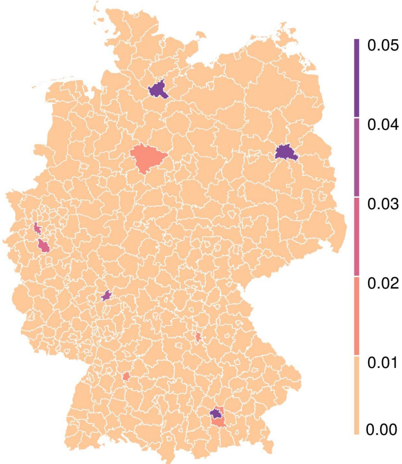
(b) Manufacturing



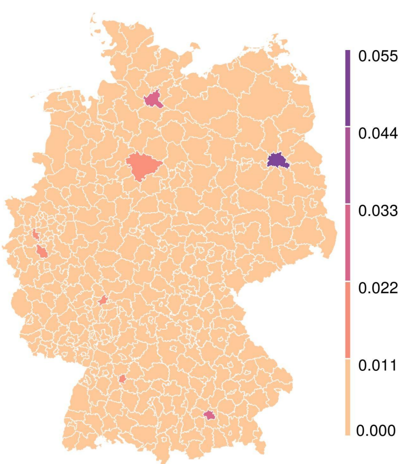
(c) Construction



(d) Trade, Communication

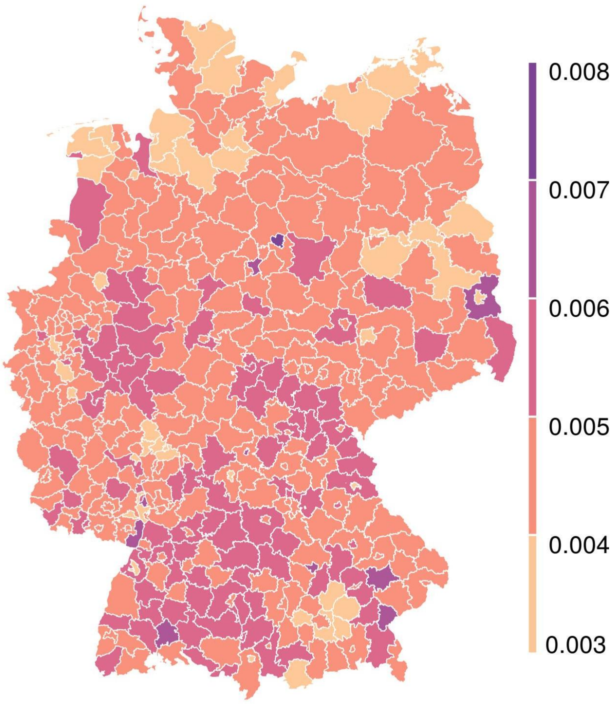


(e) Financial and Business

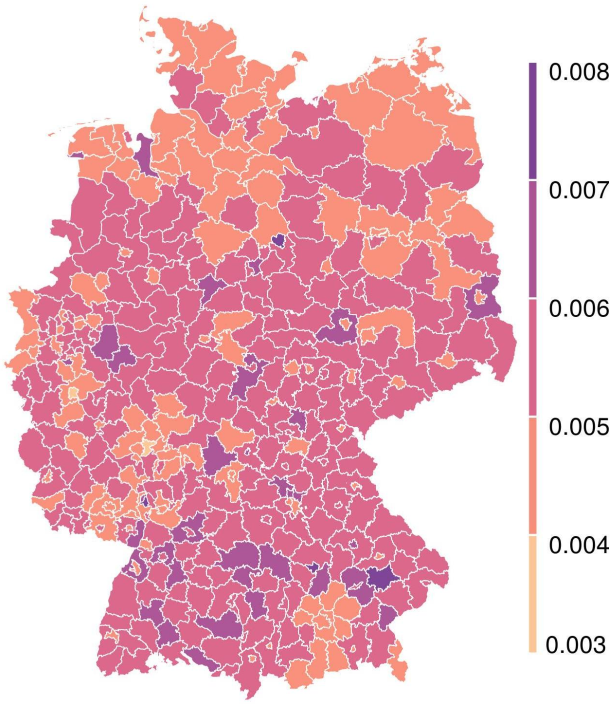


(f) Gov., Health, Education

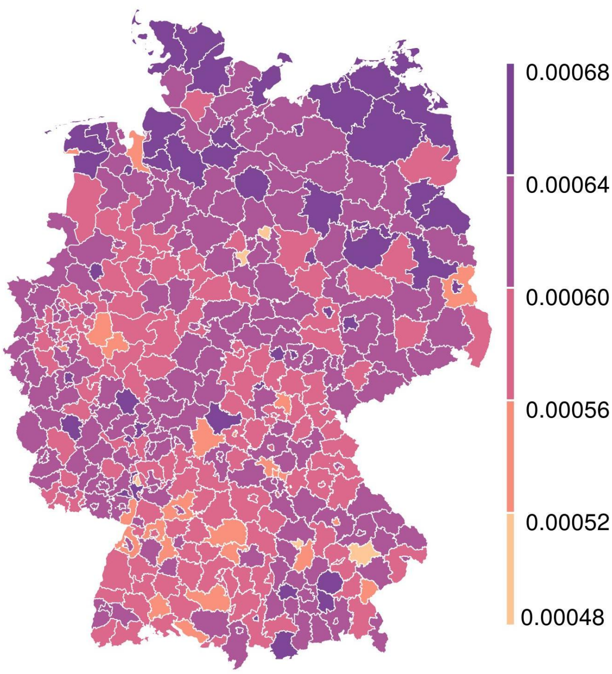
Figure A.2: Shares of a regions' industry production in Germany's total industry production



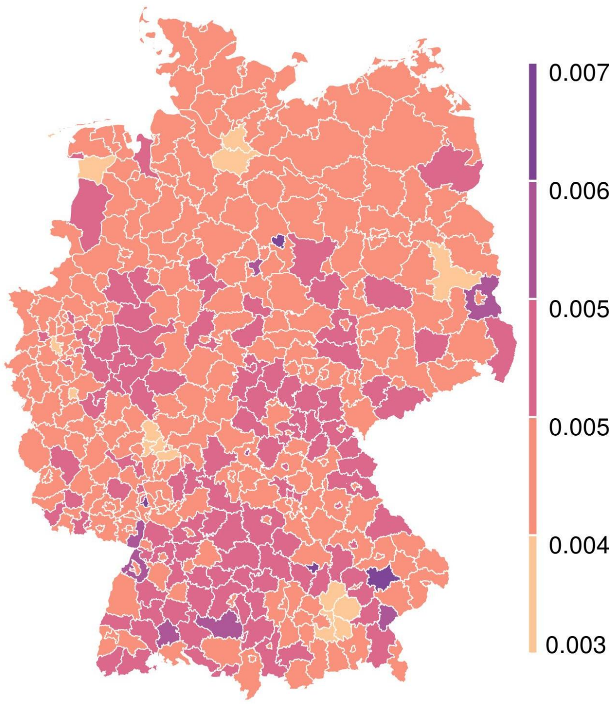
(a) Welfare



(b) Wages



(c) Prices



(d) Rents

Figure A.3: Regional disaggregation, immobile population

A Derivation of trade shares from the WIOD database

The raw WIOT data. For each combination of countries and sectors the WIOT contains an entry $X_{ni,jk}$ for the value of flows from industry k in supplier country i to industry j in destination country n, including within-country flows $X_{ii,jk}$. It also provides the values of flows from industry k in country i to country n that end up as final consumption by households $X_{ni,Ck}$, final consumption by non-profit organizations $X_{ni,Pk}$, government spending $X_{ni,Gk}$, investments $X_{ni,Ik}$ and inventory changes $X_{ni,Qk}$. All entries in these raw data (and in the following) are in value terms at current prices.

Handling of inventory changes. Of course, inventory changes can be negative and sometimes they are significantly large. If we were to calculate final demand by simply summing over consumption, investment, government spending and inventory changes we would end up with a negative final demand in some cases. To reconcile the real world data with our static model that has no room for inventories we follow Costinot and Rodríguez-Clare (2014, Online Appendix) and split the vector of inventory changes into a vector with all positive changes $X_{ni,Qk+}$ and one with all negative changes $X_{ni,Qk-}$ and treat them as follows.

Positive inventory changes are directly included in final demand as are final consumption, government spending and investments, that is, we treat the build-up of inventory as if it were consumed in the current period. Formally, final demand in country n for goods from industry k in country i, $X_{ni,Fk}$, is thus defined as $X_{ni,Fk} = X_{ni,Ck} + X_{ni,Pk} + X_{ni,Gk} + X_{ni,Ik} + X_{ni,Qk+}$.

Negative inventory changes, in contrast, are treated as if they were produced (and consumed) in the current period. To do this, we can not simply increase our output vector by the respective (absolute) value of inventory changes because the production of the inventory in the last period also required intermediates and, thus, had a larger overall effect. To see how to calculate the necessary changes consider N countries and K sectors in matrix notation. X is the original $(N \cdot K) \times 1$-vector of total outputs, A the $(N \cdot K) \times (N \cdot K)$ matrix of input coefficients, F the $(N \cdot K) \times 1$ vector of final demand including positive inventory changes and Inv the $(N \cdot K) \times 1$ vector of negative inventory changes. Then the total output can be calculated as the sum of intermediate flows, final demand, and inventory changes as $X = AX + F + Inv$. We want to calculate the new level X_{new} for which the final demand vector is unchanged but inventory changes Inv are set to 0, that is, the total output if the negative inventory changes had been produced in the current period. Rearranging terms we get $X_{new} = (E - A)^{-1}F$ where E is the unit matrix. We then obtain the new input-output matrix by combining intermediate good flows AX_{new} and the unchanged final demand vector F.

Handling of the real estate sector. For the reasons spelt out in subsection 3.2, severe data problems make it impossible to base our parameter estimates for the consumption share of land and structures and the cost shares of land and structures in intermediates on the WIOD and complementary databases. Hence, we take these parameter estimates from other sources that we have also characterized in subsection 3.2. To avoid that the impact of land is considered twice, we eliminate the real estate sector from the WIOT. We do so in the following way, which ensures that the final input-output matrix is consistent.

First, we eliminate the entry for the real estate sector in final demand and we shift entries of the real estate sector as intermediate into the respective sectoral value added. We also eliminate the entries for all shipments from the other sectors to the real estate sector. The outputs are thus recorded in an $(N \cdot (K-1)) \times 1$ vector), the matrix of input coefficients then becomes a $(N \cdot (K-1)) \times (N \cdot (K-1))$ matrix and the vector of final demands becomes an $(N \cdot (K-1)) \times 1$ vector. At this stage the system is not yet consistent since total use and total output fall apart.

To render the system consistent we calculate the input coefficients of the remaining $N \cdot (K-1)$ sectors by dividing the entries for the shipments of intermediate by the respective sectoral output (the latter are unchanged since the entries for the real estate sector have been shifted to the sectoral value added). We use this to calculate the Leontieff-inverse similarly as before. We now take the final demand as given and recalculate the intermediate demand. The resulting final input-output table is now consistent and used in all calculations.

Derivation of consumption and intermediate goods shares. This final input-output table allows us derive two parameters of the model. Firstly, we calculate the share that industry k has in the consumption of country n by dividing expenditures on industry k by total demand of country n to get $\delta_{nC}^{k} = \sum_i X_{ni,Fk} / \sum_k \sum_i X_{ni,Fk}$. Similarly, we derive the share that industry k has in the intermediate demand of industry j in country n as $\delta_{nj}^{k} = \sum_i X_{ni,jk} / \sum_k \sum_i X_{ni,jk}$.

Bilateral trade flows and handling of zeros. We also use the adjusted input-output matrix to calculate for each industry k the trade flow X_{nik} between any supplying country i to any destination country n. These bilateral trade flows are obtained by summing over all uses of k (intermediate use in all industries and final demand) in its destination country, $X_{nik} = \sum_j X_{ni,jk} + X_{ni,Fk}$. When looking at the data, several of these bilateral trade flows are zero owing to the high level of sectoral and geographical disaggregation. While trade between any two countries in any industry can become arbitrarily small in the Eaton-Kortum model, it would only become zero if trade costs between those two countries were infinitely high. In this case it could no longer hold true that direct trade between those countries would be cheaper than trade via some partner country (with finite trade costs). To avoid these problems, we set all zero trade flows equal to a value of US$1. To put this procedure into perspective, recall that we have aggregated industries such that each country produces output in each industry (cf. subsection 3.2). Since this output will be in the millions, setting some bilateral trade flows at US$1 has a negligible effect on the other countries' trade shares that we will use.

Country production and spending. Summing over all importing countries n we obtain the value of country i's total production in industry k, that is, the revenue of firms in industry k, $X_{ik} = \sum_n X_{nik}$. The value of total production (revenue) in country i is then given by summing these across all industries, $R_i = \sum_k X_{ik}$. Summing across exporting countries i we get country n's total spending in industry k, $E_{nk} = \sum_i X_{nik}$. Then summing over the spending in each industry gives country n's total spending $E_n = \sum_k E_{nk}$.

Bilateral trade shares. We derive the share π_{nik} that country i has in country n's spending in industry k by dividing industry k flows from i to n, X_{nik}, by country n's total industry spending E_{nk}. Hence, these bilateral trade shares are, $\pi_{nik} = X_{nik}/E_{nk}$.

B Trade Barriers – Robustness check

In our analysis in the body of the paper we considered a symmetric reduction of the trade barrier parameters d_{nik} between the United States and the European member states by up to 9.97 percent of their original value. This threshold reflects an estimate of the tariff equivalents of the pre-existing nontariff barriers in E.U.-U.S. trade, which is important because it gives us an upper threshold for the feasible tariff liberalization corridor (so that we are in the range of nonnegative barriers, and hence, so that subsidies are excluded).

There is no fully satisfying way to arrive at an estimate of bilateral trade costs and, hence, there is no hope to arrive at more than a best estimate for the upper threshold for trade cost reductions that we seek. Our estimate is based on a calculation of bilateral trade barriers using the Head-Ries index (Head and Mayer 2014). The Head-Ries index provides a standard – if crude - way to recover trade costs from trade data (Head and Mayer 2014). Applied to our model, we would have to use equation (8) to obtain a simple relation between bilateral trade barriers and trade shares:

$$\frac{\pi_{nik}\pi_{ink}}{\pi_{nnk}\pi_{iik}} = (d_{nik}d_{ink})^{-\theta_k} \tag{28}$$

In addition to assuming that there is frictionless trade within locations (which we do throughout our analysis), the Head-Ries index imposes the assumption that bilateral trade costs are fully symmetric, that is, $d_{nik} = d_{ink}$ (which we do not). Then (28) is immediately inverted and, given an estimate of θ_k, (symmetric) bilateral trade costs can be recovered. Symmetric barriers derived through (28) give a necessary (though not sufficient) condition for the threshold value to be feasible: the product $d_{nik}d_{ink}$ takes on the same value for different values of its components and the smaller value would give us the true threshold.

C Derivation of Regional Trade Data; Table of Regional Sectors

In order to include the German regions into the calculations we start with value added data from national accounts that are available on the regional level from the German federal and state statistical offices ("Regionaldatenbank der statistischen Ämter des Bundes und der Länder"). This data is available for all 402 regions ("Kreise") disaggregated into six groups of NACE/ISIC industries which match directly with WIOD industries as can be seen in table A.12.

Assuming that Germany's industry-specific shares of value added in production $(\beta_{ik} + \eta_{ik})$ hold for all regions, we can use the value added data to calculate a region's share in total German production for each industry.

We incorporate regions into the initial input-output table in three steps. First, we replace all German rows in the table spreading the intermediate and final demand for German goods across regions according to their production shares. This means that a region with a high output in a certain industry will satisfy a larger share of demand from any trading partner than a region with low output in that particular industry.

Secondly, we replace all German intermediate demand columns by assuming that the German intermediate demand structure in each industry holds for all regions. Under this assumption we can use production shares to determine the intermediate demand levels of each region-industry from each trading partner. Hence, a region with a high output in, say, agriculture will have a higher demand for the typical intermediate goods of this sector than a region with low output in agriculture. Moreover, this region will also feature a higher trade level with whoever is the principal supplier of such intermediates.

Finally, we need to replace the German final demand column by splitting demand across regions. To do so, notice that the value of goods consumption is equal to α times a region's total expenditure given by equation (14). Thus, a region's share of total German demand is $\frac{\alpha v_n L_n}{\sum_{i\in N^j} \alpha v_i L_i} = \frac{\sum_{k=1}^{K}(\beta_{nk}+\eta_{nk})R_{nk}+D_n}{\sum_{i\in N^j}\sum_{k=1}^{K}(\beta_{ik}+\eta_{ik})R_{ik}+D_i}$, where the denominator sums across all German regions. Both the nominator and denominator of the right-hand side consist simply of the sum of value added and trade deficits. We assume that the latter are spread across regions according to total income and consequentially, the above expenditure shares can be calculated using only our value added data as $\frac{\alpha v_n L_n}{\sum_{i\in N^m} \alpha v_i L_i} = \frac{\sum_{k=1}^{K}(\beta_{nk}+\eta_{nk})R_{nk}}{\sum_{i\in N^m}\sum_{k=1}^{K}(\beta_{ik}+\eta_{ik})R_{ik}}$.[28]

[28]Though not in the model, the implicit underlying assumption to justify this decision is that of a constant saving rate across German regions.

Table A.12: Regional Sectors

WIOD		This Paper	
#	Label	#	Label
1	Crop and animal production, hunting and related service activities		
2	Forestry and logging	1	Aricultural
3	Fishing and aquaculture		
4	Mining and quarrying		
5	Food products, beverages and tobacco products		
6	Textiles, wearing apparel and leather products		
7	Wood, cork, except furniture; articles of straw and plaiting materials		
8	Paper and paper products		
9	Printing and reproduction of recorded media		
10	Coke and refined petroleum products		
11	Chemicals and chemical products		
12	Basic pharmaceutical products and pharmaceutical preparations		
13	Rubber and plastic products		
14	Other non-metallic mineral products		
15	Basic metals	2	Manufacturing
16	Fabricated metal products, except machinery and equipment		
17	Computer, electronic and optical products		
18	Electrical equipment		
19	Machinery and equipment n.e.c.		
20	Motor vehicles, trailers and semi-trailers		
21	Other transport equipment		
22	Furniture; other manufacturing		
23	Repair and installation of machinery and equipment		
24	Electricity, gas, steam and air conditioning supply		
25	Water collection, treatment and supply		
26	Sewerage; waste collection, treatment and disposal activities		
27	Construction	3	Construction
28	Wholesale, retail trade and repair of motor vehicles and motorcycles		
29	Wholesale trade, except of motor vehicles and motorcycles		
30	Retail trade, except of motor vehicles and motorcycles		
31	Land transport and transport via pipelines		
32	Water transport		
33	Air transport		
34	Warehousing and support activities for transportation	4	Trade, Communication
35	Postal and courier activities		
36	Accommodation and food service activities		
37	Publishing activities		
38	Motion picture, video and television programme production, sound recording and music publishing activities; broadcasting activities		
39	Telecommunications		
40	Computer programming, consultancy; information service activities		
41	Financial service activities, except insurance and pension funding		
42	Insurance, pension funding, except compulsory social security		
43	Activities auxiliary to financial services and insurance activities		
44	Legal, accounting activities; head offices; management consultancy	5	Financial, Business
45	Architectural and engineering activities; technical testing and analysis		
46	Scientific research and development		
47	Advertising and market research		
48	Other professional, scientific, technical activities; veterinary activities		
49	Administrative and support service activities		
50	Public administration and defence; compulsory social security		
51	Education		
52	Human health and social work activities		
53	Other service activities	6	Government, Health, Education
54	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		
55	Activities of extraterritorial organizations and bodies		

Source: WIOD Database

Essay II

RIOTs in Germany
Constructing an interregional input-output table for Germany

RIOTs in Germany - Constructing an interregional input-output table for Germany*

Oliver Krebs†

October 28, 2018

Abstract

Despite their importance, little is known about the spatial structure of trade and production networks within Germany and their connection to the international markets. The lack of data is problematic for regional analysis of aggregate shocks such as trade agreements and to analyze network effects of regional policies. This paper takes an in-depth look at this German production structure and trade network at the county level based on a unique data set of county level trade. I find a surprisingly vast heterogeneity with respect to specialization, agglomeration and trade partners. The paper subsequently shows how to adapt recent advances in regionalization of input-output tables to derive an interregional input output table for 402 German counties and 26 foreign partners for 17 sectors that is cell-by-cell compatible with the WIOD tables for national aggregates and can be used for impact analysis and CGE model calibration.

JEL-Classification: R15, R12, F17

Keywords: Germany, regional trade, input-output tables, proportionality

1 Introduction

Regions matter! On the one hand macroeconomic shocks have vastly different effects across regions: Brexit, TTIP or US tariffs, robotization and artificial intelligence all will affect

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Berlin differently than Munich, depending not only on each city's local conditions but also on its linkages with other locations. On the other hand, shocks in individual regions, such as inventions, bankruptcies or the attraction of a major production plant can, through trade and input-output linkages, magnify to aggregate effects of macroeconomic relevance. Despite their importance, surprisingly little is known about the trade and production networks within Germany and their connection to the international markets.

Baden Wuerttemberg is the only state (of 16) in Germany that has consistently published a state level input-output table for several years but has stopped data collection in 1993 due to financial limitations (cf. Kowalewski (2015)). Only a few authors have constructed other regional input-output tables (RIOTs) usually relying on so-called "non-survey" methods that break down national input-output tables based on some locally available measure such as sectoral GDP or employment.[1] For example, Kronenberg (2009) derives such a table for the state of North Rhine–Westphalia, Koschel et al. (2006) for the state of Hessen and Schröder and Zimmermann (2014) for the German coastal region of the Baltic sea. In even fewer cases authors use a "survey" or "hybrid" approach relying on detailed regional data to construct a RIOT. Kronenberg (2010) who constructs such a table for the state of Mecklenburg West Pomerania is a case in point, as is, for example, Stäglin (2001) who derive a RIOT for the city of Hamburg. In all of these cases, however, the authors construct regional instead of inter-regional input-output tables (IRIOT). In the former "exports" are just a further category of final demand without specifying the target location and, similarly, "imports" are specified as a supply without a source location.

This paper, in contrast, analyses the trade linkages between German counties making use of a unique data set constructed by Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data provides total shipments in tons by water, train or truck for the year 2010 between 402 German counties and their trade partners, disaggregated along 25 product categories.

I use this data together with further information from the German regional statistical offices and the world input-output database (WIOD) to construct an *inter-regional* input-output table for 17 sectors across 402 German counties and 26 international trading partners.[2] To the best of my knowledge I am the first to construct such a data set for Germany. The construction method and strength of the underlying data sets allow the IRIOT to remain strongly anchored in observable data. In particular, it replicates officially reported local revenues, value added and consequently intermediate demand levels of county sectors.[3]

[1] Section 2 describes different approaches to the construction of regional input-output tables in more detail.

[2] See Timmer et al. (2015) for details on the world input-output database.

[3] As described in detail in section 3 I scale data from all sources such that national aggregates match the

Further, inter-regional trade networks are based on the data on inter-regional shipments and mirror observed international trade flows. Finally, the national aggregates of the IRIOT are, cell by cell, perfectly consistent with the international tables from the WIOD, allowing for an integrated analysis with a "closed" world wide input-output table.

The remainder of this paper is structured as follows. Section 2 provides background on the construction of regional input-output tables. Section 3 gives details on the used data sets and initial data preparation and presents a descriptive analysis of the German production structure and trade linkages. Section 4 explains the construction of the IRIOT and discusses the resulting table. The final section sums up the results.

2 Background

Data sources and previous literature detailing trade flows within Germany are scarce and only a few regional input-output tables have been produced by select authors for individual states or cities. Using survey based methods to directly derive input-output tables from collected data is usually too costly and time intensive for individual researchers to accomplish, but some approaches combine non-survey methods with detailed regional data and are therefore considered "hybrid" approaches. For example, Kronenberg (2010), in deriving the regional input-output table of the state of Mecklenburg West Pomerania uses data from the German consumer expenditure survey ("Einkommens- und Verbrauchsstichprobe") to establish unique regional consumption levels across industries. The majority of RIOTs in Germany are, however, constructed using non-survey methods, which can be broadly classified into location quotients approaches and commodity balance approaches.

The simplest form of the location quotient approach going back to Schaffer and Chu (1969) relies on a measure such as the number of workers or GDP that is regionally available at the sector level to approximate the relative size of each sector in a region. If the relative size of a sector in the region is equal to or larger than the national relative size it is assumed that the sector can meet the local demand and regional input coefficients remain the same as in the national tables. If the relative size is smaller than in the aggregate data however, imports from other regions become necessary to satisfy the regional demand for the sector and domestic input coefficients in the regional input-output table are adjusted downwards from the national values for the respective sector. Several variants of location quotients have been developed in the literature to account for further aspects when determining the adjustment factors for input coefficients. The most prominent examples consider relative industry sizes within a region (cross-industry location quotient), the overall size of a region

values reported by the WIOD, hence regional data from other sources is only matched up to scale.

(Flegg et al. 1995; Flegg and Webber 1997) and regional specialization (Flegg et al. 2000). An overview of different location quotients and their construction can be found in Flegg and Tohmo (2013). These approaches, however, treat imports and exports as residual values and can thus not capture cross-hauling, that is, the simultaneous import and export of goods from the same industry. Moreover, input-output tables constructed this way are only constructed for a single region and do not capture where imports come from nor where exports end up. This is of central importance if one wants to use input-output tables to calibrate general equilibrium models that capture a closed or world economy.

The commodity balance or supply-demand-pooling approach also attributes a share of the national sectoral revenue to a region based on a regionally available measure such as employment levels. Subsequently intermediate demand is derived by applying the national input coefficients to the regional production and final demand by scaling national final demand, for example by the regions share in total population or GDP. Having determined both total domestic supply and total demand the difference between the two, that is, the net imports or exports, is interpreted as a regions total imports or exports. The basic commodity balance approach therefore also does not allow for cross-hauling of products from the same industry, which is in strong contrast to international trade flows and also to the data used in this paper. While Kronenberg (2009) introduces a method that imposes a certain amount of cross-hauling based on measures of product heterogeneity within an industry the trade structure remains completely non-survey based. Moreover, it also applies that this method can not capture the source of imports and destination of exports that are important to understand linkages with other regions and countries.

The accuracy of such "mechanical" approaches to deriving regional from national input-output tables has been discussed intensively in the literature, often by comparing them to survey based results (recent examples include Flegg and Tohmo 2018; Kowalewski 2015; Flegg and Tohmo 2013).[4] However, comparison with survey based methods might be misleading as their construction also involves a substantial amount of uncertainty and decision making, implying that they are not error free. Overall, the earlier conclusion by Hewings and Jensen (1986) in the Handbook of Regional and Urban Economics that survey methods "remain generally regarded as 'preferred' tables in terms of accuracy, more so by analysts inexperienced in their construction" can still be considered valid.

Independent of the chosen method there are several different types of regional input-output tables that one can construct. For European Union members, including Germany, national tables follow the recommendations of the European System of Accounts (ESA). Regional tables in Germany, being derived from the national tables, therefore usually also follow this structure. As shown in figure 1 the sum of each row of these tables give the total

[4] Bonfiglio and Chelli (2008) provide an alternative approach relying on Monte-Carlo simulations.

(regional) use and the sum of each column the total (regional) supply of goods from a specific industry.[5] This means that no difference is made between domestic and imported goods in the rows of the table, with cells showing the aggregate use of domestic and imported goods as intermediate or in final demand. Similarly, as columns explain the total supply of goods from a specific industry they only include the contribution of aggregate imports of goods from each industry.[6] Importantly, total supply in these tables is the sum of domestically produced and imported goods and cells in the first two rows show where this aggregate supply is used. This means, that imports used as intermediates are counted twice. Once in the top left quadrant contributing to domestic production and once directly as "imported supply". To see this, consider an economy that without further factors uses 1 Dollar of intermediates to produce 1 Dollar of output that is then consumed. Total (domestic) output and total consumption are equal to 1 Dollar, but total supply and total use are equal to 2 Dollars: 1 Dollar domestic supply and 1 Dollar of imports, as well as 1 dollar of intermediate use and 1 Dollar of final use.

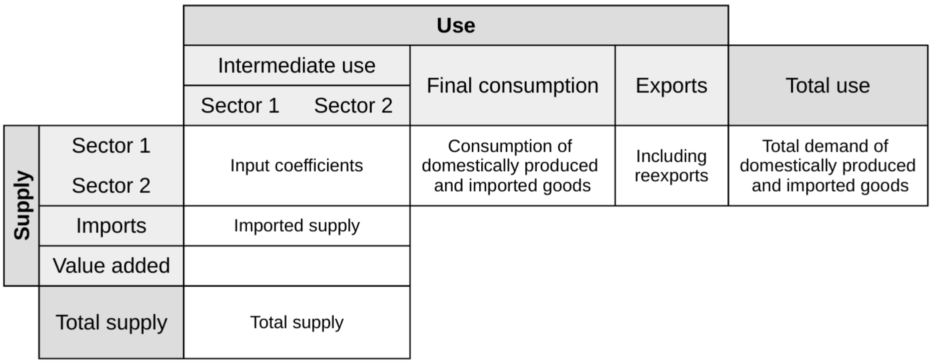


Figure 1: Input-Output table ESA standard

In contrast to this aggregate view an input-output table can also be constructed showing the use structure of domestic and imported goods separately. In this case, as depicted in figure 2, the aggregate of a row gives either the total use of domestic production or of imports from a specific sector whereas columns sum to the domestic production of each sector, to aggregate final demand and to total exports.[7]

[5]Supply tables show which products are supplied by which industries. Use tables show how much of each product is consumed and how much ends up as intermediates in each industry. Constructing input-output tables from these two tables one has to decided between a product-by-product or an industry-by-industry table. To derive the former one has to assume that each product is always produced in the same way, irrespective of the industry where it is produced. For the latter one assumes that each product serves intermediate and final demand with fixed shares, irrespective of which industry produces it. There is no clear advantage between the two approaches. Here the focus is on industry-by-industry tables as this is also the type derived in this paper.

[6]Following the ESA national input-output tables should be accompanied by two separate tables, an input-output table of domestic production and an input-output table of imports. This additional information is, however, usually not produced for regional tables in Germany.

[7]It is also important to note, that the interpretation of input coefficients that can be derived in the upper-left quadrant of both types of input-output tables differ. In their seminal handbook article Hewings

		Use				
		Intermediate use		Final consumption	Exports	Total demand
		Sector 1	Sector 2			
Domestic Supply	Sector 1	Domestic input coefficients		Consumption of domestically produced goods	Exports of domestically produced goods	Total demand of domestically produced goods
	Sector 2					
	Imports	Import coefficents		Final use of imports	Reexport	Total demand of Imports
	Value added					
	Total Output	Domestic output				

Figure 2: Input-Output table with import structure

While the second type of input-output table contains additional information on the underlying production structure both types are regional, that is imports and exports only appear aggregated across all sources or destinations, respectively. In contrast, an interregional input-output table captures the full interregional trade networks as demonstrated by the simplified two country table in figure 3.[8]

			Use						
			Intermediate use				Final consumption		
			Location 1		Location 2		Location 1	Location 2	Total use
			Sector 1	Sector 2	Sector 1	Sector 2			
Supply	Location 1	Sector 1	Domestic input coefficients		Foreign input coefficients		Consumption of location 1 goods in location 1	Consumption of location 1 goods in location 2	Total use of location 1 goods
		Sector 2							
	Location 2	Sector 1	Foreign input coefficients		Domestic input coefficients		Consumption of location 2 goods in location 1	Consumption of location 2 goods in location 2	Total use of location 2 goods
		Sector 2							
		Value added							
		Total Output	Output Location 1		Output Location 2				

Figure 3: Inter-regional Input-Output table

The great advantage of an IRIOT over a RIOT is that it distinguishes both imports and exports geographically. Since columns contain all possible trade partners including the country itself, the sum of each row equals the total use of goods produced in one sector in one location. This value must be equal to the respective column sum which includes all intermediates, domestic and imported, as well as value added in one sector in one region and hence represents the region's sectoral output. The IRIOT captures not only the sectoral but

and Jensen (1986) refer to the former as "technical" and to the latter as "trade" coefficients but criticize that the literature on regional input-output tables does not use consistent terms to distinguish these coefficients and indeed often erroneously confounds the two when applying non-survey methods.

[8]Previous literature is not consistent in its use of the term "interregional input-output table" and some authors further differentiate between "interregional" and "multiregional" input-output tables (see, for example, Hewings and Jensen 1986). Figure 3 exemplifies the meaning of the term in this paper. The input-output table provided by the WIOD is a further example of this case, albeit being international and not interregional.

also the geographic component of a production network and can consequently also be used to study how economic shocks effect non-treated locations through spatial linkages. In contrast to all previous input-output tables for German regions this paper constructs an IRIOT which, being cell-by-cell consistent with the WIOD in terms of the national aggregate, even includes world-wide input-output data.

As interregional trade data is usually unavailable there is also few literature that discusses construction methods of RIOTs or even IRIOTs that rely on this type of data. An important exception is Wang and Canning (2005) who suggest a mathematical programming method that is similar to the multidimensional RAS method applied in this paper and that allows to derive IRIOTs based on initial estimates of trade flows and technical coefficients combined with further statistics at the region sector level, such as sectoral output and demand.[9] In contrast to their approach however, I do not observe the final demand structure, or any data about trade in service sectors and must approximate these values. As explained in the next two sections I instead rely on a two step process, treating sectors with known and those with unknown trade flows separately. Moreover, Wang and Canning (2005) apply their estimation method to an artificially created aggregate region consisting of several countries to test the validity of their approach, whereas this paper aims to calibrate an actual county level IRIOT for further applications.

In terms of the underlying data set Nitsch and Wolf (2013) rely on similar shipment data as I do - albeit at a much higher level of aggregation - to study the persistence of a border effect from German separation over time.[10] Lameli et al. (2015) use the same data as Nitsch and Wolf (2013) to derive the effect of dialects on intra-national trade. In both cases the authors rely on an empirical gravity approach, that is, they estimate the effects of specific variables on aggregate trade flows. However, they use simple unit values from the national German export statistics to aggregate trade flows over all product categories in all regions and do not derive the full input-output linkages as in this paper.

3 Data and descriptive analysis

This section discusses the different data sources used to inform the final interregional input-output table as well as initial data processing steps. Section 3.1 describes the source of international trade data and international input-output tables. Section 3.2 explains the

[9] The RAS algorithm (Stone and Brown 1962; Bacharach 1965) is widely used in input-output analysis and, under different names such as proportionate fitting or matrix scaling, in a range of different fields. I discuss the algorithm in detail in section 2. Its name is not an abbreviation but originates in variable names (r, A, s) used by Stone and Brown (1962).

[10] They consider two data sets, one with 10 product categories and 101 regional entities ("Verkehrsbezirke") and another with 24 product categories but only 27 regions ("Verkehrsregionen").

derivation of regional and sectoral output values and section 3.3 shows how interregional trade flows are determined. Finally, section 3.4 provides a descriptive analysis of the obtained county level production structure and trade network.

3.1 WIOD

I use the World Input Output database (WIOD) as my main data source for the national production structure and international trade flows. This data set provides a time-series of world input-output tables compiled on the basis of officially published input-output tables in combination with national accounts and international trade statistics. The world input-output table for the year 2010 for which my subnational shipment data is available covers data from 56 industries in 44 countries, including one artificial "rest of the world" (ROW) country. To match this data to the sectors and countries for which shipment data is available I aggregate it to the 17 industries and 27 countries listed in tables 1 and 2.[11] Positive inventory changes in the WIOD are included in final demand and negative inventory changes are treated as if they had been produced in 2010 as well. The details of this process are laid out in Krebs and Pflüger (2018) and summarized in appendix B.

Table 1: List of sectors

#	Description
1	Agriculture
2	Mininig
3	Food, Beverages, Tobacco
4	Textiles, Leather
5	Wood, Paper, Printing
6	Petroleum, Coke
7	Chemicals, Pharmaceuticals
8	Non-Metallic Minerals
9	Metal
10	Machinery, Electrical Equipment
11	Transport Equipment
12	Other Manufacturing
13	Utilities
14	Construction
15	Trade, Communication, IT
16	Financial, Insurance, Business
17	Government, Education, Health

Table 2: List of countries

ISO3	Name	ISO3	Name
AUT	Austria	NLD	Netherlands
BEL	Belgium	POL	Poland
BGR	Bulgaria	PRT	Portugal
CHE	Switzerland	ROU	Romania
CZE	Czech Republic	RUS	Russia
DEU	Germany	SVK	Slovakia
DNK	Denmark	SVN	Slovenia
ESP	Spain	SWE	Sweden
EST	Estonia	TUR	Turkey
FRA	France		
GBR	United Kingdom		
HRV	Croatia		
HUN	Hungary		
ITA	Italy		
LTU	Lithuania		
LUX	Luxembourg		
LVA	Latvia		

[11] The matching of the 56 sectors in the WIOD to these 17 industries is shown in table C.1 in the appendix.

3.2 Production data

Unfortunately, revenue data for the 402 counties in Germany is not published at the level of sectoral disaggregation employed in this paper (see table 1) and therefore has to be derived from several sources. As different data is available for mining and manufacturing sectors compared to agricultural, construction and service sectors the process is reported separately for the two groups.

Firstly, for the mining and manufacturing sectors (2-12) revenue and value added data in each county, $i \in \{1, ..., 402\}$, is only available as a sectoral aggregate ($R_{i,manufac}$) from the German regional statistical offices.[12] To derive specific county sector revenues I construct a matrix as depicted in figure 4 with one row for each of the 402 German counties, one column for each of the 11 sectors in question and with individual entries $\tilde{R}_{ij}$ denoting initial estimates of the revenue generated in a mining or manufacturing sector $j \in \{2, ...12\}$ in county $i \in \{1, ..., 402\}$. These estimates are obtained by distributing the German sectoral revenue taken from the WIOD across counties based on county employment shares in the particular industry, that is, I set $\tilde{R}_{ij} = R^G_j \cdot \frac{L_{ij}}{\sum_i L_{ij}}$, where R^G_j is the national revenue in sector j and L_{ij} the number of workers employed in sector j in county i obtained from the German Federal Institute for Employment Research (IAB).[13]

	$j = 2$	$\cdots$	$j = 12$	$\sum_{j\in 2,...,12}$
$i = 1$				$\neq R_{1,manufac}$
$\vdots$		$\tilde{R}_{ij} = R^G_j \cdot \frac{L_{ij}}{\sum_i L_{ij}}$		$\vdots$
$i = 402$				$\neq R_{402,manufac}$
$\sum_{i\in 1,...,402}$	R^G_2	$\cdots$	R^G_{12}	

Figure 4: Matrix of county sector revenues

The column sums of these initial estimates equal, by construction, the national sectoral revenues obtained from the WIOD. However, the construction method counterfactually assumes that workers in each industry produce an equal amount of revenue across all counties. Consequently, county level aggregates across sectors, that is, row sums, will not (necessarily) match the sectoral aggregates $R_{i,manufac}$ collected from the regional statistical offices. Instead, if a county produces a higher than average revenue per worker row sums will be too small and vice versa. To make use of the additional information contained in the observed county level sectoral aggregates I apply an RAS algorithm. This simple method

[12] I scale county level revenue data for the aggregated mining and manufacturing sector such that the sum across all counties equals the national revenue level reported in the WIOD.

[13] Throughout this paper variables pertaining to Germany as a whole are marked by a superscript "G" to differentiate them from variables pertaining to counties or foreign countries.

iteratively scales rows and columns to match the given margin constraints. Specifically, the algorithm derives new estimates of the matrix entries by scaling each row i with a single factor $(R_{i,manufac}/\sum_{j\in 1,...,12}\tilde{R}_{ij})$, such that row sums match their target values $R_{i,manufac}$. Of course, having scaled each row by an individual value the column sums will no longer add up to the given margins (R_j^G). The algorithm then scales each column with a single value such that the column sums are again correct, but leaving the row constraints violated again. An iterative repetition of this process of row and column scaling approaches a set of new values R_{ij} that deliver the correct row and column sums. Interestingly, this simple method delivers the same results as an entropy maximizing approach (McDougall 1999). Intuitively, this means that the method preserves as much of the initial matrix structure as possible while ensuring that both the observed national sectoral revenues and county level aggregate revenues across sectors are replicated by the resulting values. Particularly appealing to my application is that in the process of iteratively scaling rows and columns the bilateral relative sizes of industries are kept constant, that is, $\frac{\tilde{R}_{ij}/\tilde{R}_{ik}}{\tilde{R}_{nj}/\tilde{R}_{nk}} = \frac{R_{ij}/R_{ik}}{R_{nj}/R_{nk}}$ for non-zero revenues.

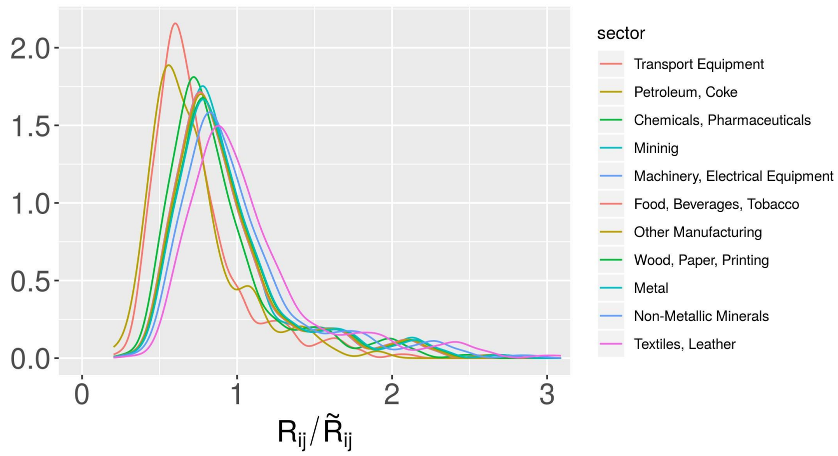


Figure 5: Effects of RAS algorithm on revenues

Figure 5 depicts the density distribution of relative county level revenues in sectors 2 through 12 before and after the application of the RAS algorithm. The matrix balancing approach distorts the initial revenue values to account for differences in revenue per worker across locations, while keeping the national aggregate of sector revenues constant. Clearly the initial assumption of an equal revenue per worker in each sector can not be upheld. Instead revenue per worker has to be strongly adjusted upwards in a few counties and slightly lowered in a large number of counties.[14] The same process is applied to derive county sector level value added (V_{ij}) from the national sectoral value added given by the WIOD (V_j^G) and the county level aggregates across sectors from the regional statistical offices, defining the initial matrix entries as $\tilde{V}_{ij} = V_j^G \cdot \frac{R_{ij}}{\sum_i R_{ij}}$.

[14]It should be noted that differences in revenue per worker do not necessarily imply a higher productivity. The highest average difference between initial and final revenues, for example, is observed in Hamburg. This result is partly due to Hamburg being a trading hub with a particular high share of intermediates in production and hence a higher revenue per worker.

Secondly, for agriculture, utilities, construction and service sectors the regional statistical offices directly provide value added data at the county level.[15] In these cases I use sectoral value added shares to split national sectoral revenues across counties, that is, for sectors $j \in \{1, 13, ..., 17\}$ I set $R_{ij} = R_j^G \cdot \frac{V_{ij}}{\sum_i V_{ij}}$, where V_{ij} denotes value added in sector j in location i.[16]

Having calculated all county sector revenues R_{ij} and value added V_{ij}, aggregate intermediate demand M_{ij} in each sector and county can also easily be derived as the difference between the two, that is, $M_{ij} = R_{ij} - V_{ij}$. Descriptive statistics for all results are provided in section 3.4.

3.3 Shipment data

My transport data stems from Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data set gives the total shipments in tons by water, train or truck for 2010 between German counties and their trade partners, disaggregated along 25 product categories.[17]

The trade partner can be either a further German county (including the county itself), one of 153 foreign regions aggregating into 41 third countries (of which 29 are also in the WIOD Database), or a major German or international port.[18] The latter two appear as origin or destination whenever the actual origin or final destination is unknown or not in the explicit country sample, for example, shipments to and from Japan. Moreover, the data thus differentiates between shipments to/from, e.g. Hamburg and Hamburg port. I assign all shipments to and from international ports as well as shipments to and from countries not in the WIOD to ROW.

The data on rail and river transport is based on data sets from the federal statistical office specially compiled to publicly unavailable levels of spatial and sectoral disaggregation. Data on truck shipments relies, firstly, on a similar special report at the county level prepared by

[15] Again, I scale county level value added data for each sector such that the sum across all counties equals the national revenue level reported in the WIOD.

[16] For the "utilities" sector (13) county level value added data is only available combined with the mining sector. I still opt to use this aggregate to split sectoral revenues across counties, since the possible alternative, that is, spreading the national sectoral revenue across counties by county sector employment shares, produces several counties with revenue values smaller than the reported value added.

[17] Air transport is not included in the data set. However, air transport only makes up about 0.1 percent of total transported weight in Germany (4.2 mio tons compared to 3.7 billion tons, cf. Schubert et al. 2014) and only about 1 percent of the value of total foreign trade (212 billion Euros compared to 2050 billion Euros in 2014, Source: "Bundesverband der deutschen Luftverkehrswirtschaft").

[18] The data set includes 43 third countries, but Iceland and Cyprus have no recorded shipments to Germany, that is, shipments from these countries are recorded with a German international port as origin.

the department of motor vehicles (“Kraftfahrtbundesamt”) from a one week 0.5‰ mandatory sample of German registered trucks with a gross vehicle weight rating above 3.5 tons and, secondly, on complementary NUTS-3 level shipment data for foreign owned trucks from Eurostat.

Shipments of goods from their source to their destination often occur via several "sub-shipments" with potential changes in the mode of transport, for example, a supplier delivering goods by truck to a container terminal where they are loaded onto a boat together with other goods, transported to another terminal and then sent to their final destination via truck. In these cases the product category in the data set of the first and/or last part of the route will be a specific category, while the middle part might be of type “unknown” or “mixed”.[19]

Similarly, if complete trucks are transported via train across the Alps, as is common in German-Italian shipments, the weight of the truck will be added to the transported weight for the middle part of the shipment and the weight in the first and/or last part gives the true weight of the transported commodity.

Of the 25 product categories 18 can be directly matched to my agriculture, mining and manufacturing sectors 1 to 12 as shown in table C.1 in the appendix.[20] In two cases, “mining” and “petroleum, coke” several product categories are matched with the respective industries. In these cases I weight transported tons with unit values from the German trade statistics before aggregating them. Three categories have no match in my data (“mail”, “moving items, not-for-market items”, “Equipment and material for transportation, packaging”) and are dropped. The remaining three categories that can occur in the data are “mixed”, “unknown” and “other” goods. These are used to scale trade in all other sectors for the respective pair of trade partners.[21] Finally, while the category “Secondary raw materials; municipal wastes and other wastes” would match to the sector “utilities” of this paper, it only makes up for a small share of that sector. The much larger share, that is, electricity, gas and steam supply, as well as, water treatment, collection and supply, is (usually) transported by means not captured in the shipment data. Consequently, I do not use the category to proxy for trade in

[19] In the case of such "intermodal" shipments Schubert et al. (2014) use data from container terminals to match shipments to the source container terminal with shipments from the destination container terminal. In some instances, however, a clear match is impossible, for example, if a truck delivers a specific product category to a boat but only "mixed" product trucks leave the ship's destination terminal. In these cases matches might ultimately be assigned randomly and the product category of the first and last part of a shipment can diverge with one being unspecific. In these cases I assume that the specific product category holds for the complete shipment as matched in the data set.

[20] Shipments are given in terms of product categories whereas employment, revenue and value added data are for industries and I therefore have to assume that each industry produces only goods from the matched product category.

[21] Some select reporter-partner pairs only have shipments in the category “unknown”. In these cases I assume that these shipments consist of the exporter's average export mix.

sector "utilities". Instead I drop the category from the shipment data and treat the "utilities" sector as the service sectors below.

Overall I obtain trade flows in terms of weight between the 402 German counties and 26 foreign partners, including ROW, in 17 sectors.[22] These flows include own trade, that is, goods that are produced and used in the same location. Thus, total weight flows with the same origin county must, in each sector, add up to the weight of the total production in the sector. To calculate the value of trade flows $X_{n,ij}$ from sector j goods in a German county $i \in \{1, ..., 402\}$ to location n I therefore multiply the weight share with the county sector revenue. Specifically, I set $X_{n,ij} = R_{ij} \cdot \frac{W_{n,ij}}{\sum_n W_{n,ij}}$, where $W_{n,ij}$ denotes the weight of flows from sector j in location i to location n. In the case of foreign countries exporting to Germany, I split the national level trade flows from the WIOD across counties according to weight shares, that is, for $i \in \{403, ..., 428\}$ the trade value is $X_{n,ij} = X^G_{ij} \cdot \frac{W_{n,ij}}{\sum_{n=1,...402} W_{n,ij}}$, where X^G_{ij} are German imports from sector j in location i. In a final step I rescale all counties intranational flows and exports to foreign locations such that the aggregate German exports to foreign locations match the values given in the WIOD.[23] Compared to the alternative approach of using national unit values to translate weight flows into value flows my method accounts for the fact that goods in the same sector but from different counties can have very different values per ton. I turn to a descriptive analysis of the final trade network in the next subsection.[24]

3.4 Descriptive analysis

Production. Table 3 provides an overview of the derived production structure in Germany. As shown in the last column, almost all counties are active in the production of almost all sectors with strong exceptions in the "mining" and "petroleum, coke" industries. The three service sectors are by far the largest sectors in the German economy. Adding up the respective values in columns 5 and 6 of table 3 their combined share in total revenue is 0.57 and their share in value added is 0.68. The largest manufacturing sectors in terms of revenue are "machinery, electrical equipment", "petroleum, coke" and "chemicals, pharmaceuticals", the smallest ones are "mining", "textiles, leather" and "non-metallic minerals". The unweighted

[22]Ireland, Greece, Finland and Norway show a large number of zero trade flows compared to other countries, likely due to the fact that a large share of trade with these countries occurs via international ports. For this reason I chose to aggregate these countries with ROW.

[23]In the "petroleum, coke" sector there are two countries, Latvia and Portugal, to which no German county reports exports, despite the WIOD reporting a country to country flow. Again, this is likely due to this sector relying heavily on pipeline transport. In these case I therefore assume that all producers of "petroleum, coke" export equal shares of their output to these countries.

[24]It should be noted that in contrast to the full IRIOT calculated in section 4, the interregional trade flows derived in this section contain no information about their use category, that is, whether they serve as intermediates in a specific sector or as final consumption at their destination.

mean of value added in output across counties is constant in "agriculture", "construction" and service sectors by assumption but varies profoundly in the remaining sectors with a range from 0.05 to 0.97, albeit the mean being relatively similar around 35% to 45% in most sectors.

The Herfindahl-Hirschman-Index (HHI) provides a measure of concentration of production.[25] It is strongest in "petroleum, coke", "mining" and "transportation equipment". In the first two cases this is driven by the availability of necessary resources, in the latter case it mirrors the strong concentration of the industry among a few large German car producers. Concentration is lowest in the "agriculture", "construction" and "food, beverages, tobacco" sectors. As an absolute measure of concentration, however, the HHI is influenced by the large size differences of counties in Germany, that is, the large size of Berlin, Hamburg and Munich in most sectors increases the HHI and their low significance for agriculture greatly reduces it in this sector. In contrast the Krugman (1991) specialization index (KS) and the spatial Gini coefficient provide measures of relative specialization, comparing the relative county level specialization to the national relative specialization.[26] For both measures "petroleum, coke" and "mining" continue to exhibit the highest level of concentration, followed by "agriculture" and "transport equipment".

These simple measures of concentration still hide important aspects of production patterns. Figure 6 exemplifies this by showing the relative share of "agriculture", "metal" and "transport equipment" in each county's total output. All three show some agglomeration in the KS and Gini coefficient. However, since these indices do not account for distances between counties they fail to capture agglomerations that do not conform to administrative borders. Clearly, the "metal industry" industry shows a strong agglomeration in the Ruhr-area of Germany, albeit spread over several counties. Similarly agriculture is strongly agglomerated in the north and north-east of Germany, whereas single counties highly specialized in "transport equipment" can be found spread out across the map. Moran's I ($-1 < MI < 1$, see Gibbons et al. 2015) tries to capture this by measuring the strength of spatial correlation in industry

[25]Here the HHI is measured as $HHI_j = \sum_i \left(\frac{R_{ij}}{\sum_i R_{ij}} \right)^2$.

[26]These indices are calculated as:

$$KS = \sum_i \left| \frac{R_{ij}}{\sum_i R_{ij}} - \frac{\sum_j R_{ij}}{\sum_i \sum_j R_{ij}} \right|$$

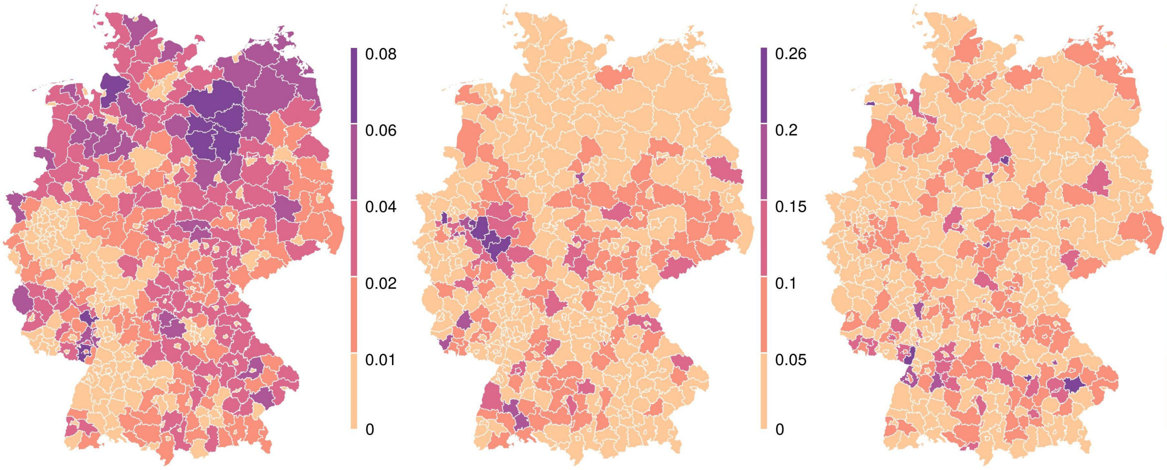
$$Gini = \frac{2}{402^2 \bar{LQ_j}} \sum_i r_{ij} \left(LQ_{ij} - \bar{LQ_j} \right)$$

$$LQ_{ij} = \frac{\frac{R_{ij}}{\sum_j R_{ij}}}{\frac{\sum_i R_{ij}}{\sum_i \sum_j R_{ij}}}$$

where LQ_{ij} is a location quotient for region i in sector j, $\bar{LQ_j}$ the mean location quotient in sector j and r_{ij} the rank of county i with respect to location quotients in sector j.

Table 3: Sectoral production structure across 402 Germancounties.

	R_{ij}						V_{ij}/R_{ij}								
Sector	min	median	mean	max	$\sum R_{ij}$	$\sum V_{ij}$	min	median	mean	max	HHI	KS	Gini	MI	$R_{ij} > 0$
Agriculture	1	120	153	1026	61611	24900	0.40	0.40	0.40	0.40	0.005	1.02	0.52	0.42	402
Mininig	0	8	42	904	16761	7789	0.00	0.62	0.53	0.66	0.021	1.26	0.79	0.12	357
Food, Beverages, Tobacco	16	350	526	7491	211327	54305	0.07	0.28	0.29	0.58	0.006	0.53	0.36	0.25	402
Textiles, Leather	0	30	80	1021	32194	11117	0.00	0.35	0.35	0.71	0.009	0.96	0.64	0.27	400
Wood, Paper, Printing	6	164	276	3176	110812	34954	0.08	0.34	0.34	0.69	0.007	0.54	0.39	0.09	402
Petroleum, Coke	0	0	207	19559	83259	13817	0.00	0.00	0.07	0.50	0.092	1.53	0.94	0.05	120
Chemicals, Pharmaceuticals	2	349	804	24201	323250	129320	0.11	0.44	0.44	0.89	0.014	0.65	0.47	0.04	402
Non-Metallic Minerals	1	80	130	958	52261	19920	0.10	0.41	0.41	0.83	0.006	0.81	0.55	0.22	402
Metal	6	357	671	8594	269571	88873	0.08	0.35	0.35	0.72	0.008	0.72	0.43	0.35	402
Machinery, Electrical Equipment	18	613	1207	18825	485167	205554	0.11	0.45	0.45	0.91	0.009	0.51	0.38	0.25	402
Transport Equipment	0	213	1123	35187	451391	141551	0.00	0.36	0.36	0.73	0.029	0.98	0.68	0.07	396
Other Manufacturing	16	160	272	5882	109458	47557	0.11	0.47	0.48	0.97	0.009	0.52	0.38	0.14	402
Utilities	15	281	637	12429	256199	115320	0.05	0.46	0.44	0.48	0.011	0.56	0.40	0.09	402
Construction	84	588	766	9579	307845	136702	0.44	0.44	0.44	0.44	0.005	0.38	0.23	0.22	402
Trade, Communication, IT	280	1729	3211	73891	1291013	648894	0.50	0.50	0.50	0.50	0.011	0.25	0.17	0.20	402
Financial, Insurance, Business	370	1849	3418	66457	1373878	847507	0.62	0.62	0.62	0.62	0.012	0.25	0.15	0.20	402
Government, Education, Health	393	1597	2436	53477	979179	712082	0.73	0.73	0.73	0.73	0.008	0.30	0.20	0.18	402



(a) Agriculture (b) Metal (c) Transport Equipment

Figure 6: Shares of different industries in regional total production

location, that is, whether counties specialized in a sector are more closely located to similarly specialized counties (positive values) or further away (negative values).[27] With this measure "agriculture" and "metal" are reported as the most strongly agglomerated industries whereas "transport equipment" with its randomly spread production centers drops to the third last position.[28] Further important aspects, such as the clear and intuitive difference between cities and rural counties in the production of agricultural goods, can only be captured through individual observation or by using additional data.

Trade. To gain an overview over the derived interregional trade matrix I begin by looking at the strength of intra-industry trade, as measured by the Grubel-Lloyd (GL) index in figure 7.[29] The left hand panel shows the density distribution of Grubel-Lloyd indices across all

[27]Due to the lack of firm level data, more evolved distance based agglomeration measures such as the Duranton-Overman (Duranton and Overman 2005) index can not be derived here.

[28]Moran's I is calculated as:

$$MI = \frac{402}{\sum_i \sum_l w_{il}} \frac{\sum_i \sum_l w_{il} \left(s_{ij} - \bar{s}_j\right) \left(s_{lj} - \bar{s}_j\right)}{\sum_i \left(s_{ij} - \bar{s}_j\right)^2}$$

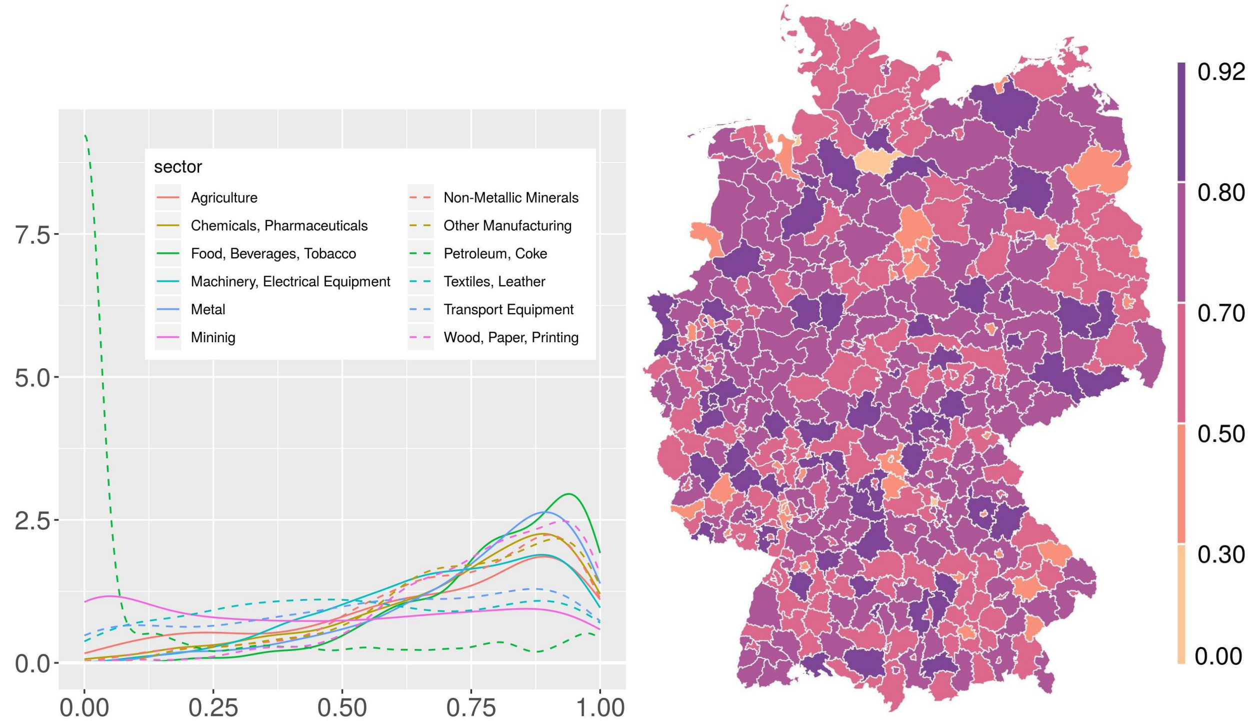
where $s_{ij} = R_{ij} / \sum_j R_{ij}$ is sector j's share in the total output of location i and w_{il} are elements of a 402 by 402 matrix that take the value 1 if counties i and l have a common border and 0 otherwise (or if $i = l$).

[29]The Grubel-Llyod index for an individual sector j in location i is calculated as

$$GL_{ij} = 1 - \frac{|Exports_{ij} - Imports_{ij}|}{Exports_{ij} + Imports_{ij}}$$

and for the aggregate economy of location i as

$$GL_i = 1 - \frac{\sum_j |Exports_{ij} - Imports_{ij}|}{\sum_j \left(Exports_{ij} + Imports_{ij}\right)}$$



(a) Density of sectoral GL-Indices

(b) Aggregate GL-Index

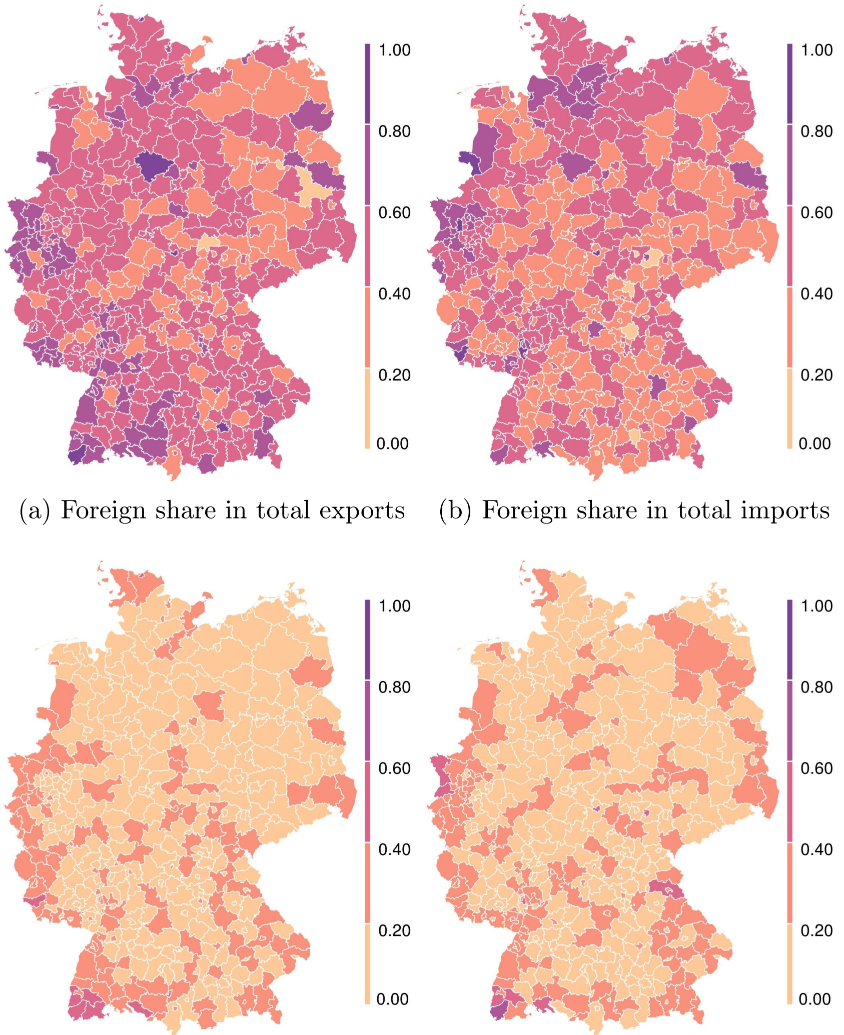
Figure 7: Intra-industry trade

402 German counties for the 12 manufacturing sectors for which trade data was derived.[30] Clearly, one way trade is exceptionally prominent in the "petroleum, coke" sector, which is inline with the previous result of a limited number of counties active in this industry. "mining", "textiles, leather" and "wood, paper, printing" include both counties with strong inter-industry and intra-industry trade whereas the remaining sectors have GL indices above 0.5 in most counties.

The GL index for aggregate trade in each location is depicted in the right hand panel of figure 7. It is above 0.5 for most counties indicating a strong prevalence of intra-industry trade for German counties. Some exceptions exists in and around the cities of Munich, Frankfurt and the largest VW producer Wolfsburg, as well as a handful of further counties.

Foreign trade plays a relatively large role for all counties in Germany. The top row of figure 8 depicts the share of foreign trade in each counties exports and imports respectively. Overall these values are very high, with maximum foreign shares of 0.91 for exports, 0.98 for imports and respective (unweighted) means of 0.5 and 0.44. Surprisingly, counties with higher foreign trade shares are not necessarily located closer to the border. One explanation for this is that a lot of trade occurs via international ports and water ways as witnessed by the high values in the north of Germany. To support this claim the bottom row depicts

[30] As noted, this figure, but also the remainder of this section refers only to trade in the agriculture, mining and manufacturing sectors 1-12 for which shipment data is available.



(a) Foreign share in total exports (b) Foreign share in total imports

(c) Foreign neigbors' share in total exports (d) Foreign neighbors' share in total imports

Figure 8: Foreign trade shares

the share of the nine neighboring countries of Germany in each county's total exports and imports respectively.[31] As these countries are a subset of all foreign countries the trade shares are obviously reduced. However, it is now clearly visible that being close to the border has a much larger influence on the trade share compared to trade with all foreign countries. Importantly, trade shares of northern counties that either host large international ports or are connected to them via waterways are strongly reduced, as this mode plays a reduced role in trade with immediate neighbors. The differences in these patters are a stark reminder for the necessity to better understand regional trade networks. The IRIOT developed in this paper captures such features and can hence help to understand for example the heterogeneity in effects of international trade agreements signed with different partners.

[31] These countries are Denmark, Belgium, the Netherlands, Luxembourg, France, Switzerland, Austria, the Czech Republic, and Poland.

Lastly, I estimate the effect of internal distance on sectoral trade flows through a gravity estimation. Specifically, trade is approximated by exporter and importer fixed effects as well as by a measure of physical distance between counties.[32] Hence, for imports of county n from sector j in location i I estimate

$$X_{n,ij} = \frac{Im_{nj} \cdot Ex_{ij}}{dist_{ni}^{\theta_j}} \ , \tag{1}$$

where Im_{nj} and Ex_{ij} denote importer-sector and exporter-sector specific effects, $dist_{ni}$ is the physical distance between two locations and θ_j the elasticity of trade flows with respect to distance.

Table 4: Sectoral gravity estimates

	OLS			PPML		
Sector	estimate	se	R^2	estimate	se	R^2
Agriculture	-1.90	0.01	0.53	-2.00	0.01	0.74
Mininig	-2.78	0.01	0.69	-2.87	0.02	0.91
Food, Beverages, Tobacco	-1.81	0.01	0.43	-1.62	0.01	0.66
Textiles, Leather	-1.24	0.01	0.54	-1.47	0.01	0.66
Wood, Paper, Printing	-1.49	0.01	0.49	-1.43	0.00	0.71
Petroleum, Coke	-2.46	0.04	0.73	-1.75	0.01	0.85
Chemicals, Pharmaceuticals	-1.64	0.01	0.48	-1.70	0.01	0.65
Non-Metallic Minerals	-2.15	0.01	0.58	-2.25	0.01	0.83
Metal	-1.43	0.01	0.44	-1.55	0.01	0.68
Machinery, Electrical Equipment	-1.43	0.01	0.48	-1.49	0.01	0.74
Transport Equipment	-1.29	0.01	0.65	-1.35	0.00	0.85
Other Manufacturing	-1.07	0.01	0.44	-1.24	0.01	0.68

The first three rows of table 4 report the results of a log-linear estimation of equation (1) including only intra-national trade. All results are highly significant and within in the range usually found in the literature for other countries. Interestingly, having accounted for exporter and importer fixed effects distance suffices to explain a large share of the observed variance in trade flows as witnessed by the relatively high R^2. The inclusion of the fixed effect implies that residuals must be driven by sector specific bilateral factors such as, for example, plants in two counties belonging to the same company. Turning to the actual estimates distance effects are strongest in “mining”, “petroleum, coke” and “non-metallic minerals” and weakest in “other manufacturing”, “textiles, leather” and “transport equipment”.

[32] Distance is often measured as the distance between the centroids of two counties. However, a particularity of German counties is that often an independent "city county" is surrounded by a roughly ring shaped county, implying centroids that fall very close together. To circumvent this problem I measure distance by drawing 100 random points in each county and calculating the mean of the resulting 10,000 pairwise distances between two counties. A further benefit of this procedure is that it can also be used to derive an internal distance for each county, which allows to include own trade flows in the gravity estimation.

As the OLS estimator is potentially biased under heteroscedasticity and due to the large number of zero-trade flows that have to be excluded when log-linearizing the gravity equation I re-estimate the model in multiplicative form using PPML (Santos Silva and Tenreyro (2006)). With the exception of the "petroleum, coke" sector with its particularly high number of zero trade flows this has only a limited effect on the estimated coefficients but the explanatory power of distance (and fixed effects) increases even further. This is strong support for my use of gravity estimation for trade flows in the remaining sectors.

4 The IRIOT

The approach to constructing the interregional input-output table in this paper is unique as it relies on intra-national trade flows that are usually unavailable in the construction of such tables. Using these trade flows I proceed in two steps.

First, for agriculture, mining and manufacturing sectors for which interregional trade flows were derived in the previous section I balance an IRIOT based on national input-output coefficients from the WIOD adapting them to the given trade flows. This process also leads to approximations of each county's demand, independent of origin, for "utilities", "construction" and service sectors.

Second, as no shipment data is available in the "utilities", "construction" and service sectors, I rely on a gravity model to estimate interregional trade flows based on county level demand and production, as well as physical distance between locations. Final input-output coefficients for each exporter importer pair in these sectors are derived employing a multidimensional extension of the RAS matrix balancing approach and constraining the result to all previously derived trade flows, demand and production levels.[33] Throughout I define $X_{nk,ij}$ as the flow from industry j in location i to use category k in location n, where the use category can be one of the 17 industries (where the flow is used as an intermediate input) or final demand.[34] Moreover, for ease of notation denote as $\Omega_g \equiv \{1, ..., 402\}$ the set of all German counties in the $N = 428$ total locations.

Flows $X_{nk,ij}$ in any sector and for any use between foreign countries, that is, for $i \notin \Omega_g$ and $n \notin \Omega_g$ are taken from the WIOD and remain unchanged.

[33] Holý and Safr (2017) have recently used such an extension in input-output analysis for the Czech-Republic albeit with viewer dimensions and constraints applied. Section A in the appendix explains the multidimensional extension of the RAS approach.

[34] This notation allows for an easy interpretation of all other variables which are simply the sum of these flows over the missing indices. For example, revenue R_{ij} is the sum of flows $X_{nk,ij}$ over n and k; trade flows $X_{n,ij}$ are the sum of flows $X_{nk,ij}$ over all use categories k and so forth.

4.1 Agriculture, Mining and Manufacturing

To match the previously derived total flows from sectors 1 through 12 between each German county and each foreign partner to the specific use category I apply the proportionality assumption that the use shares of these flows are constant for all exporting counties. They can then be immediately recovered from the WIOD as the use shares of German exports in each foreign country. Hence, for $j \in \{1, ..., 12\}$, $i \in \Omega_g$ and $n \notin \Omega_g$ flows are derived as $X_{nk,ij} = X_{n,ij} \cdot U^G_{nk,j}$, where $U^G_{nk,j}$ is the share of total German exports of sector j to foreign importer n used in category k.

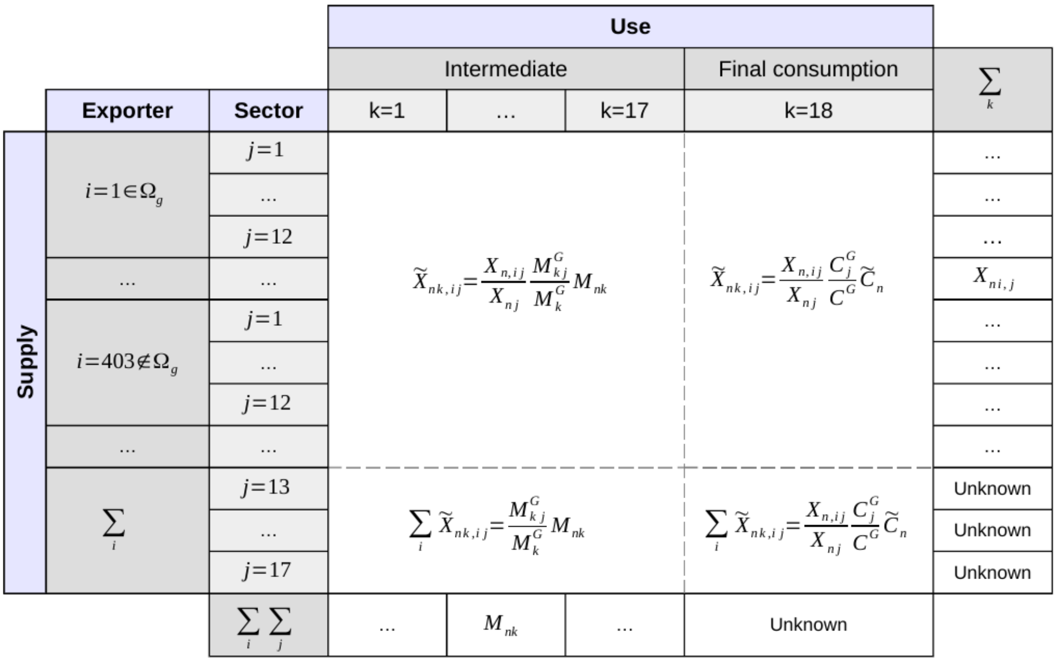


Figure 9: Matrix slice of initial RAS array for any importer $n \in \Omega_g$

For any flow in agriculture, mining or manufacturing where a German county is the importer I derive flows to different use categories through a multidimensional extension of the RAS method.[35] Specifically, for each importer $n \in \Omega_g$ I consider a matrix as shown in figure 9. For exporting sectors $j \in \{1, ..., 12\}$ the matrix depicts detailed flows from exporter to importer by use category. For the remaining 5 sectors for which no trade data exists the aggregate imports (from all potential exporters) in county n and use category k are displayed in the last 5 rows. All initial flows $\tilde{X}_{nk,ij}$ are constructed as follows:

Firstly, I use residential income data from the regional statistical offices to derive an initial estimate of aggregate consumption demand $\tilde{C}_n$ in each county $n \in \Omega_g$ by distributing the WIOD German national demand across counties based on their share in national income.

Secondly, I split these consumption demands and the previously derived total intermediate

[35]For the multidimensional extension of the RAS method see section A in the appendix.

demand M_{nk} of each sector in each county across different industries based on the proportionality assumption that national shares, that is, the size of industry j in the total intermediate demand of sector k $\left(M^G_{jk}/M^G_k\right)$ or in consumption $\left(C^G_j/C^G\right)$, hold at the county level. In sectors for which trade data exists the demand for sector j intermediate or consumption goods in each use category k in county n is then split across potential exporters i based on their share in the total imports of sector j goods by county n (i.e. $X_{ni,j}/X_{nj}$). This last step shows the great advantage of having shipment data available and is what allows to construct a data based interregional instead of just regional input output database.

Having constructed initial flows the final step applies a multidimensional RAS balancing algorithm to the array keeping its structure as close to the initial values as possible while satisfying all previously derived margins. In particular these constraints can be expressed as the following conditions:

1. For sectors $j \in \{1, ..., 12\}$ summing flows across all use categories k for a specific importer n and exporter i must equal total trade flows from i to n in sector j as derived from the shipment data, i.e. $\sum_k X_{nk,ij} = X_{n,ij}$ for $j \in \{1, ..., 12\}$.
2. For the remaining sectors $j \in \{13, ..., 17\}$ further summing the already aggregated flows in the matrix across all use categories and importing counties must result in the total national demand for goods from sector j as reported by the WIOD.[36]
3. Summing flows across all exporters i and sectors j for a fixed importer and use category $k \in \{1, ..., 17\}$ must result in the previously calculated aggregate intermediate demand levels, i.e. $\sum_i \sum_j X_{nk,ij} = M_{nk}$.
4. For a given foreign exporter $i \notin \Omega_g$, sector j, and use category k summing flows across all importers $n \in \Omega_g$ must be equal to the international flows from sector j in country i to use category k in Germany as reported by the WIOD.
5. Finally, summing flows across all importing counties and all exporters for a specific sector j and use category k gives the use of intermediate j in the national German use category k as reported by the WIOD.

In the "petroleum, coke" sector and a few further instances almost exclusively in the sector "mining" matching the derived trade flows (as imposed by the first constraint) and observed use structure (as imposed by the last three constraints) simultaneously is not possible. Specifically, from the WIOD more than 50% of the intermediate inputs of the national "petroleum, coke" sector come from the "mining" sector which includes crude oil. However, there are

[36]For sectors $j \in \{1, ..., 12\}$ the first condition already ensures that summing across all use categories k and importers n equals the total national demand for sector j goods from i.

only a few counties that are important producers of refined petroleum and coke and even if all flows of mining goods in the shipment data to these locations were attributed as inputs to the petroleum industry the national share in inputs of over 50% could not be achieved. Similarly, the national usage of "petroleum, coke" sector goods as inputs in the same industry can also not be matched given the shipment data. The reason for this is that the shipment data unfortunately do not contain pipeline transports which are the major mode of transport for both crude oil and petroleum. To solve this problem the first condition is not enforced in sector 6 and in some international flows, mainly in sector 2, representing for example German imports of Russian crude oil and gas. In these cases trade flows $X_{n,ij}$ are allowed to adapt during matrix balancing as long as the observed aggregate flows to Germany $\sum_{n \in \Omega_g} X_{n,ij}$ remain constant (cf. footnote 36).

It is also important to note, that the third condition is only binding for use categories $k \in \{1, ..., 17\}$. Hence, aggregate consumption in each county is allowed to change from the initial value estimated through income shares. The reason for this is twofold. Firstly, as there is substantial mobility of consumers and commuting at the county level (see Krebs and Pflüger (2018)) residential household income can only be an imperfect estimate of the actual final demand of goods in each county. Secondly, the use of shipment data comes with the great benefit that not only total intermediate demand in each county is directly derived from the data but, importantly, also the supply of goods from sectors 1 through 12 to each county. Therefore, if, for example total intermediate demand is small but the value of shipments to the specific location is relatively large the county must either use and consume less than the national average from sectors 13 through 17 or aggregate consumption must be higher. Making use of this the balancing procedure is allowed to adapt values along both margins.

4.2 Utilities, Construction and Services

Gravity. In the remaining five sectors only country level trade data is available from the WIOD but no county level trade data.[37] For these sectors I rely on a gravity approach to establish county level trade flows. Specifically, for $n \in \Omega_g$ and/or $i \in \Omega_g$ trade flows from location i to location n in sector j are expressed as

$$X_{n,ij} = \frac{Im_{nj} \cdot Ex_{ij}}{d_{ni,j}} \;, \tag{2}$$

where Im_{nj} and Ex_{ij} denote importer sector and exporter sector specific effects and d_{nij} is a sector specific trade barrier for flows from location i to location n. As I only need to derive trade flows where either the importer or the exporter is a German county, the exporter

[37] As explained above transport data on "secondary raw materials; municipal wastes and other wastes" is available but only makes up for a small share in the sector "utilities" and is therefore not used here.

fixed effects and importer fixed effects of foreign countries comprise any international border effects, such as having a common currency or language. As a consequence and as in the previous section I apply the common assumption that trade barriers are a log linear function of the distance between locations, i.e. $d_{ni,j} = dist_{ni}^{\theta_j}$. The parameter values θ_j are taken from Anderson et al. (2016) who are among the view that derive the effects of interregional distance on service trade.[38] Their values, which are mostly in the range of 0.91 to 1.38, are however similar to distance coefficients derived for international service trade and aggregate trade flows in the literature.

To derive the levels of exporter and importer fixed effects I can rely on the previously calculated county level sectoral revenue and demand data. Denoting location n's total demand, i.e. the sum of intermediate and final demand, for sector j goods as D_{nj} and its total demand for sector j goods produced in any country in Germany as D_{nj}^G it must hold that $\sum_i X_{n,ij} = D_{nj}$ for all $n \in \Omega_g$ and $\sum_{i\in\Omega_g} X_{n,ij} = D_{nj}^G$ for all $n \notin \Omega_g$. Plugging equation 2 into these constraints allows to solve for importer fixed effects as

$$Im_{nj} = \frac{D_{nj}}{\sum_i Ex_{ij} dist_{ni}^{-\theta_j}} \quad \forall n \in \Omega_g \tag{3}$$

$$Im_{nj} = \frac{D_{nj}^G}{\sum_{i\in\Omega_g} Ex_{ij} dist_{ni}^{-\theta_j}} \quad \forall n \notin \Omega_g \tag{4}$$

Similarly summing a specific exporter's sectoral trade flows across all importers (including the exporter itself) yields the exporter's sectoral revenue, i.e. $\sum_n X_{n,ij} = R_{ij}$, and summing across all German importer's gives the location's total exports to Germany, i.e. $\sum_{n\in\Omega_g} X_{n,ij} = X_{ij}^G$. Plugging the gravity equation 2 and the derived importer fixed effects into these constraints allows to derive exporter fixed effects as

$$Ex_{ij} = \frac{R_{ij}}{\sum_n Im_{nj} dist_{ni}^{-theta_j}} = \frac{R_{ij}}{\sum_{n\in\Omega_g} \frac{D_{nj} dist_{ni}^{-theta_j}}{\sum_l Ex_{lj} dist_{nl}^{-theta_j}} + \sum_{n\notin\Omega_g} \frac{D_{nj}^G dist_{ni}^{-theta_j}}{\sum_{l\in\Omega_g} Ex_{lj} dist_{nl}^{-theta_j}}} \quad \forall i \in \Omega_g \tag{5}$$

$$Ex_{ij} = \frac{X_{ij}^G}{\sum_n Im_{nj} dist_{ni}^{-theta_j}} = \frac{X_{ij}^G}{\sum_{n\in\Omega_g} \frac{D_{nj} dist_{ni}^{-theta_j}}{\sum_l Ex_{lj} dist_{nl}^{-theta_j}}} \quad \forall i \notin \Omega_g \tag{6}$$

Normalizing one location's exporter fixed effect to 1 in each sector allows to numerically solve this system for all remaining exporter and subsequently importer fixed effects.

Finally, plugging fixed effects and my parameterization of trade costs into the gravity equa-

[38] I use the aggregate service sector coefficient for sectors 13 and 14, the unweighted average of their transport, wholesale, accommodation and communication sectors for sector 15, of finance and business for sector 16 and of education and health for sector 17.

tion 2 allows to calculate all bilateral trade flows $X_{n,ij}$ in sectors $j \in \{13, ..., 17\}$.

Input-Output structure. Having estimated all bilateral trade flows I can assign them to use categories using a similar approach as for manufacturing sectors above. Specifically, as before, trade flows from German counties to foreign countries are distributed across use categories in the foreign country using the proportionality assumption together with use shares from the WIOD.

For all flows in sectors 13 through 17 where a German county is the importer I construct a set of initial flows $\tilde{X}_{nk,ij}$ by also imposing the proportionality assumption that counties have equal use shares for imports independent of the source. Of course, this implies that aggregate sectoral flows from foreign countries to all German counties ($X^G_{k,ij}$) will not (necessarily) match the values given in the WIOD. To ensure that these flows are replicated while keeping constant the total demand for each service sector in each county I rely on a final RAS balancing step imposing $\sum_{n \in \Omega_g} X_{nk,ij} = X^G_{k,ij}$ for all $i \notin \Omega_g$ and $\sum_i X_{nk,ij} = M_{nk,j}$ for all i.

4.3 The final IRIOT

Combining the derived data for all sectors results in the final input-output table for 402 German counties and 26 foreign countries, including ROW, across 17 sectors and 18 use categories. Summing values across all German counties leads to a matrix with 27 countries that exactly replicates all flows as given in the WIOD. In all German counties sectoral revenues, value added and, consequently intermediate demand equal the values reported by the regional statistical offices.[39] interregional trade flows, and international trade flows with German counties in agriculture, mining and manufacturing sectors match the export shares implied by shipment data in weights, with some exceptions in the petroleum and mining sector that are necessary to replicated the national input-output structure from the WIOD. Regional consumption spending is based on residential household income as reported by the regional statistical offices and adjusted using a compromise between keeping sectoral intermediate good spending shares on services constant across locations and accounting for the observed trade imbalances in agriculture, mining and manufacturing sectors. Trade in the the remaining sectors is represented by flows derived from a gravity equation with slight adjustments necessary to match the national input-output structure given by the WIOD.

This table can be used both for on impact analysis as well as to calibrate regional CGE models capturing the vast heterogeneity across regions within Germany. All code necessary

[39] Up to a scaling factor that matches national aggregates to the values given in the WIOD.

to construct the final IRIOT is available from the author upon request.[40]

5 Conclusion

This paper analysed the trade and production structure across German counties based on a unique data set of county level shipments in Germany and between German counties and foreign partners. The heterogeneity across locations is vast along a wide variety of agglomeration, specialization and trade indices and measures. For this reason it is important to account for the complicated network when analyzing the effects of international shocks on Germany. Similarly, the effects of regional shocks both on other locations and within the treated counties must also be analyzed in the context of this network. To this end I adapt several recent methods in the construction of input-output tables to the specific data availability in Germany and show how to use the shipment data to construct a county level IRIOT for Germany. Keeping the national aggregates of this table cell-by-cell compatible with the WIOD allows to embed foreign trade into the table and to provide a fully specified input-output table for the world economy that can serve as the basis for CGE based and impact analysis.

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[40] The underlying shipment data can be obtained from http://daten.clearingstelle-verkehr.de

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Appendix:
RIOTs in Germany - Constructing an interregional input-output table for Germany

A Multidimensional RAS

As explained for the revenue matrix in the main text, the simple RAS approach takes an $I \times J$ matrix $\tilde{A}$ with elements $\tilde{A}_{ij}$ and transforms it into a matrix A with elements A_{ij} that satisfies given margin constraints, that is, constraints for all row and column sums. The process consists of a simple iterative scaling of rows and columns. Specifically, given target row sums T_i^I for each row i the first step of the algorithm scales each row by a factor $T_i^I / \left(\sum_j \tilde{A}_{ij}\right)$ to obtain new values $\tilde{A}_{ij}^{t=1}$. In the second step, given the target column sums T_j^J each column is scaled by a factor $T_j^J / \left(\sum_i \tilde{A}_{ij}^{t=1}\right)$ resulting in new estimates $\tilde{A}_{ij}^{t=2}$. These two steps are repeated until the actual margin sums match the targets up to a given precision.

Importantly, one can also apply the RAS approach partially, that is, without a full set of row sum and column sum constraints. In this case the unconstrained rows and columns are simply left unscaled in the appropriate steps.[41]

The multidimensional procedure applies the same process of iterative scaling of margins to meet given constraints but for a multidimensional array. As an example, consider a three dimensional extension of the matrix $\tilde{A}$ to an $I \times J \times K$ array with elements $\tilde{A}_{ijk}$. Given a target sum T_i^I for margin I, that is, imposing $\sum_j \sum_k A_{ijk} = T_i^I$, the algorithm scales each matrix slice i by $T_i^I / \left(\sum_j \sum_k A_{ijk}\right)$ and equivalently for margins J and K. Repeating these scaling steps iteratively again leads to an array A that matches the target sums up to a given precision.

In contrast to the simple RAS approach, constraints in the multidimensional case can also be applied to combination of margins. To see this, consider again the three dimensional $I \times J \times K$ array $\tilde{A}$. This time, however, we are interested in a target array A that satisfies the two constraints $\sum_i A_{ijk} = T_{jk}^{JK}$ and $\sum_j A_{ijk} = T_{ik}^{IK}$ where T^{JK} and T^{IK} are matrices of size $I \times K$ and $J \times K$ respectively. Similar to the above we begin by scaling all elements of the array $\tilde{A}$ for a fixed j and k with a factor $T_{jk}^{JK} / (\sum_i A_{ijk})$. Cycling through all combinations of j and k we gain new array elements $\tilde{A}_{ijk}^{t=1}$. In the second step all elements of the new array $\tilde{A}^{t=1}$ for a fixed i and k are scaled by the factor $T_{ik}^{IK} / \left(\sum_j A_{ijk}\right)$. Again cycling through all combinations of i and k we obtain the new array elements $\tilde{A}_{ijk}^{t=2}$. As before, these two steps are repeated until the target margins are met up to a given precision.

Importantly, any combination of such margin constraints can be imposed upon the initial estimate $\tilde{A}$ and, again, any number of elements of each margin can be left unconstrained by simply skipping the appropriate scaling step.

[41] Leaving, for example, row i unconstrained does not mean that values in this row remain unchanged, as elements A_{ij} are still affected from column scaling. However, the size of the sum of all elements in row i is allowed to change freely.

Figure 9 in the main text presents one matrix slice of an initial array with the appropriate margin constraints. The full set of constraints in this case is given in the list in section 4.1.

B Initial WIOD preparation

As explained in the main text, I use the world input output database (WIOD) as my main data source for the national production structure and international trade flows aggregating its content to the 17 industries and 27 countries listed in tables 1 and 2.[42] The WIOD includes inventory changes as a final use category and these can sometimes be of a substantial magnitude and also, of course, negative. If I were to calculate final demand by simply summing over consumption, investment, government spending and inventory changes given in the WIOD I would end up with a negative final demand in some cases. Therefore, I directly include positive inventory changes in final demand but treat negative inventory changes as if they had been produced (and consumed) in the current period. To correctly capture all the intermediate products that would have been necessary to produce this additional output I construct a Leontief-inverse from the WIOD's input-output table which captures the intermediate requirements of final goods production. I then recalculate total production with final demand increased by the negative inventory changes and use the resulting input-output table to calibrate my model. The details of this process are laid out in Krebs and Pflüger (2018).

[42]The matching of the 56 sectors in the WIOD to these 17 industries is shown in table C.1 in the appendix.

C Industry Correspondence

	County level data (WZ08)		Shipment data (NST07)		WIOD		This paper
01	Crop and animal production, hunting and related service activities	10	Products of agriculture, hunting, and forestry; fish and other fishing products	1	Crop and animal production, hunting and related service activities	1	Agriculture
02	Forestry and logging			2	Forestry and logging		
03	Fishing and aquaculture			3	Fishing and aquaculture		
05	Mining of coal and lignite	21	Coal	4	Mining and quarrying	2	Mining
		22	Lignite				
06	Extraction of crude petroleum and natural gas	23	Crude petroleum and natural gas				
07	Mining of metal ores	31	Metal ores				
08	Other mining and quarrying	32	Fertilizers				
		33	Stones and earth, other mining products				
09	Mining support service activities						
10	Manufacture of food products	40	Food products, beverages and tobacco	5	Manufacture of food products, beverages and tobacco products	3	Food, Beverages, Tobacco
11	Manufacture of beverages						
12	Manufacture of tobacco products						
13	Manufacture of textiles	50	Textiles and textile products; leather and leather products	6	Manufacture of textiles, wearing apparel and leather products	4	Textiles, Leather
14	Manufacture of wearing apparel						
15	Manufacture of leather and related products						

16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	60	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials; pulp, paper and paper products; printed matter and recorded media	7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	5	Wood, Paper, Printing
17	Manufacture of paper and paper products			8	Manufacture of paper and paper products		
18	Printing and reproduction of recorded media			9	Printing and reproduction of recorded media		
19	Manufacture of coke and refined petroleum products	71	Coke	10	Manufacture of coke and refined petroleum products	6	Petroleum, Coke
		72	Refined Petroleum				
20	Manufacture of chemicals and chemical products	80	Chemicals, chemical products, and man-made fibers; rubber and plastic products ; nuclear fuel	11	Manufacture of chemicals and chemical products	7	Chemicals, Pharmaceuticals
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations			12	Manufacture of basic pharmaceutical products and pharmaceutical preparations		
22	Manufacture of rubber and plastic products			13	Manufacture of rubber and plastic products		
23	Manufacture of other non-metallic mineral products	90	Other non metallic mineral products	14	Manufacture of other non-metallic mineral products	8	Non-Metallic Minerals
24	Manufacture of basic metals	100	Basic metals; fabricated metal products, except machinery and equipment	15	Manufacture of basic metals	9	Metal
25	Manufacture of fabricated metal products, except machinery and equipment			16	Manufacture of fabricated metal products, except machinery and equipment		

26	Manufacture of computer, electronic and optical products	110	Machinery and equipment n.e.c.; office machinery and computers; electrical machinery and apparatus n.e.c.; radio, television and communication equipment and apparatus; medical, precision and optical instruments; watches and clocks	17	Manufacture of computer, electronic and optical products	10	Machinery, Electrical Equipment
27	Manufacture of electrical equipment			18	Manufacture of electrical equipment		
28	Manufacture of machinery and equipment n.e.c.			19	Manufacture of machinery and equipment n.e.c.		
29	Manufacture of motor vehicles, trailers and semi-trailers	120	Transport Equipment	20	Manufacture of motor vehicles, trailers and semi-trailers	11	Transport Equipment
30	Manufacture of other transport equipment			21	Manufacture of other transport equipment		
31	Manufacture of furniture	130	Furniture; other manufactured goods n.e.c.	22	Manufacture of furniture; other manufacturing	12	Other Manufacturing
32	Other manufacturing						
33	Repair and installation of machinery and equipment			23	Repair and installation of machinery and equipment		
35	Electricity, gas, steam and air conditioning supply	140	Secondary raw materials; municipal wastes and other wastes	24	Electricity, gas, steam and air conditioning supply	13	Utilities
36	Water collection, treatment and supply			25	Water collection, treatment and supply		
37	Sewerage			26	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services		
38	Waste collection, treatment and disposal activities; materials recovery						
39	Remediation activities and other waste management services						

F	Construction	27	Construction	14	Construction
G-J	Trade, transportation, storage, accommodation and food service activities, information and communication.	28	Wholesale and retail trade and repair of motor vehicles and motorcycles	15	Trade, Communication, IT
		29	Wholesale trade, except of motor vehicles and motorcycles		
		30	Retail trade, except of motor vehicles and motorcycles		
		31	Land transport and transport via pipelines		
		32	Water transport		
		33	Air transport		
		34	Warehousing and support activities for transportation		
		35	Postal and courier activities		
		36	Accommodation and food service activities		
		37	Publishing activities		
		38	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities		
		39	Telecommunications		
		40	Computer programming, consultancy and related activities; information service activities		
K-N	Financial, insurance, business, real estate activities	41	Financial service activities, except insurance and pension funding	16	Financial, Insurance, Business

		42	Insurance, reinsurance and pension funding, except compulsory social security		
		43	Activities auxiliary to financial services and insurance activities		
		44	Real estate activities		
		45	Legal and accounting activities; activities of head offices; management consultancy activities		
		46	Architectural and engineering activities; technical testing and analysis		
		47	Scientific research and development		
		48	Advertising and market research		
		49	Other professional, scientific and technical activities; veterinary activities		
		50	Administrative and support service activities		
O-T	Public and other services, education, health, private households	51	Public administration and defense; compulsory social security	17	Government, Education, Health
		52	Education		
		53	Human health and social work activities		
		54	Other service activities		
		55	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		
		56	Activities of extraterritorial organizations and bodies		

Table C.1: Industry correspondence

Essay III

On the Road (Again) Commuting and Local Employment Elasticities in Germany

On the Road (Again): Commuting and Local Employment Elasticities in Germany*

Oliver Krebs[†] Michael Pflüger[‡]

October 28, 2018

Abstract

This paper uses a quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting to address how local labor markets in Germany respond to labor demand shocks. Our particular focus are the local employment elasticities, that is, the response of local employment to these shocks. We find that the network of local German labor markets functions much smoother than what is typically presumed. The local employment elasticities in response to local productivity shocks turn out to be significantly larger than what is reported for the United States. The expenditure share devoted to housing turns out to have a striking effect on the size and heterogeneity of the elasticities but also on their predictors.

JEL-Classification: F12, F14, R13, R23

Keywords: Quantitative spatial analysis, commuting, migration, employment and resident elasticities

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1 Introduction

What once fired the imaginations of Jack Kerouac, the Canned Heat and Willie Nelson has become dreary reality for zillions of workers today, albeit in an altogether different vein. The world is on the road (again). Workers spend substantial and increasing shares of their time and budget on traveling from residences to workplaces.[1] In economies prone to shocks, workers have to balance where to live and where to work. The functioning of local labor markets is strongly affected by commuting. This issue is of paramount importance for local and national policymakers who have to decide on infrastructure investments, (local) taxes and subsidies.

The purpose of this paper is to shed light on the spatial fabrics and interactions of local labor markets in Germany, a particularly exciting scientific laboratory for a number of reasons. Improvements in its transport infrastructure appear desperately needed, a subject of heated political and public debate. Branded the 'Teflon Teuton', the strongest economy in Europe for the last couple of years, faces potholed roads, rotten bridges and repair-prone railway tracks (The Economist 2017). Moreover, Germany appears extremely interesting from the point of view of economic research because of its high population density (226 people/km2) compared to the United States (33 people/km2). This stark difference strongly feeds into commuting patterns and the functioning of the network of local labor markets. Indeed, our descriptive analysis shows that Germany's average propensity to commute is about twice the number reported by Monte et al. (2018) for the United States. It should also be pointed out that exceptionally good data are available for Germany. A special mention must be made of the traffic forecast administered by the German Federal Ministry of Transport and Digital Infrastructure. Rather than having to rely on imputations based on a proportionality between trade and the local labor force or local value added, this data allows us to obtain a detailed portrait of bilateral trade of manufactures between German counties. This is not only a big asset for the calibration of our model but also for the quality of the results of the model inversion which we perform to back out model consistent local productivities and bilateral trade costs and for our counterfactual analyses.

We use the quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting due to Monte et al. (2018) to address how local labor markets in Germany respond to labor demand shocks. We ask three sets of questions.

[1] Estimates of these costs put the mean round-trip at about 40 minutes and the mean household expenditure share devoted to transportation at 14.6% for a cross-section of advanced economies in recent years (Redding and Turner 2015). A seminal study which has taken the network of local labor markets in the United States under scrutiny documents the increasing prevalence and heterogeneity of commuting streams. Whilst in 1960 the median US county had 91% of its residents working where they lived this number is down to only 69% in 2000. There are now counties whose workforce consists of more than 80% commuters and still others where about the same share of residents flock to work elsewhere (Monte et al. 2018).

First, is commuting an important adjustment mechanism for German local labor markets and if so, how does its role compare to the findings for the United States? Second, what are the determinants of the general equilibrium employment elasticities? Are good ex ante observable variables (statistics) available to explain these general equilibrium responses? Finally, how are the results affected by the share of income that is spend on land (housing) in the economy?

Regarding the first question, we find that commuting activity between counties is very strong in Germany and even stronger than in the United States, as becomes visible from descriptive statistics, already.[2] In our baseline scenario we find that the responses of German local labor markets to a local productivity shock (a 5% increase in local productivity) are very heterogeneous and that commuting plays an important role for this heterogeneity. At the level of counties, the bulk of local employment elasticities are in a range from 1.25 to 2.25 and local resident elasticities are in a main range from 0.25 to 1. These findings are significantly larger than the results reported for the USA. Apparently, largely due to commuting, German workers respond very flexible to local shocks and German local labor markets function much smoother than typically presumed.

With respect to the second question, for our baseline scenario, a locations' own commuting share (i.e. the share of residents working at their residence) turns out to be a powerful inverse indicator for the general equilibrium employment elasticities. Furthermore, model-based partial equilibrium elasticities which are related to commuting perform similarly strong. Both model-based commuting indicators outperform standard labor market controls (for example wages, employment, housing) by far. These findings largely carry over when we look at commuting zones rather than administrative counties, except that the numbers are lower.

Answering the third question, our baseline scenario assumes that the share of income spend on land is 40% as in Monte et al. (2018) and in line with Moretti (2011). There are strong arguments that suggest that this number is far too high, from an economy-wide perspective, as we will explain in detail below. If a more plausible share of 10% is used instead, the local employment elasticities are much higher, they range from 2 to 4 and the residence elasticities are in a main range from 0.5 to 2. Importantly, commuting is still a very powerful adjustment mechanism for local labor markets. Intuitively, with the diminished congestion force associated with a lower economy-wide expenditure share on land (housing) more workers chose to migrate (i.e. change residences) instead of commute, however. Another key finding is that the overall explanatory power of the model-based commuting measures is now strongly

[2] We acknowledge that there is an issue of comparability between German counties and counties in the United States. Moreover, the same holds true even within Germany and the United States as there is much stronger commuting activity within big cities which are classified as counties (e.g. within Berlin in Germany) than in more rural counties. For these reasons we do not want to overstretch the mentioned findings.

diminished. This can be rationalized by pointing out that simple (partial equilibrium based) measures miss to capture the general equilibrium repercussions that become stronger as the congestion force in the model is weaker.

Our paper is related to various strands of previous research. The theoretical literature that addresses the separation of the location of production from the location of residences is sparse. One exception is Borck et al. (2010) who set up a simple new economic geography model with two locations, costly goods trade and commuting costs, which exhibits pecuniary externalities as agglomeration forces and crowding in goods markets and congestion in housing markets as dispersion forces. The analysis predicts that a simultaneous fall in both distance-related frictions leads to an increased spatial concentration of production and a decreased concentration of residences. Hence, even in this simple setting, an increasing role for commuting is predicted. However, the model is too stylized to derive quantitative numbers.

Quantification has become the focus of an important recent research line that incorporates an arbitrary number of locations with heterogeneous geography, productivities, amenities, and local factors, as well as trade and commuting costs into the models. This new quantitative spatial economics builds on the new economic geography (or isomorphic models) and derives its thrust from restraining the agglomeration forces so that multiple equilibria are no longer an issue. The payoff is that combining, measuring and quantifying theoretical mechanisms and identifying key structural parameters becomes possible and that counterfactuals can be meaningfully addressed as outlined in the recent survey by Redding and Rossi-Hansberg (2017). A milestone in this research is the model developed by Redding (2016) which integrates the regional model of Helpman (1998) with various trade models, such as the Armington model (Anderson 1979; Anderson and Van Wincoop 2003), the monopolistic competition model with homogeneous firms (Krugman 1980; Helpman and Krugman 1985), or heterogeneous firms (Melitz 2003) and the multi-region Ricardo model (Eaton and Kortum 2002).

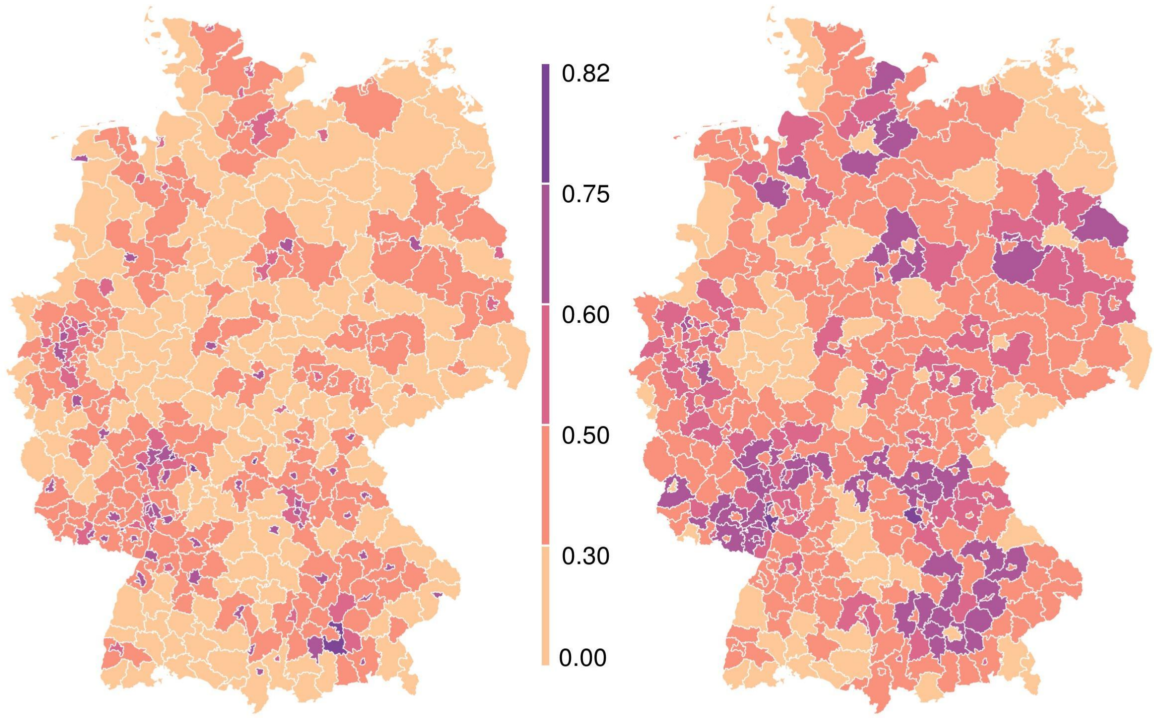
Our analysis is most closely related to the framework developed in Monte et al. (2018), who extend the model developed by Redding (2016) to include commuting, and who perform a quantitative analysis of local labor market shocks for the United States.

The structure of the remainder of the paper is as follows. Section 2 provides a descriptive analysis of German local labor markets. Section 3 introduces the model. Section 4 discusses our data and the quantification of the model with German data. Section 5 presents and discusses the findings of our quantitative analysis for the network of German local labor markets. Section 6 summarizes our conclusions.

2 Descriptive analysis

A key difference of the Germany economy as compared to the United States is its much higher propensity to commute. This fact holds both if we look at administrative local labor markets as exemplified by Germany's 402 administrative counties (Kreisfreie Städte and Landkreise) or at the 141 commuting zones in Germany which are aggregated up from the 402 counties (Kosfeld and Werner 2012; Eckey et al. 2006).

To give a perspective on German local labor markets, figure 1 starts by showing the share of total workers that commute to work in German counties in the left panel and the share of residents that commute to other workplaces in the right panel. The counties with the largest shares of inflows in workers are Schweinfurt (city), Munich (county) and Aschaffenburg, with the largest shares of outflows in workers Ludwigshafen (county), Fürth (county) and Schweinfurt (county).[3]



(a) commuter share in total workers (b) commuter share in total residents

Figure 1: Share of total workers who commute into counties (panel a) and share of residents who commute out of counties. See section 4 for the data source.

Comparing the two maps immediately reveals that the intensity of outflows exceeds the intensity of inflows.[4] To bring out this point more clearly and to have a basis for a first

[3]The largest nominal inflows can be found in Frankfurt, Munich, Hamburg and Berlin, the largest nominal outflows in Berlin, Munich, Rhein-Sieg-Kreis and Rhein-Neckar-Kreis.

[4]Repeating this exercise for the 141 German commuting zones almost halves the numbers, but leaves the general pattern documented in figure 1 intact.

casual comparison with the United States, table 1 documents statistics (unweighted) for the distribution of commuters. It can be seen that, on average, 43% of the counties' residents work at other locations and that 39% of the total workers commute into the counties to work, in Germany. These numbers are almost double compared to what Monte et al. (2018) find for the 3111 counties in the United States. Interestingly, the maximum percentage both in Germany and the United States is almost identical at 81% to 82%. The difference between the average values found for Germany and the United States arises from the fact that the minimum percentage values for Germany are at 14% and 11% for outflows and inflows, respectively whereas they are nil for the United States and that, at the lower percentiles more generally, the percentage values for Germany are much higher than for the United States as documented in Monte et al. (2018). This statement carries over when we look at commuting zones (lower panel in table 1) qualitatively. Quantitatively, as we would expect, the numbers are much lower: it turns out that they are less than half when commuting zones rather than administrative boundaries are used (Monte et al. 2018, cf.). Table 1 also provides the ratio between workers and residents at various percentiles. As one would expect from the very construction of commuting zones, the comparison of the number for counties with the numbers for commuting zones reveals that the latter are very much stronger centered around 1.

	min	p5	p10	p25	p50	p75	p90	p95	max	mean
					County Level (Kreise)					
Commuter outflow / residents	0.14	0.22	0.26	0.33	0.42	0.53	0.64	0.68	0.81	0.43
Commuter inflow / workers	0.11	0.18	0.21	0.26	0.35	0.49	0.64	0.69	0.82	0.39
workers / residents	0.39	0.59	0.66	0.76	0.87	1.08	1.53	1.77	3.38	0.99
					Commuting Zones					
Commuter outflow / residents	0.09	0.14	0.15	0.19	0.23	0.31	0.35	0.43	0.60	0.25
Commuter inflow / workers	0.09	0.13	0.14	0.16	0.20	0.25	0.30	0.33	0.42	0.21
workers / residents	0.63	0.77	0.83	0.88	0.95	1.01	1.06	1.09	1.22	0.94

Table 1: Unweighted commuting flows in and out of the 412 German counties and its 141 commuting zones. See section 4 for the data source.

The message conveyed by table 1 is reinforced by the kernel densities of the share of non-commuters in residents depicted in figure 2. This figure reveals that the peak of the distribution is at a share of non-commuters in residents of slightly more than 60% which is in comparable range to what has been established for the United States (Monte et al. 2018, see).

A further piece of evidence are the Grubel-Lloyd indices for two-way commuting in and

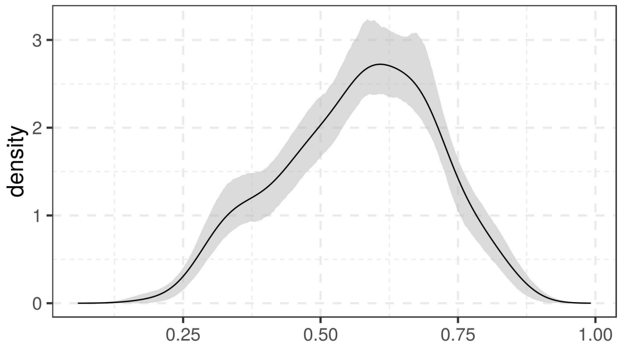
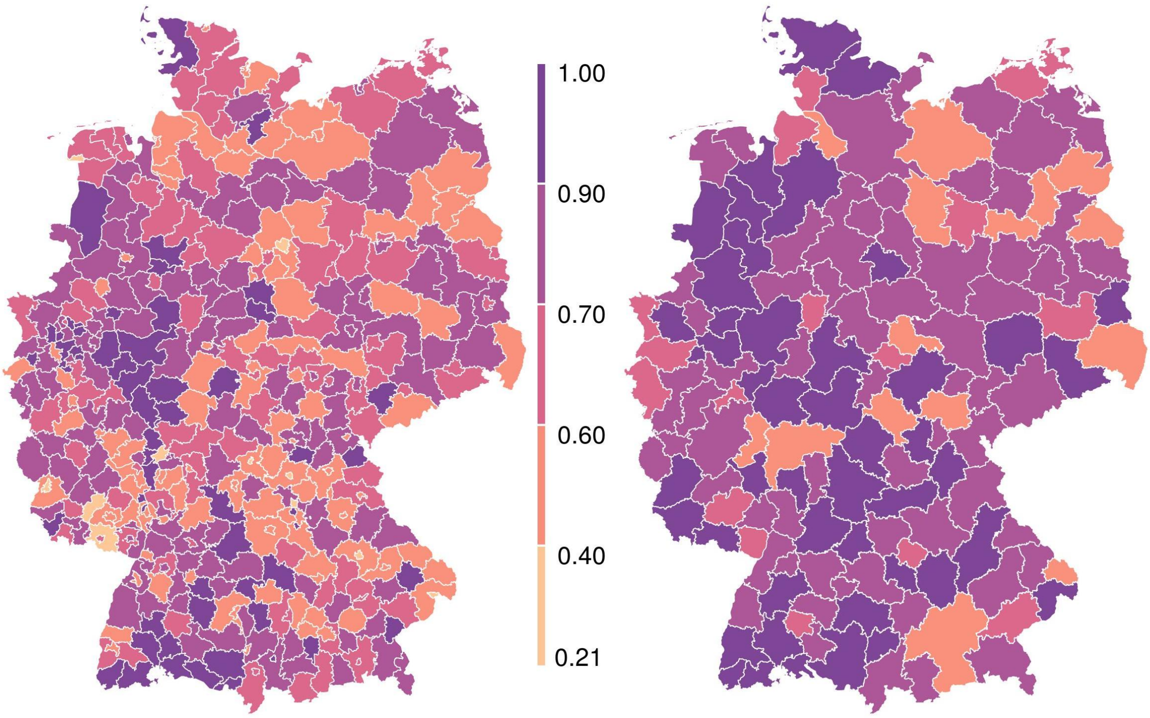


Figure 2: Kernel densities for the share of non-commuters in residents, German counties. 95 percent confidence interval shaded. See section 4 for the data source.

out of German local labor markets visualized in figure 3.[5] The left hand panel depicts this index for administrative local labor markets and the right hand panel for commuting zones in Germany.



(a) Counties (b) Commuting Zones

Figure 3: Grubel-Lloyd indices for commuting in and out of German local labor markets. See section 4 for the data source.

It is readily visible from panel (a) that two-way commuting is pervasive in Germany and

[5]Following their use in international trade, these indices are defined as $GL_i = 1 - \frac{|\sum_{n \neq i} L_{in} - \sum_{n \neq i} L_{ni}|}{\sum_{n \neq i} L_{in} + \sum_{n \neq i} L_{ni}}$, where L_{ni} is the commuter flow between residence n and workplace i, so that $\sum_{n \neq i} L_{ni}$ are location n's total 'exports' of commuters and $\sum_{i \neq n} L_{ni}$ are location i's total 'imports' of commuters from other residences. The index takes on values between $GL_i = 0$ if there is only one way commuting and $GL_i = 1$ if there is perfect two-way commuting.

strongest in large cities and regions in the West and Southwest. The mean and median of the GL-index at the county level are both at 0.70. The distribution of the Grubel-Lloyd index is similar to what is found for the United States (cf. Monte et al. 2018).[6] Yet it should be noted that Germany also has a number of counties where one-way commuting is extremely strong. These are visualized by the few bright areas in panel (a) and the most prominent one is Wolfsburg, home to the largest VW production plant, followed by Frankfurt, Germany's financial center, and a number of mid-size Bavarian cities such as Regensburg, where BMW has a large plant, Bamberg, Erlangen, Schweinfurt and their surrounding counties. With commuting zones, two way commuting is more prominent as typically counties with strong worker inflows are combined with counties with strong worker outflows, see panel (b) in figure 3. Yet the overall heterogeneity remains strong with values ranging from 0.45 to just below 1.

3 The Model

The Setup. We consider a version of the multi-location spatial general equilibrium model developed by Monte et al. (2018) as an extension of Redding (2016) who builds on Helpman (1998), in turn. Locations are linked in goods markets through trade and in factor markets through migration and commuting. Households consume land and a compound good which consists of a basket of differentiated varieties. Production of any variety takes place under increasing returns and with labor as the only factor. Space is divided into a set of locations $\Omega = 1, .., N$ which serve as workplaces and residences. Each location $n \in \Omega$ is endowed with an exogenous supply of land H_n which is owned by local immobile landlords who earn rents from the residential use of land by consumers. To allow for external and internal geographies we assume that the set of locations $\Omega = 1, .., N$ is exhaustively divided into disjoint subsets (territorial entities) $\Omega_g \subseteq \Omega$. Each subset is populated by an exogenous measure $\bar{L}_g$ of workers who supply 1 unit of labor, each. Workers are mobile and can commute to work within these subsets but not across them.

Preferences. A consumer ω who lives in location $n \in \Omega$ and works in location $i \in \Omega$ has preferences characterized by an upper-tier utility of the Cobb-Douglas-type over a final

[6] Percentiles of the distribution of the Grubel-Lloyd index are given in the following table:

	min	p5	p10	p25	p50	p75	p90	p95	max
Counties	0.21	0.44	0.50	0.58	0.70	0.83	0.93	0.960	0.999
CZ	0.45	0.57	0.60	0.72	0.82	0.92	0.97	0.986	0.999

goods basket $C_{ni\omega}$ and land $H_{ni\omega}$,

$$U_{ni\omega} = \frac{b_{ni\omega}}{\kappa_{ni}} \left(\frac{C_{ni\omega}}{\alpha}\right)^{\alpha} \left(\frac{H_{ni\omega}}{1-\alpha}\right)^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{1}$$

where $\kappa_{ni} \in [1, \infty)$ is a parameter of iceberg commuting costs in terms of utility and $b_{ni\omega}$ is a consumer specific work-residence amenity pair drawn from the Fréchet-distribution:

$$G_{ni}(b) = e^{-B_{ni} b^{-\epsilon}}, \qquad B_{ni} > 0, \quad \epsilon > 1 \tag{2}$$

The scale parameter B_{ni} indicates the average amenity level of the work-residence amenity pair and $\epsilon > 1$ parameterizes the dispersion of these amenities.
The goods basket is itself a CES-bundle of differentiated varieties j:

$$C_{ni\omega} = \left[\sum_{i \in N} \int_0^{M_i} c_{ni\omega}(j)^{\frac{\sigma-1}{\sigma}} dj\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1 \tag{3}$$

where $c_{ni\omega}(j)$ is consumption of a specific variety j, M_i is the mass of varieties, and σ is the constant elasticity of substitution between any two varieties. The price indices dual to equations 1 and 3 are respectively given by

$$P_n = p_n^{\alpha} q_n^{(1-\alpha)} \quad \text{and} \quad p_n = \left[\sum_{i \in N} \int_0^{M_i} p_{ni}(j)^{1-\sigma} dj\right]^{\frac{1}{1-\sigma}}, \tag{4}$$

where q_n is the price of housing in n, $p_{ni}(j)$ the price of variety j produced in i paid by consumers in n and consumer ω's indirect utility is

$$V_{ni\omega} = \frac{b_{ni\omega}}{\kappa_{ni}} \frac{e_{ni}}{P_n}, \tag{5}$$

and where e_{ni} denotes the total expenditure of any consumer choosing to commute from n to i. Since indirect utility is a monotonic function of the amenity draw $b_{ni\omega}$, it also follows a Fréchet-distribution, $\mathcal{G}_{ni}(U) = e^{-\Phi_{ni} U^{-\epsilon}}$, where $\Phi_{ni} = B_{ni} \left(\frac{e_{ni}}{\kappa_{ni} P_n}\right)^{\epsilon}$.

Production. Producers in each location i produce varieties under increasing returns and monopolistic competition according to the total cost function $\Upsilon_i(j) = \left(F_i + \frac{y_i(j)}{A_i}\right) w_i$ where $y_i(j)$ is output of variety j, F_i is a location-specific fixed input of labor, A_i is the location-specific productivity level and w_i is the location-specific wage.

Profit maximization implies that prices are constant markups on marginal cost. Consumers in location n pay $p_{ni}(j) = p_{ni} = d_{ni} \left(\frac{\sigma}{\sigma-1}\right) \frac{w_i}{A_i}$ for variety j produced in location i, with $d_{ni} \geq 1$ denoting iceberg type transport costs for shipments from i to n. Profit maximization and zero-profits imply the break-even output $y_i(j) = y_i = A_i(\sigma - 1) F_i$ for any firm. Total costs can then be rewritten as $\Upsilon_i(j) = \Upsilon_i = \sigma F_i w_i$. Labor demand can be recovered from the cost function by application of Shepard's lemma. The aggregate use of labor in location i, L_i, can then be used to express the equilibrium number of firms as:

$$M_i = \frac{w_i L_i}{\Upsilon_i} \tag{6}$$

Goods trade and sectoral price indices. Goods trade between any two locations is characterized by a gravity equation in this model. Using the CES-structure of demand on the part of consumers as well as the pricing rule, the measure of firms (6) and total costs $\Upsilon_i = \sigma F_i w_i$, the share of location n's expenditure on varieties produced in i (relative to location n's total spending on goods) is derived as:

$$\pi_{ni} = \frac{M_i p_{ni}^{1-\sigma}}{\sum_{m \in N} M_m p_{nm}^{1-\sigma}} = \frac{\frac{L_i}{F_i}\left(\frac{d_{ni}}{A_i}\right)^{1-\sigma} w_i^{1-\sigma}}{\sum_{m \in N} \frac{L_m}{F_m}\left(\frac{d_{nm}}{A_m}\right)^{1-\sigma} w_m^{1-\sigma}} \tag{7}$$

Making use of optimal pricing, the firm number (6), and assuming $d_{nn} = 1$ price indices can be calculated as:

$$p_n = \left(\frac{\sigma}{\sigma - 1}\right) \sigma^{-\frac{1}{1-\sigma}} \left(\frac{w_n}{A_n}\right) \left[\frac{L_n}{\pi_{nn} F_n}\right]^{\frac{1}{1-\sigma}} \tag{8}$$

Goods market clearing. In each location i it must hold true that total sales equal the production costs. Hence we can write:

$$\sum_{n \in N} \pi_{ni} X_n = w_i L_i \tag{9}$$

We follow Monte et al. (2018) in assuming that local landlords spend all their rental income on goods and that they also bear their location's trade deficit D_n. Location n's total spending on goods, X_n, is then given by:

$$X_n = \bar{w}_n R_n + D_n \tag{10}$$

The expression combines the expenses of consumers in n on goods, $\alpha \bar{w}_n R_n$, with the spending of local landlords, $(1-\alpha)\bar{w}_n R_n + D_n$, where $\bar{w}_n$ is the average wage in location n (characterized below) and R_n is the measure of residents in location n.

Housing market clearing. Land is used for consumption by residents with an associated spending of $(1-\alpha)\,\bar{w}_n R_n$. Housing market clearing in location n thus commands:

$$H_n q_n = (1-\alpha)\,\bar{w}_n R_n \tag{11}$$

Labor mobility and commuting. Each worker chooses the commute from the subset of locations available to her that offers her the highest utility taking into account her idiosyncratic preferences (5). With the Fréchet distribution of indirect utility, the probability that a worker chooses to live in location n and to work in location i is (where we now use that under the assumptions that we have imposed, $e_{ni} = w_i$),

$$\lambda_{ni|\Omega_g} = \frac{B_{ni}\left(\frac{w_i}{\kappa_{ni}P_n}\right)^{\epsilon}}{\sum_{m\in\Omega_g}\sum_{l\in\Omega_g} B_{ml}\left(\frac{w_l}{\kappa_{ml}P_m}\right)^{\epsilon}} \equiv \frac{\Phi_{ni}}{\Phi_g} \tag{12}$$

The number of workers employed by all firms in location n must match the overall probability that a worker chooses to work in this location:

$$\lambda_n^L \equiv \frac{L_n}{\bar{L}_g} = \sum_{i\in\Omega_g} \lambda_{in|\Omega_g} \tag{13}$$

Moreover, the number of residents in location n must match the overall probability that a worker chooses to live in this location:

$$\lambda_n^R \equiv \frac{R_n}{\bar{L}_g} = \sum_{i\in\Omega_g} \lambda_{ni|\Omega_g} \tag{14}$$

The expected wage conditional on living in location n equals the wages that can be obtained in all possible workplaces weighted with the probabilities of commuting to those workplaces from location n, hence:

$$\bar{w}_n = \sum_{i\in\Omega_g} \frac{B_{ni}\kappa_{ni}^{-\epsilon} w_i^{\epsilon}}{\sum_{l\in\Omega_g} B_{nl}\kappa_{nl}^{-\epsilon} w_l^{\epsilon}} w_i \tag{15}$$

The expected utility of a worker is the same for all pairs of residence and workplace within the relevant subset of locations because of population mobility. It can be calculated as:

$$\bar{U} = \mathbb{E}\left[U_{ni\omega}\right] = \Gamma\left(\frac{\epsilon}{\epsilon-1}\right)\left[\sum_{m\in N}\sum_{l\in N} B_{ml}\left(\frac{w_m}{\kappa_{ml}P_l}\right)^{\epsilon}\right]^{\frac{1}{\epsilon}} \tag{16}$$

where $\mathbb{E}$ is the expectations operator and $\Gamma(\cdot)$ is the Gamma function.

General equilibrium. The general equilibrium system involves the set w_n, π_{ni}, X_n, $\bar{w}_n$, L_n, q_n, R_n, p_n of endogenous variables which are simultaneously determined by the set of equations (7), (8), (9), (10), (11), (14), (15) and 16 after substitution of $\lambda_{ni|\Omega_g}$.

4 Data and Calibration

The data. Our commuting data stem from the German Federal Employment Agency ("Pendlerstatistik") and are based on social security data. They contain bilateral flows between all 412 German counties in existence in 2010 of all workers with social security whose workplace differs from the registered residence. We complement this data with information on total local employment from the Institute for Employment Research based on the same social security data. In combination these data sets also allow us to derive the number of non-commuters in each county.

Trade data are based on a traffic forecast („Verkehrsverflechtungsprognose 2030") administered by the German Federal Ministry of Transport and Digital Infrastructure. They contain the weight of goods shipped between German counties and their trade partners by ship, train or truck disaggregated across 17 product categories. Sources for the construction of the data set stem mainly from the respective agencies for railways and shipping and from a 0.5‰ weekly sample of truck shipments in Germany.

Total wage sums ("totales Arbeitnehmerentgelt") for German counties as well as the number of flats by county, which we use as a control in our empirical section, are available from the Regional and Federal Statistical Offices ("Statistische Ämter des Bundes und der Länder").

For the production value of the Rest of the World (ROW) we use data from the world input output database aggregating all foreign countries and scaling all values such that the WIOD total value of production in Germany equals its wage sum.

Calibration. In order to calibrate the model we need information about exogenous parameters and the initial values of w_n, π_{ni}, $\lambda_{ni|\Omega_g}$, R_n, L_n and $\bar{w}_n$. It is important to stress at the outset that taking the model to the data involves a number of choices because any model involves simplifications and, possibly even more important, because the available data are typically not comprehensive. To ease the comparison with the study by Monte et al. (2018) we follow their specifications as closely as possible. Differences to their approach are due to differences in the data sets available for Germany compared to the United States.

A first issue concerns the non-availability of data on service trade between German local labor markets. Faced with the choice to assume that all services are non-tradable, or to artificially impute service trade, or to ignore the production of services altogether, we follow Monte et al. (2018) and adopt this final option.

Our specification of labor available in Germany, $\bar{L}_g$, is to use the total number of workers employed in Germany as reported by the German Institute for Labor Market Research (IAB). This number is based on social security data which exclude any self-employed workers or workers without social security. Combining county level labor market data from the same source with commuting data ("Pendlerstatistik") from the Federal Employment Agency ("Bundesagentur für Arbeit") we calculate all $\lambda_{ni|\Omega_g}$.

Wages at the county level w_n are obtained by dividing county level total wage bills ("totales Arbeitnehmerentgelt") as reported by the German Federal and Regional Statistical Offices ("Statistische Ämter des Bundes und der Länder") by the local working population.

Using the values for $\bar{L}_g$, $\lambda_{ni|\Omega_g}$ and w_n, the total number of residents R_n and the total number of workers L_n can immediately be calculated from (13) and (14), respectively, and the average wage of residents follows as $\bar{w}_n = \left(\sum_{i\in\Omega_g} \lambda_{ni|\Omega_g} \bar{L}_g w_i\right) / R_n$.

We derive the exogenous deficit transfers D_n and the trade shares π_{ni} from transportation data provided as part of a traffic forecast ("Verkehrsverflechtungsprognose 2030") by the Federal Ministry of Transport and Digital Infrastructure. The sectorally disaggregated shipments in these data are given in terms of weight. Before aggregating regional trade data to a single sector and matching it to the total wage sum, we scale transport weights in each sector with the average value per ton of German total exports in the respective sector from the UN-Comtrade Database. More specifically, we set

$$\pi_{ni} X_n = sf_i \cdot \sum_s Weight_{nis} \cdot \frac{ExportValueGermany_s^{comtrade}}{ExportWeightGermany_s^{comtrade}} ,$$

where the sum is over all products s in the transport data and the scale factor sf_i is chosen such that $\sum_{n\in N} \pi_{ni} X_n = w_i L_i$, that is, such that worldwide demand for goods from i equals its total production value.[7]

We obtain deficit transfers as $D_n = \sum_{i\in N} \pi_{ni} X_n - R_n \bar{w}_n$.[8] Having calculated trade deficits we obtain total expenditure X_n in n as $R_n \bar{w}_n + D_n$ and we can calculate import shares π_{ni} from trade flows $\pi_{ni} X_n$.

[7] Monte et al. (2018) scale trade values from the Commodity Flow Survey to match the total wage bill in each county. We follow them as close as possible and therefore also use the total wage bill despite the fact that this sum includes the service sector whereas trade flows from the Commodity Flow Survey and our shipment data do not.

[8] Note that due to commuting the value of total sales $w_n L_n$ in n differs from total income $R_n \bar{w}_n$. Therefore, deficit transfers can differ (in absolute terms) from trade imbalances $\sum_{i\in N} \pi_{in} X_i - \sum_{i\in N} \pi_{ni} X_n$.

Our estimate of the commuting elasticity is based on the probability $\lambda_{ni|\Omega_g}$. We follow the approach as laid out by Monte et al. (2018) to arrive at a regression equation which we estimate via ordinary least squares, see appendix D. We obtain a highly significant coefficient $\epsilon = 4.61$ which is substantially higher than what is found for the US case. However, this is in line with our observation of stronger commuting flows in Germany.

All remaining parameters for our baseline scenario are taken from Monte et al. (2018). In particular we set the share of housing in consumption $(1-\alpha)$ equal to 0.4 and the substitution elasticity of the CES goods bundle σ_s equal to 4.

5 Looking into the Fabrics of German Local Labor Markets

This section turns to our analysis of the workings of German local labor markets. Section 5.1 establishes the findings of our quantitative model for bilateral trade costs and productivities which are informative in their own right. We then move on to study the effects of local labor demand shocks on local employment and residences. We establish and discuss the respective elasticities for administrative counties in section 5.2 and for commuting zones in section 5.3. Section 5.4 addresses the quantitative importance of consumers' expenditures on land (housing).

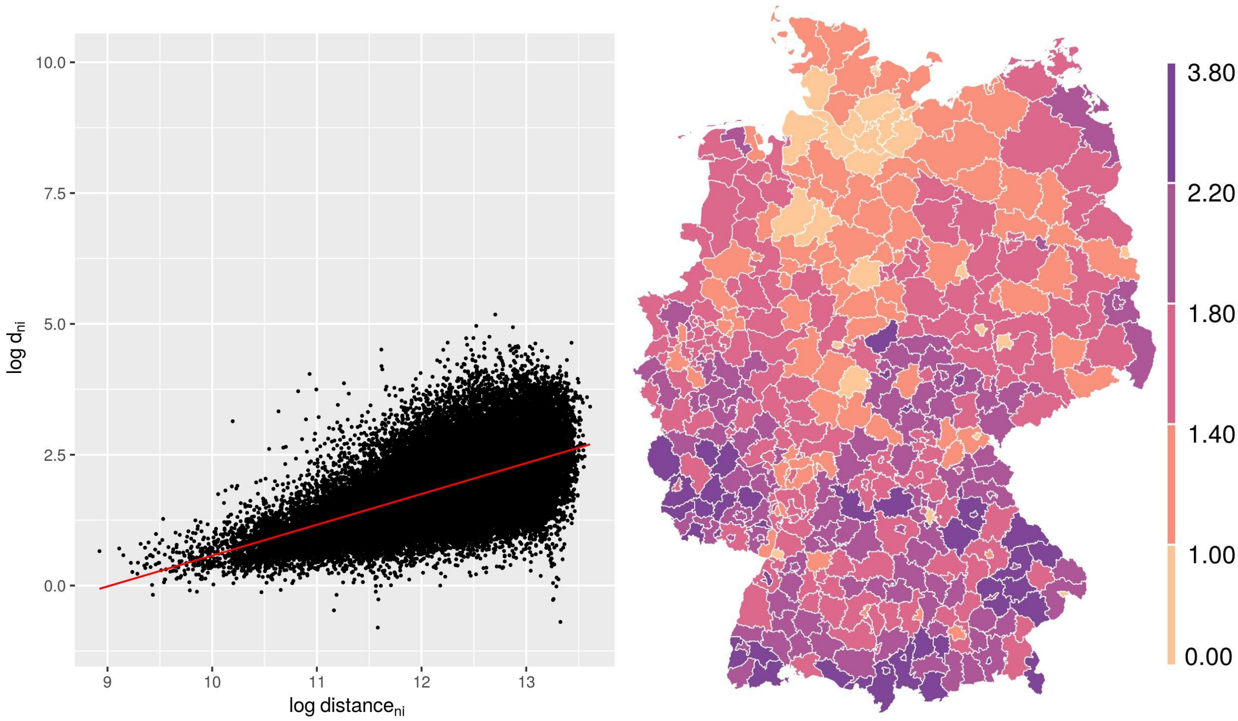
5.1 Model inversion: Bilateral trade costs and local productivities

Model Inversion. Given the rich German dataset, the general equilibrium can readily be inverted to identify model consistent values for bilateral trade costs and local productivities as we now show. Imposing the condition that the fixed input of labor in production is the same in all locations, share equation 7 simplifies to $\pi_{ni} = \frac{L_i w_i^{1-\sigma}\left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{\sum_{m\in N} L_m w_m^{1-\sigma}\left(\frac{d_{nm}}{A_m}\right)^{1-\sigma}}$. Since we used our shipment data to calculate bilateral trade shares π_{ni} and since we directly observe L_n and w_n we can directly back out the bilateral barriers d_{ni} using a variant of the Head-Ries-Index (Head and Ries (2001); see Head and Mayer (2014) for similar ratio-methods) as follows. Using own shares and bilateral trade shares we immediately have $\frac{\pi_{nn}\pi_{ii}}{\pi_{ni}\pi_{in}} = (d_{ni}d_{in})^{\sigma-1}$. Imposing symmetry on trade costs between German counties, bilateral trade barriers follow as $d_{ni} = \left(\frac{\pi_{nn}\pi_{ii}}{\pi_{ni}\pi_{in}}\right)^{\frac{1}{2(\sigma-1)}}$.

Once we have identified bilateral trade barriers, the county level technology parameters A_i

can also be recovered up to a proportionality factor from the ratio of bilateral trade share and own share, $\frac{\pi_{ni}}{\pi_{nn}} = \frac{L_i w_i^{1-\sigma}\left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{L_n w_n^{1-\sigma}\left(\frac{1}{A_n}\right)^{1-\sigma}}$. After imposing the normalization $A_n = 1$, we obtain productivities of any location i relative to location n as $A_i = d_{ni}\frac{w_i}{w_n}\left(\frac{\pi_{nn}L_i}{\pi_{ni}L_n}\right)^{\frac{1}{1-\sigma}}$.

Bilateral trade costs. Figure 4, left-hand panel, displays the relationship between our calculated barriers and observable distances between counties.[9] We expect distance to be strongly correlated with our measure of iceberg trading costs and indeed this is what we find with an OLS regression leading to a log-linear coefficient of 0.59.



(a) Trade costs and distances (b) Trade barriers with respect to Hamburg

Figure 4: Model consisten trade costs

We can also look at county level barriers with respect to a specific location. The right-hand panel of figure 4 depicts the log barriers implied by the model between all German counties and Hamburg. It is clearly visible that trade barriers increase with distance to Hamburg in general. However, barriers between far-away locations may effectively be low when locations

[9] The easiest way to meassure the distance between two counties is to take the great circle distance of their geometric centroids. This is problematic for German counties which often consist of a free city ("Kreisfreie Stadt") which is a county of its own, surrounded by a (roughly) ring shaped county. In this case the centroids of both counties can fall extremly close together leading to a misrepresentation of the average distance that commuters between those two locations face. For this reason we establish the bilateral distance between locations by calculating the mean of 10,000 pairwise distances between 100 random points in each of the counties.

are connected by important railway lines or waterways or established personal, firm or cultural ties. Figure 4 shows that there are some cities in the middle and south of Germany – Munich, the bright area in the southeast of the map, is a case in point - that feature very low trade frictions with Hamburg despite their considerable distance. Moreover, barriers with respect to other cities appear to be lower than with respect to rural areas, in general.

Our county level shipment data allow us to directly derive the model consistent barriers instead of relying on estimates based on distance. In order to compare differences in the connection between barriers and distance in Germany with the U.S. case studied in Monte et al. (2018) we do follow their analysis here and estimate the correlation based on our gravity equation. Our preferred estimate derived from using a poisson pseudo-maximum likelihood (PPML) estimator yields an elasticity of trade flows with respect to barriers in Germany of -1.42 which is slightly larger than what is found for the US (see appendix C).

Local productivities. To look at the technology levels implied by the model we normalize productivity in Hamburg at 1 and depict all productivities relative to that in Hamburg in figure 5. Strinkingly, with the data from 2010 and thus almost 20 years after the reunification, productivity levels in the east of Germany are – with the exception of some emerging cities - still considerably lower than in the rest of the country. In line with expectations, given observable trade flows, our model implies that cities in the south and west of Germany, as well as their surrounding areas are the most productive locations in the country.

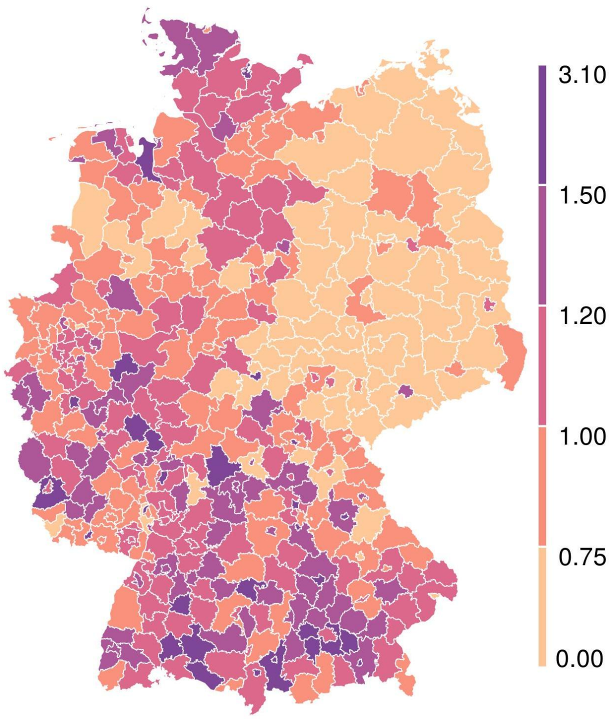


Figure 5: Model consistent local productivities relative to Hamburg

5.2 Productivity shocks and Local Employment Elasticities

In order to explore the workings of the German network of local labor markets we now expose the general equilibrium system with local productivity shocks. Our analysis builds on the 'exact hat'-algebra due to Dekle et al. (2007).[10]

We calculate 402 counterfactual equilibria, each representing a 5% productivity shock in one of the 402 German counties. Figure 6 shows the kernel densities of the resulting general equilibrium elasticities of employment and residents in the shocked counties, with the 95% confidence intervals given by the shaded area.[11] The heterogeneity in employment elasticities across German counties is large with a main range from 1.25 to 2.25.

Perhaps surprisingly, the average employment elasticity of 1.91 is above the average employment elasticity across U.S. counties of 1.52 reported in Monte et al. (2018). Also in contrast with their results, we find that almost no county in Germany has an employment elasticity below 1, pointing towards much stronger home market and commuting effects. One key finding is the same, however: the local employment elasticities exhibit a very strong heterogeneity in Germany, similar as in the United States, so the use of average employment elasticities for policy and planning purposes would substantially distort results at the local level. The general equilibrium elasticities of residents are much lower with a main range from 0.25 to 1 and a mean of 0.52.

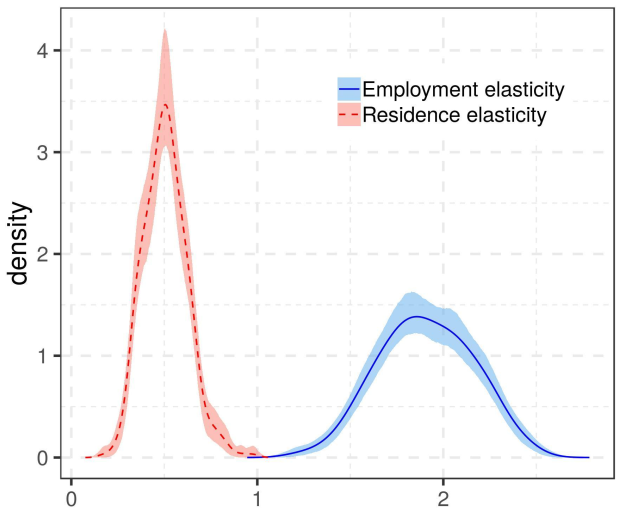


Figure 6: Kernel densities of the resulting general equilibrium elasticities of employment and residents

[10]The appendix documents the equilibrium system in changes well as the algorithm we use to obtain counterfactual equilibrium values.

[11]Given our counterfactual equilibrium these elasticities can be calculated as $\frac{\hat{L}-1}{\hat{A}-1}$ and $\frac{\hat{R}-1}{\hat{A}-1}$, respectively, where the relative change of a variable is denoted by a hat, $\hat{x} \equiv x'/x$, and x' is the value of a variable in the counterfactual equilibrium. Note that these counterfactual general equilibrium elasticities follow deterministically from the model, the depicted confidence bands relate to the estimation of the kernel density.

Obviously, differences in the elasticities of employment and residents can only stem from commuting. In the general equilibrium several mechanisms, which cannot be disentangled completely, simultaneously drive the reaction of workers. Firstly, workers are attracted to the county that experiences a positive productivity shock because of the implied higher wages. When changing their workplace decision some workers, depending on their bilateral amenity draws, will prefer to move to the new county whereas others will commute to it. Secondly, lower prices due to the increased productivity will attract additional residents, some of which will also change their workplace whereas others, based on their amenity draws, will prefer to commute outwards. Thirdly, an increased number of residents drives up housing costs, a congestion effect. Fourthly, the general equilibrium is driven by spillover effects through commuting, that is, through changes in the number of workers and residents in untreated counties, and through trade linkages with untreated counties.

Table 2: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\log(L_i)$		-0.104^{***}	-0.383^{***}	-0.392^{***}				-0.249^{***}	-0.339^{***}
		(0.017)	(0.046)	(0.048)				(0.018)	(0.027)
$\log(w_i)$			0.622^{***}	0.686^{***}				0.017	0.161^{***}
			(0.086)	(0.131)				(0.033)	(0.053)
$\log(H_i)$			0.270^{***}	0.260^{***}				0.256^{***}	0.336^{***}
			(0.047)	(0.047)				(0.018)	(0.028)
$\log(L_{-i})$				0.122^{***}					
				(0.027)					
$\log(w_{-i})$				-0.405^{**}					
				(0.173)					
$\lambda^R_{ii\|i}$					-1.693^{***}				
					(0.035)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.068^{***}		0.060^{***}	
						(0.012)		(0.010)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.369^{***}		-1.418^{***}	
						(0.041)		(0.035)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.567^{***}		0.381^{***}	
						(0.040)		(0.034)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.278^{***}		0.231^{***}
							(0.022)		(0.020)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-1.334^{***}		-1.474^{***}
							(0.076)		(0.070)
Constant	1.906^{***}	3.025^{***}	-3.673^{***}	-1.600	2.872^{***}	1.983^{***}	2.055^{***}	1.745^{***}	0.266
	(0.013)	(0.189)	(0.901)	(1.186)	(0.020)	(0.033)	(0.025)	(0.350)	(0.554)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.081	0.209	0.249	0.857	0.839	0.626	0.900	0.733
Adjusted R^2	0.000	0.079	0.203	0.239	0.856	0.837	0.624	0.898	0.730

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. *p<0.1; **p<0.05; ***p<0.01

In order to gain a better understanding of the driving forces behind these local labor market elasticities and their heterogeneity we try to predict these general equilibrium elasticities using a range of control variables which are traditionally highlighted in the local labor market literature and also a number of controls suggested by the model. Table 2 presents the results of these regressions. Column 1 regresses the employment elasticities on a constant capturing the mean across the 402 German counties. Column 2 uses the log of the location's employment as a measure for the size of the local labor market, in addition. Column 3 further adds the local wage and, as a measure of the local housing stock, H_i, the number of flats in the county. Column 4 complements our standard controls by adding the total workforce and the average wage which prevails in surrounding labor markets. We define these surrounding labor markets following Monte et al. (2018) as all counties with a distance of less than 120km from the county that is exposed to the productivity shock.

The regressions reported in columns (5), (6) and (7) turn to explanatory variables which are model-based. Column (5) considers the share of a county's residents that also work in that county, $\lambda^R_{ii|i}$, as a baseline measure for commuting suggested by the model, where the definition g $\lambda^R_{ni|n} = \frac{\lambda_{ni|\Omega_g}}{\lambda^R_n}$ is used. The lower $\lambda^R_{ii|i}$ the more open is a local labor market to commuting, hence, the higher is the expected elasticity of employment. As can be seen by the regression's R-squared this variable alone – along with the constant –explains over 85% of the variation in employment elasticities. This contrasts sharply with the regressions reported for the standard controls, which explain hardly more than 25% even if all of them are included.

Column 6 includes measures which build on three partial equilibrium elasticities of the model, the partial equilibrium elasticities of employment and residents with respect to wages and the partial equilibrium elasticity of wages with respect to productivity.[12]

These partial equilibrium elasticities imply a measure of commuting linkages, $\sum_{n\in N}\left(1-\lambda^R_{ni|n}\right)\vartheta_{ni}$ where $\vartheta_{ni} \equiv \lambda^R_{ni|n} R_n/L_i$ indicates the fraction of the workforce in location i that resides in n and commutes to work in i, a measure of migration linkages $\vartheta_{ii}\left(\frac{\lambda_{ii|\Omega_g}}{\lambda^R_i} - \lambda^L_i\right)$, and as a measure of what Monte et al. (2018) call 'trade linkages', the partial elasticity of wages with respect to productivity, $\frac{\partial w_i}{\partial A_i}\frac{A_i}{w_i}$. The explanatory power of these three measures with respect to the heterogeneity of the general equilibrium employment elasticities is similar to the explanatory power of the own share $\lambda^R_{ii|i}$. Both regressions strongly outperform the standard controls as can be seen by the far higher R-squared values.

In column 7 the three measures of linkages are combined by multiplying the previous commuting and migration linkage with the partial equilibrium elasticity of wages with respect to productivity. In contrast to Monte et al. (2018), the explanatory power of these two combined measures is lower compared to the three measures from which they were formed, but it is still higher than with standard controls. In columns 8 and 9 we combine the standard

[12]These partial equilibrium elasticities are derived from total differentiation of equations (9), (13) and (14) along with (7) and evaluating the result for a productivity change in one county. The values of all other endogenous variables, including productivities in other counties are held constant.

controls with the measures inspired by the model. While this does improve the R-squared in specification (8), the wage in the location becomes insignificant. In specification (9), the intercept becomes insignificant and the overall explanatory power of the regression is much lower compared to specifications considered in column (5) and (6) which perform best.

In sum we find, that the model-based measures, the simple inverse measure of openness, $\lambda^R_{ii|i}$, in particular, perform well in explaining the heterogeneity of employment elasticities across counties and that these measures outperform standard controls by far.

5.3 Commuting Zones

We now repeat the analysis of local productivity shocks for the 141 German commuting zones rather than counties. Figure 7 depicts the kernel densities of the general equilibrium elasticities of employment and residents with the original county level results lightly shaded in the background.

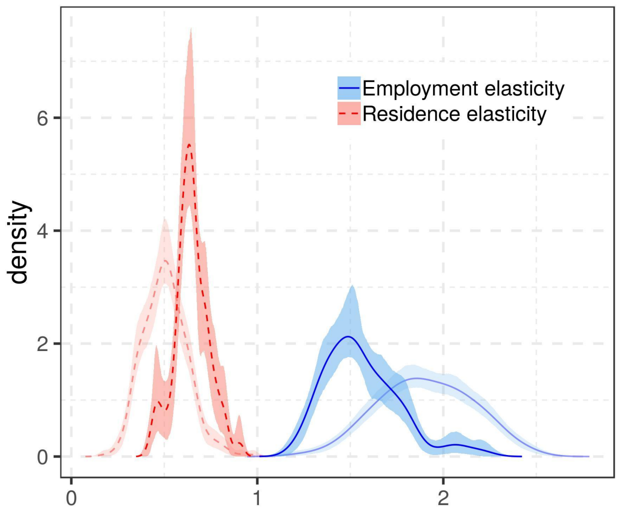


Figure 7: Kernel densities of general equilibrium elasticities of employment and residents (commuting zones)

While it is immediately apparent that the general equilibrium employment elasticities exhibit less heterogeneity with commuting zones, these remain substantial with most values between 1.3 and 2 and with a mean of 1.56. This reduction compared to the results found for counties captures the fact that commuting is more costly across commuting zones than across counties. Therefore, commuting to the treated location is more costly in comparison to the county level experiments and fewer workers will choose to do so. The increase in the average elasticity of residents to 0.65 mirrors this fact as well. Workers are attracted to the commuting zone which experiences a positive productivity shock but since commuting costs are generally higher than in the county case workers are more likely to completely relocate to the treated location instead of choosing to commute to it. Yet there still is a significant

Table 3: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level (commuting zones).

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(L)		-0.097^{***}	-0.540^{***}	-0.570^{***}				-0.144^{***}	-0.117
		(0.017)	(0.111)	(0.103)				(0.041)	(0.084)
log(w)			0.283^{**}	0.313				-0.001	0.040
			(0.123)	(0.197)				(0.043)	(0.089)
log(H)			0.454^{***}	0.476^{***}				0.130^{***}	0.135
			(0.115)	(0.107)				(0.040)	(0.084)
$\log(L_{-i})$				0.148^{***}					
				(0.030)					
$\log(w_{-i})$				-0.435^{*}					
				(0.240)					
$\lambda^R_{ii\|i}$					-1.913^{***}				
					(0.064)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.039^{***}		0.013	
						(0.010)		(0.012)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						-1.539^{***}		-1.572^{***}	
						(0.072)		(0.071)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.381^{***}		0.365^{***}	
						(0.054)		(0.052)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.270^{***}		0.275^{***}
							(0.026)		(0.030)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							-0.592^{***}		-0.583^{***}
							(0.139)		(0.144)
Constant	1.560^{***}	2.697^{***}	-0.678	1.598	2.987^{***}	2.203^{***}	1.639^{***}	2.367^{***}	0.934
	(0.017)	(0.197)	(1.281)	(1.483)	(0.048)	(0.066)	(0.059)	(0.464)	(0.934)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.194	0.280	0.392	0.866	0.909	0.652	0.921	0.661
Adjusted R^2	0.000	0.188	0.264	0.369	0.865	0.907	0.647	0.918	0.649

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. *p<0.1; **p<0.05; ***p<0.01

amount of commuting even across commuting zones, which explains the strong remaining heterogeneity in employment elasticities.

The regression results shown in table 3 are qualitatively similar to the results at the county level. Local labor market variables are much more important both in terms of their strength and their significance than the wages and workforce of surrounding labor markets, as can be seen in column 4. Overall the explanatory power of the inverse measure of openness (see column 5) and of the measures based on partial equilibrium elasticities (see columns 6 through 9) in explaining the variation of the general equilibrium employment elasticities rises, albeit slightly. These model-based measures again clearly outperform the traditional controls.

5.4 The Role of Housing

Next we explore the quantitative importance of housing expenditures for the employment elasticities derived from the general equilibrium model. Our quantitative analyses in sections 5.2 and 5.3 are based on the assumption imposed by Monte et al. (2018) that the share of housing in consumer's spending is at 40%.

This number appears already very high from the perspective of the data provided by the United States' Bureau of Economic Analysis (BEA) to which Monte et al. (2018) refer.[13]

If the perspective of the aggregate economy is taken, which is what quantitative spatial equilibrium analyses typically aim at, then the share devoted to housing is yet very much smaller. Building on information from the World Input Output Database (WIOD) with its Socioeconomic Accounts (SEA's) and an EU-KLEMS data, Krebs and Pflüger (2018) arrive at expenditure shares for land at around 10% both for Germany and for the United States.[14]

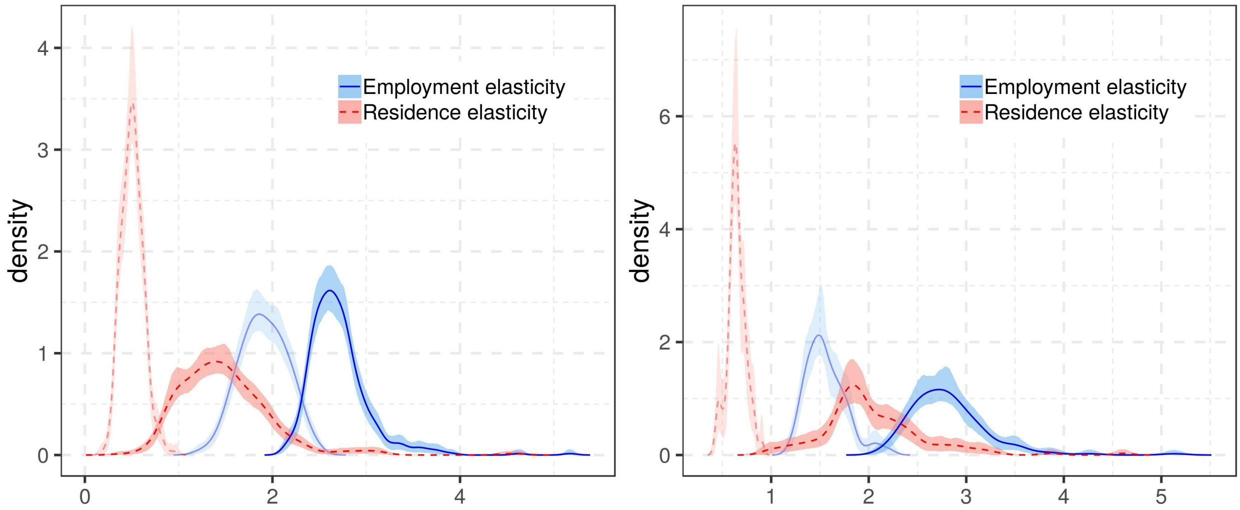
The large discrepancy between these numbers can readily be explained. First, from the perspective of the aggregate economy, total final expenditure - which includes government spending and investment - is relevant, not only consumption expenses where the expenditure share on land is particularly high. Second, personal consumption expenditure is much smaller than the income generated in an economy, so that the 'denominator' to which housing expenditures are related is much smaller. Finally, the category 'housing expenditures' is not sharply defined. In some definitions it is just the rent paid by households, other also include spending for utilities or even furniture. However, even taking into account that there is some fuzziness, it is hard to come up with numbers much larger than 10-15%.

Rerunning the counterfactual local productivity shocks with an expenditure share of $(1-\alpha) = 0.1$ yields dramatically different results. Figure 8 shows the strong impact of this change on the kernel densities of the general equilibrium elasticities of employment and residents. The left panel depicts the results at the county level, the right panel shows the findings for commuting zones. For reference we depict our results from sections 5.2 and 5.3 with a spending share of housing in consumption of 40% lightly shaded in the background. It is readily seen that the elasticities in both cases increase substantially and become more heterogeneous across locations. This is especially true for the elasticity of residents. For county

[13] For the year 2016 the BEA lists total personal consumption expenditure for the US at \$12,816,386 million and personal consumption expenditure in the category "housing and utilities", which includes imputed rents for owner occupied housing, at \$2,331,526 million. These numbers imply a spending share of 18.2% including utilities, which should not be included in spending on the non-traded factor housing or land for housing. The corresponding values for 2010 are \$10,196,850 million for personal consumption and \$1,908,992 million for 'housing and utilities', resulting in a share of 18.7%.

[14] See Timmer et al. (2015) on the WIOD and on its SEA's and O'Mahony and Timmer (2009) on EU-KLEMS.

level shocks, 90% of the density mass lies in the range from 0.9 to 2.34 compared to a range from 0.34 to 0.7 for a housing share of 0.4. For commuting zones the effect is even more dramatic with 90% of residence elasticities now in the range from 1.29 to 2.97 compared to a range from 0.48 to 0.79 with the higher housing share. Obviously, with the smaller expenditure share on housing, the role of housing costs as a congestion force is very strongly diminished, implying that more workers will choose to migrate to instead of commute to the treated labor market. These findings of higher levels and increased heterogeneity of employment elasticities strongly reinforce the previous finding that seriously wrong conclusions result if an average employment elasticities across local labor markets is applied.



(a) counties (b) commuting zones

Figure 8: Kernel densities of general equilibrium elasticities of employment and residents (counties and commuting zones), expenditure share of 10 percent on housing.

Taking a much lower expenditure share on housing into account also has a dramatic effect on the attempt to explain the (now even increased) heterogeneity of the general equilibrium labor market elasticities as can be seen in table 4. Rerunning the regressions for a housing share of 10% we find that the explanatory power of standard labor market controls is lower but yet in the same ballpark as with the higher housing share, see columns 1 to 4. Strikingly, the inverse measure of openness to commuting, $\lambda^R_{ii|i}$ which turned out to be so powerful in the previous regression loses its explanatory power altogether and becomes insignificant as can be seen in column 5.[15] Furthermore, as shown in columns 6 and 7, the measures based on the partial equilibrium elasticities of the model which turned out to be very good predictors previously now perform hardly better than the full set of standard controls considered in regression (4).

[15]We report the analysis for commuting zones in the appendix. As can be seen there, $\lambda^R_{ii|i}$ remains significant in this case. However, its explanatory power drops to 7.7% and thus far below even the R^2 of the standard controls.

The specifications with the highest explanatory power are the ones which combine the model-based measures with standard controls, see columns 8 and 9. In stark contrast to the previous regression, the R-squared moves up to 0.24 by combining theses measures, cf. columns 8 and 6 and columns 9 and 7. In the appendix we redo the analysis with commuting zones rather than counties and we find similar results.

Table 4: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level (counties) with an expenditure share of 10 percent for housing.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(L)		0.083***	−0.190***	−0.216***				−0.028	−0.124**
		(0.023)	(0.064)	(0.064)				(0.063)	(0.062)
log(w)			0.147	0.314*				0.233**	0.355***
			(0.118)	(0.178)				(0.118)	(0.119)
log(H)			0.307***	0.348***				0.152**	0.242***
			(0.065)	(0.064)				(0.064)	(0.063)
$\log(L_{-i})$				−0.218***					
				(0.037)					
$\log(w_{-i})$				0.276					
				(0.235)					
$\lambda^R_{ii\|i}$					0.131				
					(0.117)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						0.001		0.084**	
						(0.034)		(0.036)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						0.219*		0.334***	
						(0.121)		(0.125)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						0.944***		0.969***	
						(0.118)		(0.121)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.135***		0.202***
							(0.044)		(0.045)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							0.971***		1.025***
							(0.151)		(0.157)
Constant	2.704***	1.805***	−0.276	−1.991	2.629***	2.034***	2.409***	−2.007	−2.823**
	(0.016)	(0.249)	(1.246)	(1.610)	(0.069)	(0.098)	(0.050)	(1.250)	(1.243)
Observations	402	402	402	402	402	402	402	402	402
R^2	0.000	0.032	0.083	0.161	0.003	0.156	0.096	0.225	0.185
Adjusted R^2	0.000	0.029	0.076	0.150	0.001	0.149	0.092	0.213	0.175

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. *p<0.1; **p<0.05; ***p<0.01

6 Conclusion

This papers uses a quantitative spatial model with heterogeneous locations linked by costly goods trade, migration and commuting to shed light on the spatial fabrics and interactions of local labor markets in Germany which, due to its much higher population density, poses an appealing contrast to the United States.

We find that commuting is a very strong adjustment mechanism for German local labor markets. Descriptive statistics show that the average propensity to commute is about twice as high than what is reported for the United States. Our simulation results show that employment and resident elasticities are very heterogeneous, even across commuting zones. Hence, our analysis reveals that the network of local German labor markets functions much more flexible than what is assumed by the commonly held view in public and strong commuting is key for this finding.

We made a strong argument that the economy-wide share of income devoted to land (housing) is much lower than typically assumed in recent new quantitative spatial analyses. It is important to point out that the mentioned results hold true qualitatively irrespective of whether the economy-wide share of income devoted to land (housing) is at this high level or, more realistically, at a much lower level. The role of commuting as an adjustment mechanism for local labor markets remains very strong and it remains very heterogeneous across counties. However, predictive power of simple model based partial equilibrium commuting statistics in explaining general equilibrium elasticities is much reduced. Quite intuitively, simple partial equilibrium based measures miss to capture the full general equilibrium effects that become stronger as the congestion force in the model becomes weaker.

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Appendix: On the Road (Again): Commuting and Local Employment Elasticities in Germany

A Equilibrium in changes

We rewrite our equilibrium system in terms of changes. Following the literature, we use a prime to denote variables from a counterfactual scenario and a hat to denote the relative change of a variable, i.e. $\hat{x} = \frac{x'}{x}$. The equilibrium system of equations (7) through (15), together with the price index of consumption and commuting shares thus becomes:

$$\hat{\pi}_{ni} = \frac{\frac{\hat{L}_i}{\hat{F}_i}\left(\frac{\hat{d}_{ni}}{\hat{A}_i}\right)^{1-\sigma}\hat{w}_i^{1-\sigma}}{\sum_{m\in N}\pi_{nm}\frac{\hat{L}_m}{\hat{F}_m}\left(\frac{\hat{d}_{nm}}{\hat{A}_m}\right)^{1-\sigma}\hat{w}_m^{1-\sigma}} \tag{7'}$$

$$\hat{p}_n = \frac{\hat{w}_n}{\hat{A}_n}\left[\frac{\hat{L}_n}{\hat{\pi}_{nn}\hat{F}_n}\right]^{\frac{1}{1-\sigma}} \tag{8'}$$

$$\sum_{n\in N}\hat{\pi}_{ni}\pi_{ni}\hat{X}_n X_n = \hat{w}_i\hat{L}_i w_i L_i \tag{9'}$$

$$\hat{X}_n X_n = \hat{\bar{w}}_n\hat{R}_n\bar{w}_n R_n + D_n\hat{D}_n \tag{10'}$$

$$\hat{q}_n = \hat{\bar{w}}_n\hat{R}_n \tag{11'}$$

$$\hat{\lambda}_{ni|\Omega_g} = \frac{\hat{B}_{ni}\hat{P}_n^{-\epsilon}\hat{\kappa}_{ni}^{-\epsilon}\hat{w}_i^{\epsilon}}{\sum_{m\in\Omega_g}\sum_{l\in\Omega_g}\lambda_{ml|\Omega_g}\hat{B}_{ml}\hat{P}_m^{-\epsilon}\hat{\kappa}_{ml}^{-\epsilon}\hat{w}_l^{\epsilon}} \tag{12'}$$

$$\frac{\hat{L}_n L_n}{\bar{L}_g} = \sum_{i\in\Omega_g}\hat{\lambda}_{in|\Omega_g}\lambda_{in|\Omega_g} \tag{13'}$$

$$\frac{\hat{R}_n R_n}{\bar{L}_g} = \sum_{i\in\Omega_g}\hat{\lambda}_{ni|\Omega_g}\lambda_{ni|\Omega_g} \tag{14'}$$

$$\hat{\bar{w}}_n\bar{w}_n = \sum_{i\in\Omega_g}\frac{\lambda_{ni|\Omega_g}\hat{B}_{ni}\hat{\kappa}_{ni}^{-\epsilon}\hat{w}_i^{\epsilon}}{\sum_{m\in\Omega_g}\lambda_{nm|\Omega_g}\hat{B}_{nm}\hat{\kappa}_{nm}^{-\epsilon}\hat{w}_m^{\epsilon}}\hat{w}_i w_i \tag{15'}$$

where

$$\hat{P}_n = \hat{p}_n^{\alpha}\hat{q}_n^{1-\alpha}$$

B Algorithm

For any shock defined by $\hat{B}_{ni}$, $\hat{\kappa}_{ni}$, $\hat{F}_n$, $\hat{A}_n$, $\hat{d}_{ni}$ for all n, i, and initial guesses for $\hat{w}_i$ and $\hat{\lambda}_{ni|\Omega_g}$ we use our data for $\bar{w}_n$, w_n, L_n, R_n, π_{ni} and $\lambda_{ni|\Omega_g}$ to solve the equilibrium in changes using the following algorithm.

Step 1: We calculate new values for $\hat{L}_n$, $\hat{R}_n$ and $\hat{\bar{w}}_n$ using equations (13)' through (15)'.

Step 2: Using the obtained values we derive changes in housing costs as $\hat{q}_n = \hat{R}_n \hat{\bar{w}}_n$ via equation ((11)') and in trade shares as $\hat{\pi}_{ni} = \frac{\frac{\hat{L}_i}{\hat{F}_i}\left(\frac{\hat{d}_{ni}}{\hat{A}_i}\hat{w}_i\right)^{1-\sigma}}{\sum_{m\in\Omega_g}\pi_{nm}\frac{\hat{L}_m}{\hat{F}_m}\left(\frac{\hat{d}_{nm}}{\hat{A}_m}\hat{w}_m\right)^{1-\sigma}}$.

Step 3: Given the changes in trade shares we solve for changes in the consumer goods price index via $\hat{p}_n = \frac{\hat{w}_n}{\hat{A}_n}\left[\frac{\hat{L}_n}{\hat{\pi}_{nn}\hat{F}_n}\right]^{\frac{1}{1-\sigma}}$.

Step 4: Given all new variables we solve for temporary values of $\hat{w}_i^{tmp}$ and $\hat{\lambda}_{ni|\Omega_g}^{tmp}$ using equations (9)' and (10)' in combined form, that is, $\hat{w}_i = \frac{1}{\hat{L}_i}\sum_{n\in N}\pi_{ni}\hat{\pi}_{ni}\left(R_n\hat{R}_n\bar{w}_n\hat{\bar{w}}_n + D_n\hat{D}_n\right)$ as well as equation (12)'.

Step 5: We update our guess for $\hat{w}_i$ to $\hat{w}_i + \zeta\left(\hat{w}_i^{tmp} - \hat{w}_i\right)$ and our guess for $\hat{\lambda}_{ni|\Omega_g}$ to $\hat{\lambda}_{ni|\Omega_g} + \zeta\left(\hat{\lambda}_{ni|\Omega_g}^{tmp} - \hat{\lambda}_{ni|\Omega_g}\right)$ where $0 < \zeta < 1$ represents a dampening factor.[16]

We keep repeating these steps until the equilibrium is reached with a sufficiently small tolerance, that is, until $\hat{w}_i^{tmp} - \hat{w}_i$ and $\hat{\lambda}_{ni|\Omega_g}^{tmp} - \hat{\lambda}_{ni|\Omega_g}$ converge to 0.

C Gravity

Our county level shipment data allow us to directly derive the model consistent barriers instead of relying on estimates based on distance. In order to compare differences in the connection between barriers and distance in Germany with the US case studied in Monte et al. (2018) we do follow their analysis here and estimate the correlation based on our gravity equation. Assuming that the fixed input of labor is the same across locations ($F_i = F_m \quad \forall i, m \in N$), equation (7) becomes $\pi_{ni} = \frac{L_i w_i^{1-\sigma}(d_{ni}/A_i)^{1-\sigma}}{\sum_{m\in N} L_m w_m^{1-\sigma}(d_{nm}/A_m)^{1-\sigma}}$ so that trade flows from location i to n can be written as

$$\pi_{ni}X_n = \frac{L_i w_i^{1-\sigma}\left(\frac{d_{ni}}{A_i}\right)^{1-\sigma}}{\sum_{m\in N} L_m w_m^{1-\sigma}\left(\frac{d_{nm}}{A_m}\right)^{1-\sigma}}\left(R_n\bar{w}_n + D_n\right) \ ,$$

[16] Throughout a broad range of counterfactuals $\zeta = 0.3$ has proven to be an acceptable compromise between speed of convergence and preventing an overshooting of the algorithm.

which in turn can be decomposed into exporter and importer specific effects as well bilateral barriers. Parameterizing trade barriers by $d_{ni} = dist_{ni}^{\psi}\tilde{e}_{ni}$, where $dist_{ni}$ is the physical distance between locations n and i, $\psi > 0$ a parameter, and $\tilde{e}_{ni}$ a stochastic error term, we can write the above equation in its stochastic version as

$$\log \pi_{ni} X_n = S_i + M_n + (1-\sigma)\,\psi \log dist_{ni} + \log e_{ni} \ ,$$

where M_n and S_i are importer and exporter fixed effects capturing their respective variables and $\log e_{ni} \equiv (1-\sigma)\log \tilde{e_{ni}}$ is the adapted error term. In the figure below we depict the conditional relationship between log trade flows and log distance, i.e. the correlation after cleaning importer fixed effects M_n and exporter fixed effects S_i from both variables.[17]

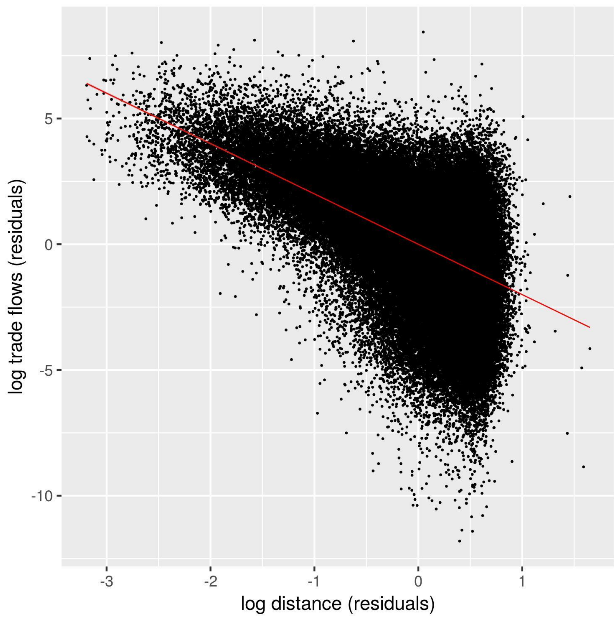

Figure A.1: Gravity estimation for goods trade

Log linearizing the gravity equation commands that we have to drop all observations with zero trade flows. The figure indicates heteroscedasticity in the data leading to OLS becoming a biased estimator for our sought distance elasticity and we therefore re-estimate the gravity equation in its multiplicative form using PPML (see Santos Silva and Tenreyro (2006) for a discussion of the problem and the PPML method).

[17] Specifically, we separately regress $\log \pi_{ni} X_n$ and $\log dist_{ni}$ on importer and exporter dummies and then regress the residuals of the first regression on those of the latter.

	OLS	PPML
log_distance	-2.002	-1.424
robust s.e.	0.008	0.010
Observations	121824	161202
(Pseudo) R2	0.29	0.70

Table A.1: Gravity in goods trade

The table shown above demonstrates that with $(1-\sigma)\,\psi = -1.42$ we obtain an, in absolute terms, slightly larger elasticity of trade flows with respect to barriers in Germany compared to the US. Given our assumption of $\sigma = 4$ the effect of distance on barriers measured by ψ is equal to 0.475 and thus slightly larger than in the US.

D Commuting

The figure below depicts the relationship between the log of uncensored commuting flows and the log of distance. There is a strong sign of discontinuity at a commuting distance of 120 km, similar similar to the one found in Monte et al. (2018). The red OLS regression lines for all commuting flows below and above 120 km respectively have highly significant slopes of -3.65 and -0.97.

One explanation for this discontinuity has to do with the construction of the data. The raw data set is generated based on company reports of each worker's registered residence adress as well as the county of the plant where she is employed. This process involves two problems. Firstly, it can introduce lumping to the data when firms wrongly report the county of their headquarter or main plant instead of the actual plant of the worker's employment. Secondly, workers can be registered as residents at a main ("Haupt-") and a secondary ("Nebenwohnsitz") adress potentially introducing "fake" commuters to the data. One interpretation of the discontinuity is that commuting flows above 120km are unlikely to be true commuting flows but instead originate with misreporting. Since misreporing is independent of distance, the effect of distance on worker inflow and hence the slope of the regression line becomes neglible beyond 120 km.

Similar to the gravity estimation of goods trade above, we can use the commuting equation 12 to derive a gravity equation of commuter flows. We follow Monte et al. (2018) in defining $\mathcal{B}_{ni} = B_{ni}\kappa_{ni}^{-\epsilon}$ as a measure for the ease and average attractivity of commuting between locations n and i and in assuming that, for the purpose of estimation, $\mathcal{B}_{ni}$ can be decomposed in the folowing way: $\log \mathcal{B}_{ni} = \log \mathbb{B}_n + \log \mathbb{B}_i + \psi_\lambda \log dist_{ni} + \log \mathbb{B}_{ni}$. The first and second term on the right hand side capture residence and workplace fixed effects respectively, distance is

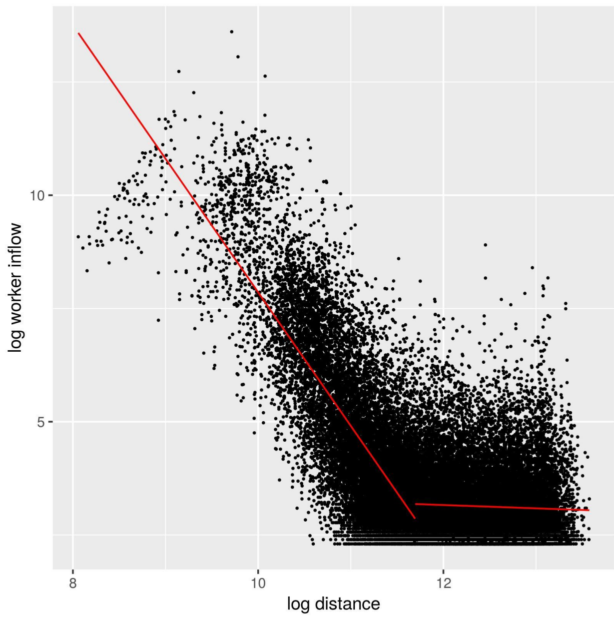

Figure A.2: Commuting flows and distance

used to parameterize bilateral effects and $\log \mathbb{B}_{ni}$ captures the residual. Taken together we can rewrite our gravity of commuting flows in its stochastic version as

$$\log \lambda_{ni|\Omega_g} = S_{\lambda,i} + M_{\lambda,n} + \psi_\lambda \log dist_{ni} + \log \mathbb{B}_{ni} \ ,$$

where $S_{\lambda,i}$ and $M_{\lambda,n}$ capture all residence (exporter) and workplace (importer) specific effects. Estimating the regression with OLS we find a highly significant $\psi_\lambda = -3.76$. The figure below depicts the conditional relationship, that is, log worker inflows and log distances cleaned of importer and exporter fixed effects.

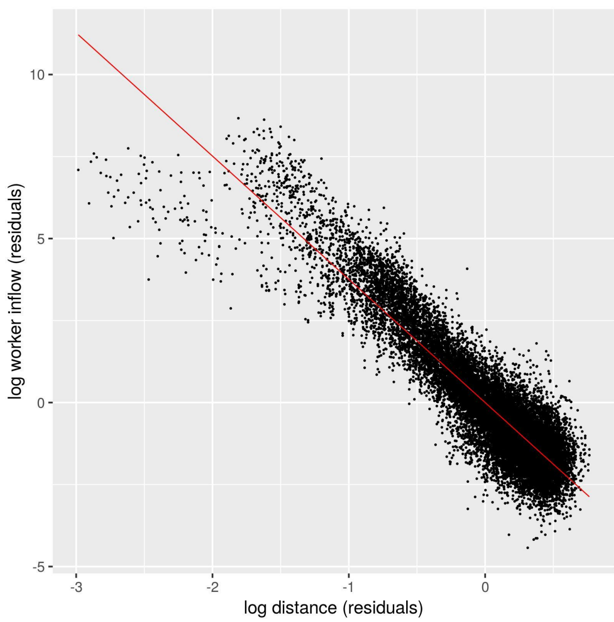

Figure A.3: Gravity estimation for commuting flows

In contrast to goods trade there is no clear indication of heteroscedasticity in the data and re-estimating the gravity in commuting equation in its multiplicative form using PPML leads to a similar coefficient as shown in the table below.

	OLS	PPML
log_distance	-3.757	-3.241
robust s.e.	0.021	0.015
Observations	18912	18912
(Pseudo) R2	0.83	0.96

Table A.2: Gravity in commuting flows

Finally we can back out the commuting elasticity ϵ by using the fact that from equation 12 residence fixed effects are given by $S_{\lambda,i} = \epsilon \log w_i$. Fixing the estimate of $\psi_\lambda = -3.76$ we rerun our gravity in commuting equation, explicity inluding the residence fixed effect this time.

$$\log \lambda_{ni|\Omega_g} = \epsilon \log w_i + M_{\lambda,n} + \psi_\lambda \log dist_{ni} + \log \mathbb{B}_{ni} \ ,$$

The resulting highly significant coefficient on log wages is $\epsilon = 4.61$ and thus substantially higher than in the US case. This is in line with our observation of stronger commuting flows in Germany.

E Additional Tables

Table A.3: Analysis of the general equilibrium local employment elasticities in response to 5 percent productivity shocks at the local level (commuting zones) with an expenditure share of 10 percent for housing.

	Dependent variable:								
	Employment Elasticity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(L)		0.159***	−0.437*	−0.377*				−0.597**	−0.662***
		(0.035)	(0.241)	(0.219)				(0.243)	(0.242)
log(w)			0.094	0.629				0.429*	0.480*
			(0.266)	(0.418)				(0.256)	(0.256)
log(H)			0.636**	0.553**				0.757***	0.815***
			(0.249)	(0.227)				(0.240)	(0.239)
$\log(L_{-i})$				−0.320***					
				(0.063)					
$\log(w_{-i})$				0.143					
				(0.508)					
$\lambda^R_{ii\|i}$					1.027***				
					(0.340)				
$\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$						−0.013		0.104	
						(0.061)		(0.070)	
$\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$						0.863*		1.268***	
						(0.438)		(0.421)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}$						1.431***		1.473***	
						(0.328)		(0.310)	
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\sum_{n\in N}\left(1-\lambda^R_{ni\|n}\right)\vartheta_{ni}$							0.063		0.175**
							(0.080)		(0.087)
$\frac{\partial w_i}{\partial A_i}\frac{w_i}{A_i}\cdot\vartheta_{ii}\left(\frac{\lambda_{ii}}{\lambda^R_i}-\lambda^L_i\right)$							2.102***		2.212***
							(0.430)		(0.414)
Constant	2.816***	0.957**	−0.814	−3.076	2.050***	1.444***	2.028***	−5.740**	−5.374**
	(0.034)	(0.413)	(2.771)	(3.145)	(0.256)	(0.400)	(0.183)	(2.762)	(2.676)
Observations	141	141	141	141	141	141	141	141	141
R^2	0.000	0.128	0.170	0.325	0.062	0.185	0.176	0.312	0.315
Adjusted R^2	0.000	0.122	0.152	0.300	0.055	0.167	0.164	0.281	0.290

Note: L_{-i} refers to the sum of employment and $\bar{w}_{-i}$ to the employment weighted average wage in all counties with a centroid distance of less than 120km from i. *p<0.1; **p<0.05; ***p<0.01

Essay IV

Shocking Germany
A spatial analysis of German regional labor markets

Shocking Germany - A spatial analysis of German regional labor markets*

Oliver Krebs†

October 29, 2018

Abstract

This paper quantifies the surprisingly large heterogeneity of real income and employment effects across German counties in response to local productivity shocks. Using a quantitative model with imperfect mobility and sector-specific labor market frictions together with an outstanding data set of county level goods shipments, I identify the sources of the heterogeneity in Germany's complex interregional linkages. I find that population mobility reduces the magnitude of local employment rate responses by a striking 70 percent on average. In all but a few counties, changes in the sectoral composition of production have a much milder effect on employment elasticities. National employment rates are less dependent on mobility with worker in- and outflows in individual counties partially cancelling out effects. For productivity shocks affecting individual sectors across all regions the composition effect is substantially magnified, the mobility effect reduced. In line with recent real world observations I find that real income and employment effects, while correlated, do not need to be of the same sign. Finally, the spatial propagation of real income effects closely follows trade linkages whereas employment effects are more complex to predict.

JEL-Classification: F16, F17, R13, R23

Keywords: Quantitative spatial analysis, unemployment, migration, search and matching, labor market frictions

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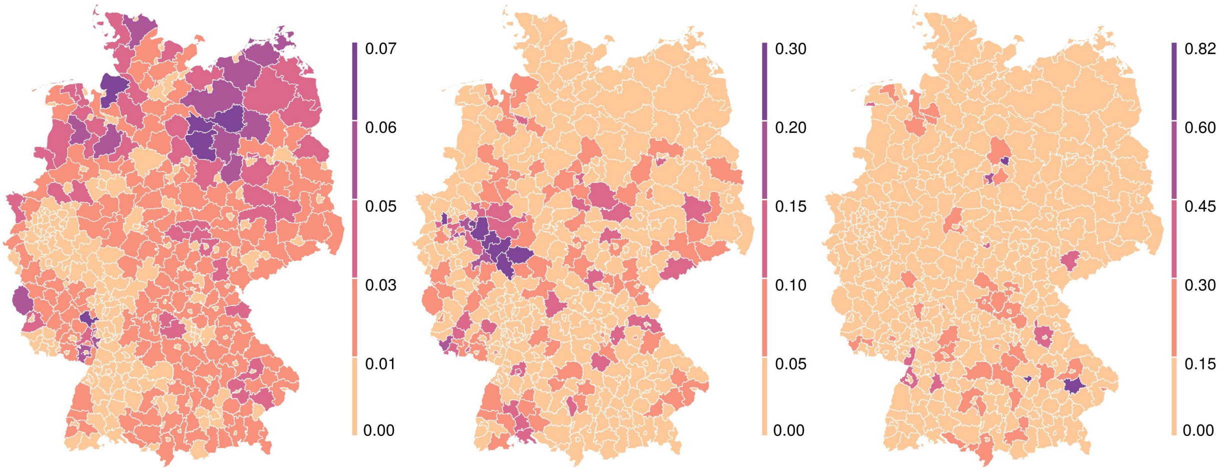
1 Introduction

Economic activity is very unevenly distributed across German counties. The revenue generated in Berlin, for example, is about 100 times larger than that of the smallest German county. Similarly, the industries that counties depend on vary profoundly. Figure 1 exemplifies this by showing the share of three sample industries in each county's total revenue. Agriculture is more important in counties in the northeast of Germany than in the rest of the economy, the heavy industry (metal) is the economic base in the Ruhr area and transport equipment is of enormous importance for a handful of locations which host production plants of major car manufacturers (VW in the north, Audi and BMW in the southeast and Mercedes in the southwest). The arrangement of clusters differ as well. The metal industry is agglomerated in a single region but car manufacturing clusters are spread out across Germany.[1]



(a) Agriculture (b) Metal (c) Transport Equipment

Figure 1: Sectoral shares in total county revenue

Plausibly, this uneven distribution of economic activity implies that regional markets will respond differently to local and sectoral shocks and policies. A new technology in the automotive industry will affect regions differently than a new communications technology and a bankruptcy in Berlin will result in different effects than one in Munich. In fact, most economic shocks or policies possess a sectoral (e.g. industry innovations, product standards) or regional component (e.g. natural disasters, local policies, bankruptcies) and even a seemingly aggregate shock, such as a rise in import competition, translates into different regional shocks depending on the strength of foreign trade linkages with each county.

The goal of this paper is not to analyse a specific such event. Instead, in line with recent

[1]This is, of course, only a crude look at the production structure and agglomeration in Germany. Krebs (2018) provides a complete analysis of both the German production structure and interregional trade network, something that is beyond the scope of this paper.

research (see Caliendo et al. 2018; Monte et al. 2018; Krebs and Pflüger 2018a), I quantify the heterogeneity of responses to standardized local productivity shocks in a general equilibrium framework and, crucially, identify the drivers of the resulting differences. I am the first to do so for German counties in a general equilibrium model. The resulting heterogeneity of effects is surprisingly large. The local employment elasticities vary by a factor of 3.6 and real income elasticities by a factor of 2.3 depending on where a productivity shock takes place geographically. This quantification is vital for regional policy makers to project the impact that policies or productivity shocks, such as investments or bankruptcies, will have in a specific location. Moreover, these results are also informative in light of the growing body of empirical literature in the wake of Autor et al. (2013) that is concerned with analysing local labor market responses to aggregate shocks and that only derives single average elasticities of employment across regions.[2]

Importantly, I find that the heterogeneity of effects from regional productivity shocks persists with respect to resulting effects at the national level. Specifically, even after controlling for the size of the treated county, that is, looking at regional productivity shocks that are indistinguishable in the aggregate national data, national German welfare elasticities vary by a factor of 3.7 and national employment rate elasticities by a factor of 5.6 depending on where the shock occurs geographically. Clearly this implies that any analysis of national productivity shocks that ignores the underlying geography can be extremely misleading.

Moreover, the result that some local shocks have large aggregate consequences while others do not is in line with a sizable literature that explains how disaggregate shocks can be of aggregate importance. Long and Plosser (1983) and Horvath (1998, 2000), for example, show that sectoral shocks can magnify substantially through input-output networks in the real business cycle context. Similarly, Acemoglu et al. (2012) use network theory to show conditions under which "cascade effects" can lead from small disturbances in a production network to large aggregate effects. Gabaix (2011) demonstrate that even firm level shocks can magnify to important magnitudes if the size distribution of firms is sufficiently fat-tailed. Yet, all of these studies abstract from the geographical component of disaggregate shocks that this paper focuses on. One reason for this is that data on regional production and trade linkages between regions is rarely available at the necessary level of detail. At the heart of this paper, however, is a unique data set on shipments by truck, train or waterway among German counties and between counties and third countries that allows me to model Germany's complex sectoral and geographical input-output network. Based on this outstanding data I simulate how local productivity shocks ripple through the economy's network, po-

[2]Autor et al. (2013) analyse the effects of the rise in Chinese import competition on U.S. local labor markets. Further recent examples of this literature include Dauth et al. (2014) who perform a similar analysis for the German economy or Acemoglu and Restrepo (2017) and Dauth et al. (2018) who analyse the effect of robotization on U.S. and German local labor markets, respectively.

tentially multiply and affect the national German economy. In particular, I construct an Eaton and Kortum (2002) type spatial quantitative international and interregional trade model with multiple sectors and input-output relations as in Caliendo and Parro (2015) and with a geographically disaggregated Germany.[3] Moreover, in a regional context population movements are arguably also important linkages between locations and I therefore extend the model with imperfect labor mobility between German counties in the style of Redding (2016). In this setting workers have individual preferences for living in a particular region. Consequently, they will accept a lower real income to live in a location for which they have a strong preference and vice versa. Thus, in contrast to models with perfect mobility these models can replicate observed real income differentials across space in equilibrium if calibrated accordingly. The introduction of land and structures as a fixed factor in production similar to Krebs and Pflüger (2018b) serves as an exogenous factor determining agglomeration sizes. A large endowment of land ceteris paribus implies lower land prices and thus lower production costs and a more attractive location for firms.[4]

Finally, one of the key variables of interest regarding both local and national outcome is unemployment. Nevertheless, unemployment is often absent from trade models following the idea that any shock that raises real income, will in the presence of labor market frictions also lead to a higher employment rate and that both are thus simply two sides of the same coin. This notion, however, has come under heavy debate in the past years, as rising employment rates in the United States and European Union have gone hand in hand with stagnating real wages (The Economist 2018b). In line with this idea I find that for regional shocks aggregate welfare and employment effects are correlated but this correlation is far from perfect with a rank correlation of 0.61. Thus productivity increases in regions that have a large effect on national average or expected welfare need not have a large effect on the national employment rate and vice versa. It has been pointed out that the decoupling of the real income from the employment rate is in part due to an increase in jobs in low paying sectors with "The Economist" 2018a poignantly noting that the number of hairdressers in the UK has increased by 50 percent since 2010.

To model how the growth and decline of specific sectors can influence the employment rate I

[3]Spatial quantitative models as surveyed by Redding and Rossi-Hansberg (2017) allow for a range of underlying trade structure. Using an Eaton-Kortum type model comes with two advantages. Firstly, it keeps my modelling approach closely related to Caliendo et al. (2018) who perform a similar study for the U.S., allowing me to compare my results with theirs. Secondly, sectoral size adjustments due to changes in comparative advantage match with the idea that different sectoral matching frictions drive unemployment effects as discussed below.

[4]As explained above, my modelling of trade follows Caetal2015 and is, thus not based on monopolistic competition and increasing returns to scale. Models of this type (see, for example, Krebs and Pflüger 2018a) feature an additional agglomeration force. However, in quantitative analysis parameters are usually chosen to restrict this force thus that circular effects, endogenous agglomeration and, subsequently, multiple equilibria can not arise (see Redding and Sturm 2008). Any agglomeration is, in both models, therefore exogenously determined by the initial calibration and choice of parameters.

follow Carrère et al. (2015) and incorporate industry-specific Diamond-Mortensen-Pissarides search and matching frictions into the model. In this setting firms can not directly hire new workers but instead open vacancies that lead to a successful match with a rate dependent on the number of job seekers and vacancies in the market. The sector specificity of frictions implies that given the same number of job seekers and vacancies in two different sectors vacancies will always be filled less likely in the one with the higher frictions. Carrère et al. (2015) and Carrère et al. (2014) demonstrate such differences in sectoral frictions using time series data for 25 OECD countries. To provide independent evidence for Germany I rely on time series data from the federal institute of employment research (IAB) containing information on job vacancies, unemployed (job seekers) and the average number of days that a job vacancy remains open beyond a company's preferred hire date. The data is on a yearly bases from 2012 to 2017 for the 16 German states and for 37 fields of occupation.[5] I use the log of the vacancy duration as a measure of labor market frictions and regress it on fixed effects of occupational fields, state-time fixed effects and the log of the number of unemployed per vacancy. Figure 2 depicts the deviation of fixed effects of occupational fields from their mean. Thus, for a given ratio of vacancies to job seekers filling a new vacancy takes about 32 percent longer than average in "security services" and 57 percent less time in "law and administration". Moreover, it is clear to see from the depicted 95 percent confidence intervals that in almost all cases these deviations are highly significant. A Wald test for a common fixed effects across occupational fields, that is, a common matching friction, is strongly rejected with an F-Value of 133.8.

Including such sector-specific frictions into the model has a central implication in line with the real world feature discussed above: changes in the employment rate no longer only depend on changes in the real wage. Instead, the employment effect can be decomposed into three separate channels. First, the initial productivity shock leads to an "expansion effect" that transmits through the trade network via terms of trade effects and induces firms to adapt the number of vacancies they open to hire workers. The change in the number of vacancies per job seeker then implies a change in the number of successful matches and the local employment rates. Secondly, shifts in comparative advantage in the trade network lead to structural transformation in each county. This "composition effect" shifts workers between sectors with different matching frictions and thereby influences the employment rate. Lastly, changes in the real income in each county lead to migration. An increase in the population size implies a larger number of job seekers per vacancy and vice versa for a decreasing population. This "mobility effect" consequently changes the number of successful matches per person and hence the employment rate in each county.[6]

[5] Cf. "Engpassanalyse" in "Berichte: Analyse Arbeitsmarkt" (2017) by the German institute for employment research.

[6] This is, in essence, the effect first described by Harris and Todaro (1970).

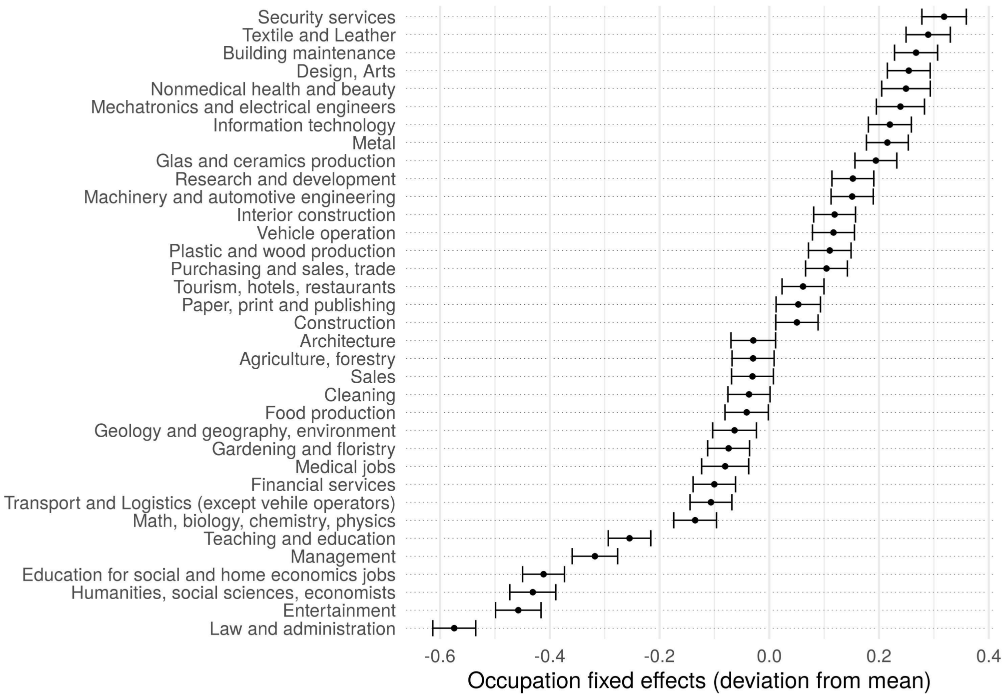


Figure 2: Matching frictions across occupational fields in Germany

A further key contribution of this paper is to quantify the role of these three effects in determining the overall local and national employment elasticities with respect to regional productivity shocks. Population inflow in response to a local productivity shock reduces the local employment elasticity by a striking 70 percent on average. Interestingly, the average influence of mobility on the national employment elasticity is much milder with only 3.64 percent as the employment effects of in- and outflows across counties mostly cancel each other out. The composition effect in contrast plays a much lower role on average. For shocks in some specific regions, however, it can reduce or increase local employment elasticities by up to -13 and 21 percent respectively and influence national employment elasticities by -9 to 13 percent. Moreover, looking at the detailed regional effects of local productivity shocks I find many regions that experience real income and employment effects of opposite signs in line with recent observations discussed above.

A final important result concerns the predictability of effects across locations. For real income gains the geographic dissipation of effects closely follows the treated county's trade network. The strength and sign of employment effects across counties, however, exhibits a more complex pattern depending not only on the trade network but also on population elasticities that are in turn influenced by individual preferences and locations' endowment with land.

Previous literature. In the broader context, this paper belongs to a branch of literature relying on (spatial) quantitative trade models that connect theory with numbers to quantify theoretical effects. Redding and Rossi-Hansberg (2017) provide a lucid survey of this literature that shows how quantitative models can be combined from a range of possible components. The specification of the model in this essay particularly relies on the seminal work by Caliendo and Parro (2015), providing a multisector specification of quantitative models, and Redding (2016) who introduces (imperfect) worker mobility. My work also builds on the recent literature that introduces the static Helpman and Itskhoki (2010) version of search and matching frictions into gravity type models. Felbermayr et al. (2013) and Heid and Larch (2016) build an Armington-type model with such frictions.[7] However, their model features no geographical disaggregation or population mobility and is constructed around one sector economies, which can not feature the sectoral reallocation effect on employment discussed in this paper. Carrère et al. (2015) instead build an Eaton-Kortum type multisector model with sector-specific search and matching frictions. They show that such a sectoral disaggregation implies that the real wage and employment rate are no longer perfectly correlated, as shocks to an economy induce shifts of workers between high and low friction industries. Yet, their model does not incorporate intermediates, which Caliendo et al. (2018) show to be crucial in the propagation of local shocks, nor do they include multiple production factors, or a regional context. Moreover, in contrast to their setting I also introduce population mobility which turns out to be crucial for quantitative effects.

My analysis is closely related to Caliendo et al. (2018) who study welfare and population elasticities of regional shocks in U.S. counties. Differences in modelling notwithstanding the magnitude of the heterogeneity of welfare elasticities in Germany that I find in this paper is similar to what Caliendo et al. (2018) find for U.S. counties. However, apart from studying a different country and using imperfect instead of perfect labor mobility, the superior data available for Germany allows me to model German counties integrated into the world economy whereas Caliendo et al. (2018) abstract from any international trade relations due to a lack of data. More importantly, however, their study rests on a full employment model and thus can not differentiate between employment and population elasticities. In contrast I explicitly model the strain that population inflows exert on local labor markets and find a strikingly large influence of mobility on employment rates. My study is also related to Monte et al. (2018) and Krebs and Pflüger (2018a) who use the same methodology to study the effects of commuting on local labor markets in the U.S. and Germany respectively albeit also using full employment models. Krebs and Pflüger (2018b) study the effects of a specific shock, the transatlantic trade and investment partnership (TTIP), at the German county level using a full employment model and constructing interregional trade flows based on proportionality assumptions. In contrast to their study, however, I can make use of a far superior data set to derive the subnational trade and production structure in Germany.

[7] Anderson and Van Wincoop (2003) for the Armingtons specification in gravity type models.

The remainder of the paper is structured as follows. Section 2 develops the theoretical model. Section 3 explains my empirical strategy and the calibration of the model, including the data sets used. Section 4 presents my results beginning with the aggregate, national effects of both regional and sectoral shocks and then turning to the disaggregated effects.

2 The model

Setup. I assume that the world economy consists of N locations, indexed by n or i. A subset $N^G \subset N$ of these locations represents German counties, the remainder are other countries and a modeled rest of the world (henceforth: ROW). Each location is endowed with an exogenous quality-adjusted amount of structures $\bar{S}_n$. The number of consumers in location n, denoted L_n, is exogenously given for countries but emerges endogenously in the case of German counties. Thus, the assumption is that the exogenous measure of German consumers $\bar{L}^G$, who supply 1 unit of labor each, are (imperfectly) mobile within Germany but not across countries. Land and labor are used to produce a continuum of differentiated goods in each of K sectors, indexed by k or j. Each of these sectors is subject to search and matching frictions between workers and firms that result in equilibrium unemployment. Workers will be perfectly mobile between sectors ex-ante but bound to their decision once they learn whether or not they will be unemployed. Hence, while the model features heterogeneous wages and unemployment rates across sectors a common ex-ante expected (or per capita) wage w_n across sectors emerges at each location. All locations can trade all varieties with each other subject to iceberg trade costs so that $d_{nik} \geq 1$ units of a good produced in industry k in location i have to be shipped in order for one unit of the good to arrive at location n. I assume that goods trade within a location is costless, $d_{nnk} = 1$. For each industry in each location another group of firms, operating under perfect competition and without adding value, sources all varieties from the cheapest supplier after trade costs to produce an industry aggregate. This compound good is non-traded and used either for consumption or as an input in the production process of varieties.

2.1 Consumers

Preferences. The preferences of a consumer Ω in location n are defined over the consumption of a goods bundle $C_n(\Omega)$ as follows:

$$U_n(\Omega) = a_n(\Omega)\, C_n(\Omega)\,, \tag{1}$$

where $a_n(\Omega)$ is a consumer specific amenity for living in location n discussed below. The consumption aggregate $C_n(\Omega)$ is defined over the consumption $C_{nk}(\Omega)$ of compound goods from each of K industries in a Cobb-Douglas fashion. Specifically,

$$C_n(\Omega) = \prod_{k=1}^{K} \left(C_{nk}(\Omega)\right)^{\delta_{nC,k}}, \tag{2}$$

where $\delta_{nC,k}$ are the constant and location specific shares in consumption spending on industry k, with $0 \leq \delta_{nC,k} \leq 1$ and $\sum_{k=1}^{K} \delta_{nC,k} = 1$. The Cobb-Douglas price index for the consumption bundle is then

$$P_n = \prod_{k=1}^{K} P_{nk}^{\delta_{nC,k}}, \tag{3}$$

where P_{nk} denotes the price of the compound good of industry k in location n.

Mobility. I follow Redding (2016) and Tabuchi and Thisse (2002) in assuming that the location and consumer specific amenity $a_n(\Omega)$ is drawn independently by all consumers from location dependent distributions. As in Redding (2016) this distribution is of the Fréchet type with cumulative density functions given by

$$G_n(a) = e^{-A_n a^{-\epsilon}}. \tag{4}$$

Here A_n is a measure of average preference for location n and ϵ an inverse measure of the dispersion of amenities across workers. I assume that workers make their location decision after the amenity draw but before deciding on the sector in which to search for a job and before they know whether or not they will be unemployed. Hence, they will base their decision where to locate on their expected (indirect) utility from living in location n, which for risk neutral agents is given by

$$\mathcal{V}_n(\Omega) = a_n(\Omega) \frac{v_n}{P_n},$$

with v_n denoting the expected income of a consumer in location n. Since the right hand side fraction is independent of the individual worker Ω the expected indirect utility is also distributed Fréchet with the distribution function

$$G_n(\mathcal{V}) = e^{-A_n \left(\frac{v_n}{P_n}\right)^{\epsilon} \mathcal{V}^{-\epsilon}}.$$

Workers are mobile across German counties $N^G \subset N$ and move to the location that offers the highest level of utility ex-ante. With labor being infinitely divisible the share $L_n/\bar{L}^G$ of German workers living in a county $n \in N^G$ is equal to the probability that a German worker chooses to live in that county. Using the properties of the Fréchet distribution, the share of population λ_n that a location n has in its country's population is thus

$$\lambda_n = \begin{cases} \frac{A_n \left(\frac{v_n}{P_n}\right)^{\epsilon}}{\sum_{i \in N^G} A_i \left(\frac{v_i}{P_i}\right)^{\epsilon}} & \text{if } n \in N^G, \\ 1 & \text{otherwise.} \end{cases} \tag{5}$$

2.2 Production with search and matching

In any industry k at any location n a perfectly elastic supply of firms can produce each variety ω with constant returns to scale by combining labor, structures and potentially each industry's compound good. Locations and industries differ in terms of their input mix and firms in their productivities $z_{nk}(\omega)$. I follow Eaton and Kortum (2002) and Caliendo and Parro (2015) in assuming that the latter are drawn independently from location and industry specific Fréchet distributions with cumulative density functions given by

$$F_{nk}(z) = e^{-z^{-\theta_k}}$$

where θ_k is the shape parameter that controls the dispersion of productivities across varieties within each sector k, with a bigger θ_k implying less variability. As in Caliendo et al. (2018) I set the scale parameter of the Fréchet distribution to 1 and instead model differences in the average productivity between locations and sectors through the introduction of a second, non-random but factor augmenting technology parameter T_{nk} directly into the following production function,

$$q_{nk}(\omega) = z_{nk}(\omega) T_{nk}^{1-\beta_{nk}^M} (H_{nk}(\omega))^{\beta_{nk}^H} (S_{nk}(\omega))^{\beta_{nk}^S} (M_{nk}(\omega))^{\beta_{nk}^M}. \tag{6}$$

Here $q_{nk}(\omega)$ is the quantity of variety ω produced in location n and industry k, $H_{nk}(\omega)$ and $S_{nk}(\omega)$ are the amounts of labor and structures used in production, $M_{nk}(\omega)$ is a Cobb-Douglas aggregate of compound goods from potentially all K industries and β_{nk}^H, β_{nk}^S and β_{nk}^M, with $\beta_{nk}^H + \beta_{nk}^S + \beta_{nk}^M = 1$, control the cost shares of labor, structures and intermediates in the production process. Of course, the specification of technology is analytically equivalent to setting the scale parameter of the distribution function equal to $T_{nk}^{1-\beta_{nk}^M}$. However, as Caliendo et al. (2018, p. 2052) argue, it ensures that technological shocks do not generate output increases in sectors which merely process intermediates ($1 - \beta_{nk}^M = 0$) and thus prevents overproportional real GDP effects in the quantitative analysis below.

I assume that the labor market in each location and industry is subject to Diamond-Mortensen-Pissarides search and matching frictions.[8] Hence, firms can not employ workers

[8]See Pissarides (2000).

directly but instead need to open vacancies $V_{nk}(\omega)$. These result in successful matches depending on the total number of open vacancies (V_{nk}) and total number of workers searching for jobs (L_{nk}) in the respective industry and location according to the matching function

$$H_{nk} = \mu_{nk} V_{nk}^{\iota} L_{nk}^{1-\iota}, \tag{7}$$

where H_{nk} is the total number of successful matches in location n and industry k, $\mu_{nk} > 0$ is a measure of the matching efficiency and $0 \leq \iota \leq 1$ a parameter denoting the vacancy share in the matching process. Since each individual variety has zero weight in the industry no single firm can influence the matching rate through the number of vacancies $V_{nk}(\omega)$ it opens. Hence, this decision is made knowing that the firm needs to open V_{nk}/H_{nk} vacancies for each worker it wants to hire. I assume that the opening of vacancies comes at a cost ν_{nk} that has to be paid in terms of the final consumption bundle. Therefore, the cost b_{nk} of hiring per worker for a firm in location n and industry k is given by

$$b_{nk} = P_n \nu_{nk} \frac{V_{nk}}{H_{nk}}. \tag{8}$$

Wage bargaining. Following Helpman and Itskhoki (2010) the matching process is modeled as a one shot game, i.e. if a worker is unmatched he will be unemployed and receive no wage.[9] Likewise, if a matched worker or firm breaks the match the output generated by the additional worker is considered lost and there is no possibility to search for a replacement match. Hence, once a firm is matched with a worker the successful match creates a rent over which workers and firms bargain. I assume that bargaining takes the form of a Stole and Zwiebel (1996a,b) bargaining game which extends Nash bargaining to the case of multiple workers. More specifically, the assumption is that firms can negotiate with each worker individually and simultaneously without dependency on the outcome of other negotiations. Hence, the rent that workers and firms split is the marginal profit created by a worker acknowledging the marginal worker's influence on the negotiated wage for all workers. As in Nash bargaining the split occurs according to the bargaining weights $0 \leq \varphi_{nk} \leq 1$ for workers and $1 - \varphi_{nk}$ for firms. Thus,

$$\varphi_{nk} \frac{\partial \left(R_{nk}(\omega) - H_{nk}(\omega) w_{nk}(H_{nk}(\omega))\right)}{\partial H_{nk}(\omega)} = (1 - \varphi_{nk}) w_{nk}(H_{nk}(\omega)),$$

where $R_{nk}(\omega) = p_{nk}(\omega) q_{nk}(\omega)$ is the firm's revenue, $p_{nk}(\omega)$ the variety's mill price, and $w_{nk}(H_{nk}(\omega))$ the negotiated wage in the production of variety ω in location n and industry

[9] While it is possible to introduce unemployment benefits into the framework I abstract from it here.

k. The solution to the above differential equation is

$$w_{nk}\left(H_{nk}\left(\omega\right)\right)=\frac{\varphi_{nk}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}\frac{\partial R_{nk}\left(\omega\right)}{\partial H_{nk}\left(\omega\right)} \tag{9}$$

Intuitively, for a given number of workers the higher their negotiation power the higher their wage. On the other hand a higher β_{nk}^{H} reduces the relative effect of a marginal worker leaving the match on the marginal revenue and hence decreases the share of marginal revenue they can obtain in the wage negotiations. However, as can immediately be seen by substituting $\frac{\partial R_{nk}(\omega)}{\partial H_{nk}(\omega)}=\beta_{nk}^{H}\frac{R_{nk}(\omega)}{H_{nk}(\omega)}$, at a given H_{nk} a larger β_{nk}^{H} also raises the level of marginal revenue. Since the latter effect dominates an increase in β_{nk}^{H} also increases the wage. Moreover, given the nature of the constant returns to scale production function this result implies that the negotiated wage is independent of firm size.

Optimal employment and input bundle costs. Using the negotiated wage rate (9) firm profits $\Pi_{nk}\left(\omega\right)$ can be written as

$$\Pi_{nk}\left(\omega\right)=\frac{1-\varphi_{nk}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}R_{nk}\left(\omega\right)-b_{nk}H_{nk}\left(\omega\right)-r_{n}S_{nk}\left(\omega\right)-\rho_{nk}M_{nk}\left(\omega\right) \tag{10}$$

where r_n denotes the rent for structures in location n and ρ_{nk} is the price index for an intermediate bundle used by producers in industry k in location n given by

$$\rho_{nk}=\prod_{j=1}^{K}P_{nj}^{\delta_{nk,j}} \tag{11}$$

with $0\leq\delta_{nk,j}\leq1$ being the share of industry j compound good in the intermediate input mix of firms in industry k and location n, for which $\sum_{j=1}^{K}\delta_{nk,j}=1$. Solving the firm's profit maximization problem then leads to the optimal employment condition for workers:

$$w_{nk}\left(H_{nk}\left(\omega\right)\right)=\frac{\varphi_{nk}}{1-\varphi_{nk}}b_{nk} \tag{12}$$

Thus, firms employ workers until the negotiated wage is equal to the hiring costs multiplied with the relative negotiation power of workers. Intuitively, the perfectly elastic supply of competitors ensures that vacancies are opened until the expected profits of a vacancy are driven down to zero. Since, hiring costs depend only on location and industry but not on the produced variety, all firms in location n and industry k will pay the same wage despite having heterogeneous productivity levels $z_{nk}\left(\omega\right)$.

Deriving the remaining optimal input conditions, combining them with the negotiated wage rate (9) and defining the constant shares $\tilde{\beta}_{nk}^{H}\equiv\frac{\varphi_{nk}\beta_{nk}^{H}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}$, $\tilde{\beta}_{nk}^{S}\equiv\frac{(1-\varphi_{nk})\beta_{nk}^{S}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}$ and $\tilde{\beta}_{nk}^{M}\equiv$

$\frac{(1-\varphi_{nk})\beta_{nk}^{M}}{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}$ the industry wide factor payments and vacancy costs can be calculated as

$$\begin{aligned} H_{nk}w_{nk} &= \tilde{\beta}_{nk}^{H}R_{nk} \quad S_{nk}r_{n} = \tilde{\beta}_{nk}^{S}R_{nk} \\ M_{nk}\rho_{nk} &= \tilde{\beta}_{nk}^{M}R_{nk} \quad H_{nk}b_{nk} = \left(1-\tilde{\beta}_{nk}^{H}-\tilde{\beta}_{nk}^{S}-\tilde{\beta}_{nk}^{M}\right)R_{nk} \end{aligned} \tag{13}$$

where, with a slight abuse of notation, I denote industry aggregates by dropping the dependency on ω. Using optimal inputs in the cost function the implied cost of an input bundle is

$$c_{nk} = \zeta_{nk} w_{nk}^{\beta_{nk}^{H}} r_{n}^{\beta_{nk}^{S}} \rho_{nk}^{\beta_{nk}^{M}}, \tag{14}$$

where ζ_{nk} is defined as the constant $\zeta_{nk} \equiv \left(\beta_{nk}^{H}\right)^{-\beta_{nk}^{H}} \left(\beta_{nk}^{S}\right)^{-\beta_{nk}^{S}} \left(\beta_{nk}^{M}\right)^{-\beta_{nk}^{M}} \frac{1-\varphi_{nk}\left(1-\beta_{nk}^{H}\right)}{(\varphi_{nk})^{\beta_{nk}^{H}}(1-\varphi_{nk})^{1-\beta_{nk}^{H}}}$.

Trade shares and prices With perfect competition firms face mill prices equal to unit costs, which can be calculated by dividing the input bundle cost by the industry specific and randomly distributed variety specific parts of productivity. The price $p_{nik}(\omega)$ in location n of buying one unit of ω in sector k from a producer in location i also depends on the iceberg trade costs $d_{nik} \geq 1$ between the two locations, resulting in

$$p_{nik}(\omega) = \frac{d_{nik}c_{ik}}{z_{ik}(\omega)\,T_{ik}^{1-\beta_{ik}^{M}}}.$$

Perfectly competitive compound good producers in each location and industry costlessly combine all of the industry's varieties into an industry aggregate good. They treat varieties across locations as homogeneous and consequently source each variety from the location that provides it at the lowest price. Hence the price paid in location n for a variety ω from industry k is given by $p_{nk}(\omega) = \min\{p_{nik}(\omega); i = 1...N\}$ and, using the properties of the Fréchet distribution as in Eaton and Kortum (2002), the share of location n's expenditure in industry k on varieties produced in i becomes

$$\pi_{nik} = \frac{\left(d_{nik}c_{ik}T_{ik}^{1-\beta_{ik}^{M}}\right)^{-\theta_{k}}}{\sum_{s=1}^{N}\left(d_{nsk}c_{sk}T_{sk}^{1-\beta_{sk}^{M}}\right)^{-\theta_{k}}}, \tag{15}$$

where by construction $\sum_{i=1}^{N}\pi_{nik} = 1$.

Compound goods producers in each location and industry have a CES-type production function given by

$$Q_{nk} = \left(\int_{0}^{1} q_{nk}^{D}(\omega)^{\frac{\sigma_{k}-1}{\sigma_{k}}}\,d\omega\right)^{\frac{\sigma_{k}}{\sigma_{k}-1}},$$

where Q_{nk} is the quantity of industry k's compound good produced in location n, $q_{nk}^{D}(\omega)$ is location n's use of variety ω and $\sigma_k > 1$ denotes the (constant) within-industry elasticity of substitution between any two varieties. Profit maximization of compound good producers then results in

$$q_{nk}^D(\omega) = \left(\frac{p_{nk}(\omega)}{P_{nk}}\right)^{-\sigma_k} Q_{nk},$$

where P_{nk} is the implied perfect CES price index for industry aggregates, i.e. the price of a compound good from industry k in location n. Given the properties of the Fréchet distribution this price index can be calculated as

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} \left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^M}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}}, \tag{16}$$

where $\gamma_k \equiv \left[\Gamma\left(\frac{\theta_k+1-\sigma_k}{\theta_k}\right)\right]^{\frac{1}{1-\sigma_k}}$, $\Gamma(\cdot)$ denotes the gamma function and I assume that $1+\theta_k > \sigma_k$.

2.3 Unemployment

Due to labor market frictions, as long as $H_{nk} < L_{nk}$, there will be unemployment. By (7) the probability χ_{nk} of a worker finding a job in sector k in location n conditional on searching in this sector is[10]

$$\chi_{nk} \equiv \frac{H_{nk}}{L_{nk}} = \mu_{nk}\left(\frac{V_{nk}}{L_{nk}}\right)^{\iota}.$$

As explained above, I assume that workers can freely choose in which sector to work before the matching process. Hence, with risk neutral agents, in equilibrium a common ex-ante expected wage or wage per capita $w_n = \chi_{nk} w_{nk}$ for workers in location n emerges across all sectors. Using the optimal employment condition (12) and cost of opening vacancies (8) for any industry k in location n this wage is given by

$$w_n = \frac{\varphi_{nk}}{1-\varphi_{nk}} P_n \nu_{nk} \mu_{nk}^{-\frac{1}{\iota}} \chi_{nk}^{\frac{1}{\iota}} \tag{17}$$

Defining an inverse measure of the frictions in each labor market $\tilde{\mu}_{nk} \equiv \frac{\mu_{nk}}{\nu_{nk}^{\iota}}\left(\frac{1-\varphi_{nk}}{\varphi_{nk}}\right)^{\iota}$ that consists of a combination of the matching efficiency, the relative bargaining power of workers and the cost of opening vacancies, the employment rate χ_{nk} in sector k in location n can be written as

$$\chi_{nk} = \tilde{\mu}_{nk}\left(\frac{w_n}{P_n}\right)^{\iota}. \tag{18}$$

[10]It is easier for expositional purposes to work with the employment rate χ_{nk} but, of course, this immediately delivers the unemployment rate as $1-\chi_{nk}$.

Consequently, the sector specific employment rates are proportional to the inverse measure $\tilde{\mu}_{nk}$ with the common multiplicator being an increasing function of the real wage. However, as each location's total employment rate $\chi_n \equiv \frac{\sum_{k=1}^{K} H_{nk}}{L_n}$ can be obtained by summing over sectoral rates χ_{nk} weighted by industry size in terms of potential workers, policies that are real wage augmenting must not necessarily increase a location's overall employment rate. More specifically, while they do increase the region's sectoral employment rates via the real wage, the change in the overall regional employment rate also depends on the policy induced shift of workers between sectors. This can be seen by using sectoral employment rates (18) and sectoral wage sums (13) to write location n's total employment rate as

$$\chi_n = \frac{\sum_{k=1}^{K} L_{nk}\chi_{nk}}{L_n} = \left(\frac{w_n}{P_n}\right)^{\iota} \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk}\tilde{\mu}_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk}}, \tag{19}$$

where the second term captures the sectoral composition of production.

2.4 Equilibrium

Wages and rents. The sector specific equilibrium wages can be calculated by combining per capita wages (17) with the employment rate (18), resulting in

$$w_{nk} = \frac{w_n^{1-\iota} P_n^{\iota}}{\tilde{\mu}_{nk}}. \tag{20}$$

Moreover, for any location n land market clearing requires that total rent income must equal total spending on land and structures. Using the factor payment shares (13),

$$r_n \bar{S}_n = \sum_{k=1}^{K} \tilde{\beta}_{nk}^{S} R_{nk},$$

where $\bar{S}_n$ is region n's endowment with land and structures. This immediately gives the local rent level r_n as

$$r_n = \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{S} R_{nk}}{\bar{S}_n}. \tag{21}$$

Deficits. Traditionally, trade theory has emphasized the role of intertemporal consumption and saving decisions in the origin of the observed trade imbalances. In quantitative applications of static models trade imbalances are, thus, usually accounted for by exogenous (monetary) transfers. However, trade imbalances also emerge in a static context through foreign ownership of factors.[11] Value generated in one location is spend by the owner of

[11]From an accounting perspective the standard approach balances current accounts by setting direct transfers equal to the observed trade imbalances but with opposite sign, essentially ignoring net income.

this factor who lives in a different location. Arguably, the latter plays a larger role in the regional than in the international context, especially at the high level of regional disaggregation applied here, that is, owners of land would have to live in the same county where they possess land for this effect not to matter. For this reason I adopt a twin strategy with regards to the observed trade imbalances. Firstly, at the international level I model trade deficits through exogenous transfers D_n (negative for trade surpluses) in line with the idea that international trade deficits are mainly driven by differences in national savings rate. This trade deficit is borne on a per capita basis via the mechanism explained below. Secondly, at the level of German counties I follow Caliendo et al. (2018) in assuming that a share $0 \leq (1-\Psi_n) \leq 1$ of each county's land rents is equally divided among its inhabitants via a lump sum transfer, while the remaining share Ψ_n is payed into a national portfolio. The (negative) *national* German deficit transfer D^G is added to this portfolio before it is redistributed across all counties on a per capita basis.[12] The portfolio shares Ψ_n can then be calibrated such that the remittances from and payments to the portfolio account for the *interregional* trade imbalances, representing the foreign ownership of land. The total deficit transfer D_n^{tot} then is

$$D_n^{tot} = \begin{cases} \lambda_n \left(\sum_{i \in N^G} \Psi_i \sum_{k=1}^K \tilde{\beta}_{ik}^S R_{ik} + D^G \right) - \Psi_n \sum_{k=1}^K \tilde{\beta}_{nk}^S R_{nk} + D_n^{reg} & \text{if } n \in N^G \\ D_n & \text{otherwise,} \end{cases} \tag{22}$$

where D_n^{reg} is an additional exogenous transfer accounting for cases in which the observed interregional trade deficits can not be explained even by remitting all ($\Psi_n = 1$) or none ($\Psi_n = 0$) of the land rents to the national portfolio.

Income. The total income $Y_n \equiv v_n L_n$ of all inhabitants of region n in equilibrium must be equal to locally generated factor income plus the (partly) endogenous deficit transfer. Using the factor payment shares in industry revenue (13) this total income can be expressed as

$$Y_n = \sum_{k=1}^{K} \left(\tilde{\beta}_{nk}^H + \tilde{\beta}_{nk}^S \right) R_{nk} + D_n^{tot}. \tag{23}$$

Goods market clearing. Market clearing in the non-traded compound goods sectors implies that the value of production $P_{nk}Q_{nk}$ equals expenditure for local consumption, local intermediate use and local vacancy costs. Formally,

$$P_{nk}Q_{nk} = \delta_{nC,k} Y_n + \sum_{j=1}^{K} \delta_{nj,k} M_{nj} \rho_{nj} + \sum_{j=1}^{K} \delta_{nC,k} b_{nj} H_{nj}. \tag{24}$$

[12] Caliendo et al. (2018) analyse regional trade between US states abstracting from foreign relations and hence international trade imbalances.

For variety producers market clearing entails that the value of production in industry k in location n must be equal to world expenditure for varieties from this industry. Since individual varieties are only directly demanded by compound good producers I make use of (13), (23) and (24) to write goods market clearing as

$$R_{nk} = \sum_{i=1}^{N} \pi_{ink} \left\{ \delta_{iC,k} D_i^{tot} + \sum_{j=1}^{K} \left[\delta_{ij,k} \tilde{\beta}_{ij}^{M} + \delta_{iC,k} \left(1 - \tilde{\beta}_{ij}^{M} \right) \right] R_{ij} \right\}. \tag{25}$$

Equilibrium. The equilibrium of the model consists of a set of industry location specific price indices P_{nk} and revenues R_{nk}, industry specific bilateral trade shares π_{nik}, and population shares λ_n that solve the equations for population mobility (5), expenditure shares (15), price indices (16) and market clearing (25) given by

$$\lambda_n = \begin{cases} \frac{A_n\left(\frac{v_n}{P_n}\right)^{\epsilon}}{\sum_{i\in N^G} A_i\left(\frac{v_i}{P_i}\right)^{\epsilon}} & \text{if } n \in N^G \\ 1 & \text{otherwise,} \end{cases}$$

$$\pi_{nik} = \frac{\left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^{M}}\right)^{-\theta_k}}{\sum_{s=1}^{N}\left(d_{nsk} c_{sk} T_{sk}^{1-\beta_{sk}^{M}}\right)^{-\theta_k}}$$

$$P_{nk} = \gamma_k \left[\sum_{i=1}^{N} \left(d_{nik} c_{ik} T_{ik}^{1-\beta_{ik}^{M}}\right)^{-\theta_k} \right]^{-\frac{1}{\theta_k}}$$

$$R_{nk} = \sum_{i=1}^{N} \pi_{ink} \left\{ \delta_{iC,k} D_i^{tot} + \sum_{j=1}^{K} \left[\delta_{ij,k} \tilde{\beta}_{ij}^{M} + \delta_{iC,k} \left(1 - \tilde{\beta}_{ij}^{M} \right) \right] R_{ij} \right\},$$

where the input bundle costs c_{nk} are given by (14), the expenditure per capita v_n by (23), the rental rate of structures r_n by (21) the price index for intermediates ρ_{nk} by (11) and the sectoral wages are calculated by combining (20) with (13) and (3).

3 Empirical strategy

3.1 The model in changes

The goal of this paper is to quantify the economic responses to local productivity shocks that can be interpreted as standardized labor demand shocks. Their heterogeneity thus translates to other events that create local labor demand shocks. However, solving the above equilibrium for any counterfactual scenario requires specifying the new *levels* of the shocked variables and identifying a vast number of variables that are not directly observable from the data, including any unchanged sectoral bilateral trade costs d_{nik} or productivities T_{nk}, substitution elasticities σ_{nk}, quality-adjusted housing stocks $\bar{S}_n$, and regional preference parameters A_n. To avoid these problematic tasks I turn to the method introduced by Dekle et al. (2007), which was applied to the multisector setting by Caliendo and Parro (2015) and to a setting with imperfect mobility by Redding (2016), and rewrite the model in terms of changes.

To this end, I denote all variables x in the counterfactual equilibrium, i.e. after the shock, with a prime and relative changes from the old to the new equilibrium with a hat, such that $\hat{x} = x'/x$. The four counterfactual equilibrium equations can then be rewritten in terms of $\hat{P}_{nk}$, R'_{nk}, π'_{nik}, and $\hat{\lambda}_n$ as follows:

$$\hat{\lambda}_n = \begin{cases} \frac{\left(\frac{\hat{Y}_n}{\hat{\lambda}_n \hat{P}_n}\right)^{\epsilon}}{\sum_{i\in N^G} \lambda_i \left(\frac{\hat{Y}_i}{\hat{\lambda}_i \hat{P}_i}\right)^{\epsilon}} & \text{if } n \in N^G \\ 1 & \text{otherwise} \end{cases} \tag{26}$$

$$\pi'_{nik} = \frac{\pi_{nik}\left(\hat{d}_{nik}\hat{c}_{ik}\hat{T}_{ik}^{1-\beta^M_{ik}}\right)^{-\theta_k}}{\sum_{s=1}^{N} \pi_{nsk}\left(\hat{d}_{nsk}\hat{c}_{sk}\hat{T}_{sk}^{1-\beta^M_{sk}}\right)^{-\theta_k}} \tag{27}$$

$$\hat{P}_{nk} = \left[\sum_{i=1}^{N} \pi_{nik}\left(\hat{d}_{nik}\hat{c}_{ik}\hat{T}_{ik}^{1-\beta^M_{ik}}\right)^{-\theta_k}\right]^{-\frac{1}{\theta_k}} \tag{28}$$

$$R'_{nk} = \sum_{i=1}^{N} \pi'_{ink}\left\{\delta_{iC,k} D_i^{tot\prime} + \sum_{j=1}^{K}\left[\delta^k_{ij}\tilde{\beta}^M_{ij} + \delta_{iC,k}\left(1-\tilde{\beta}^M_{ij}\right)\right] R'_{ij}\right\}, \tag{29}$$

where

$$\hat{Y}_n = \frac{\sum_{k=1}^{K}\left(\tilde{\beta}^H_{nk}+\tilde{\beta}^S_{nk}\right) R'_{nk} + D_n^{tot\prime}}{\sum_{k=1}^{K}\left(\tilde{\beta}^H_{nk}+\tilde{\beta}^S_{nk}\right) R_{nk} + D_n^{tot}}, \quad \hat{c}_{nk} = \hat{r}_n^{\beta^S_{nk}}\hat{\rho}_{nk}^{\beta^M_{nk}}\hat{w}_{nk}^{\beta^H_{nk}}, \quad \hat{r}_n = \frac{\sum_{k=1}^{K}\tilde{\beta}^S_{nk}R'_{nk}}{\sum_{k=1}^{K}\tilde{\beta}^S_{nk}R_{nk}},$$

$$\hat{\rho}_{nk} = \prod_{j=1}^{K}\hat{P}_{nj}^{\delta_{nk,j}}, \qquad \hat{w}_{nk} = \left(\frac{\sum_k \tilde{\beta}^H_{nk}R'_{nk}}{\sum_k \tilde{\beta}^H_{nk}R_{nk}}\right)^{1-\iota}\hat{\lambda}_n^{-(1-\iota)}\left(\prod_{k=1}^{K}\hat{P}_{nk}^{\delta_{nC,k}}\right)^{\iota},$$

and

$$D_n^{tot\prime} = \begin{cases} \lambda_n\left(\sum_{i\in N^G}\Psi_i\sum_{k=1}^{K}\tilde{\beta}^S_{ik}R'_{ik} + D'_n\right) - \Psi_n\sum_{k=1}^{K}\tilde{\beta}^S_{nk}R'_{nk} + D_n^{reg\prime} & \text{if } n\in N^G \\ D'_n & \text{otherwise.} \end{cases}$$

This "equilibrium in changes" no longer depends on any of the parameters that were deemed difficult to observe above. In fact, the only two parameters that can not be directly observed in the data are the Fréchet shape parameters for firm specific productivities θ_k and for consumer specific regional amenities ϵ. I will return to these two parameters in the data subsection below.

Unemployment Similar to Carrère et al. (2015) the method of Dekle et al. (2007) can also be applied to the employment rates defined in (19). Rewriting this equation in terms of changes yields:

$$\hat{\chi}_n = \left(\frac{\hat{w}_n}{\hat{P}_n}\right)^{\iota} \left(\frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R_{nk} \tilde{\mu}_{nk}} / \frac{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R'_{nk}}{\sum_{k=1}^{K} \tilde{\beta}_{nk}^{H} R'_{nk} \tilde{\mu}_{nk}}\right) \tag{30}$$

The first term shows the positive correlation between real wages and employment rates. The second terms gives effect of shifts in the sectoral specialization pattern on employment. To see this consider an increase in the revenue of an industry with high frictions (low $\tilde{\mu}_{nk}$) that is (in terms of the wage sum) exactly offset by a decrease in revenue of an industry with low frictions (high $\tilde{\mu}_{nk}$): the numerator of both fractions in the second term then remains the same but the denominator is larger for the second lowering the overall employment rate. Hence, as stated by Carrère et al. (2015) the conventional wisdom that real wages and employment always move in the same direction is only partially true.

Finally, the change in the total German employment rate $\hat{\chi}^G$ can be calculated by weighing county employment rates with the population share both in the ex-ante and the counterfactual scenario:

$$\hat{\chi}^G = \frac{\sum_{n \in N^G} \chi_n \hat{\chi}_n \lambda_n \hat{\lambda}_n}{\sum_{n \in N^G} \chi_n \lambda_n}$$

Welfare Turning to welfare I follow Redding (2016) and note that through the properties of the Fréchet distribution the expected (or average) utility U^G of a German worker conditional on living in location $n \in N^G$ is equal across all locations and for Germany as a whole.[13] Defining $\xi \equiv \Gamma\left((\epsilon - 1)/\epsilon\right)$ the common expected utility can be written as

$$U^G = \xi \left[\sum_{i \in N^G} A_i \left(\frac{v_i}{P_i}\right)^{\epsilon}\right]^{\frac{1}{\epsilon}} = \xi \left[\frac{A_n \left(\frac{v_n}{P_n}\right)^{\epsilon}}{\lambda_n}\right]^{\frac{1}{\epsilon}},$$

where the second equality makes use of equation 5 and holds for any n. However, this does not imply that individual consumers have the same utility everywhere, nor that the real income will be equalized across regions. Instead the interpretation is that in regions with low real per capita income only consumers with high amenity draws for that region remain (low λ), keeping the average utility up. In contrast rich regions will attract even people with lower amenity draws for that region (high λ), thus arriving at the same expected utility level. Rewriting the average utility in terms of changes to a counterfactual scenario immediately

[13]This is the consumer equivalent to the result of Eaton and Kortum (2002) that sectoral and regional price indices are the same conditioning on the source and for the importing country as a whole.

yields

$$\hat{U} = \hat{\lambda}_n^{-\frac{1}{\epsilon}} \frac{\hat{v}_n}{\hat{P}_n}. \tag{31}$$

The relative change in a county's expected real income directly increases the average utility of its consumers. Yet, when the higher expected income attracts additional workers, who on average have a lower amenity draw for the county than the workers already living there, the increase in λ dampens the utility gains. Conversely, counties that are the source for migrating workers lose population that has, on average, a lower amenity draw than the workers remaining in the county leading to a higher average welfare even if the average real income and the individual utility level of consumers remaining in the location was unchanged.

3.2 Data

My analysis relies on three main data sources. Firstly, country production data, international trade data, input-output structure and consumption structure for countries are taken from the World Input Output Database (WIOD). Secondly, county level sectoral revenue and unemployment data relies on publications by the German federal and regional statistical offices ("Statistische Ämter des Bundes und der Länder"). Finally, trade data at the German county level is derived using a recent data set containing information on shipments by truck, train or ship that start or end in one of the 402 German counties. I discuss all three data sources and the final calibration of the model in the following.

Country level data. My main data source for country level data is the world input-output database (WIOD).[14] It provides a time-series of world input-output tables compiled on the basis of officially published input-output tables in combination with national accounts and international trade statistics. The tables cover data from 56 industries in 44 countries, including one artificial "rest of the world" (ROW) country. The countries include all current members of the European Union, Switzerland and Norway, as well as most non-European major German trade partners. The complete list is provided in table A.1 in the appendix. In order to match the information with my other data sources I rely on the year 2010 and aggregate the 56 industries into 17 as given in table A.2 in the appendix.[15] I use the resulting input-output table to derive the sectoral consumption and intermediate good shares ($\delta_{nC,k}$ and $\delta_{nj,k}$), the share of value added ($1 - \tilde{\beta}^M_{nk}$) and the bilateral industry trade shares (π_{nik}) at the country level. Appendix D.1 explains this derivation in detail.

[14]See Timmer et al. (2015) for an introduction to the WIOD.

[15]The full matching between sectors of all classifications used by the different data sources to the final 17 sectors can be found in a supplementary appendix available online.

County level data. Sectorally disaggregated revenue data for Germany is, unfortunately, only published at the state and not at the county level. Therefore, in the mining and manufacturing sectors, where such information is available, I rely on sectoral county level employment data from the German federal and regional statistical offices to split sectoral state revenues across individual counties based on each county's share in its state's total sector employment. In instances where employment data is unavailable I instead rely on firm number shares. Final county production values are then calculated by scaling the sector totals to match with the German sectoral revenues from the WIOD. In the agriculture, construction and service sectors I proxy for county shares in the German total revenue with value added shares for which disaggregated data is available. A detailed description of the process can be found in section D.2 in the appendix.

An important problem for regional analysis in Germany is that data on interregional trade flows is usually unavailable. Therefore researchers have to rely on some kind of proportionality assumption or simple gravity equations to model linkages within Germany.[16] Such approaches are, however, unable to correctly capture trade driven by a rich structure of underlying motives like the connections with subsidiaries, the availability of highly specialized components or trust in long term relationships. In contrast in this paper I rely on an outstanding data set of county level trade in the mining and manufacturing sectors provided by Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data set gives the total shipments in tons by water, train or truck for 2010 (which explains my choice of base year) between German counties and their partners, disaggregated along 25 product categories. The trade partner can be either a further German county (including the county itself), one of 32 third countries (of which 25 are also in the WIOD Database), or a major German or international port. The latter two appear as origin or destination whenever the actual origin or final destination is unknown or not in the explicit country sample, for example shipments to and from Japan. I use this data to calculate the share of exports to each partner in the production of each county and sector, including own trade. Subsequently, I combine this information with the county revenues from above to obtain the bilateral industry trade and import shares π_{nik} at the county level. Again the details of these calculations are provided in section D.3 in the appendix. This section also explains how I disaggregate German WIOD trade flows in the utilities, construction and service sectors for which there is no shipment data available.

The final result of the above calculations is a data set containing information on revenues,

[16]See, for example, Krebs and Pflüger (2018b) who analyse county level effects of the transatlantic trade and investment partnership (TTIP) deriving trade shares based on regional sectoral production and demand shares.

value added and trade among 442 locations (402 German counties, 39 other countries and a modeled ROW) in 17 sectors for the year 2010. Overall, the shipment data set allows me to capture a much more accurate picture of interregional trade in Germany. Known trade connections between parent companies and subsidiaries or other suppliers are clearly visible in the data. While in itself highly informative, a detailed descriptive analysis of the German subnational trade and production network at this level of regional and sectoral disaggregation is beyond the scope of this paper. Krebs (2018) provides a thorough analysis of the structure.

Calibration. In calibrating the model I need to choose values for some of the remaining parameters. Specifically, I set ι, the weight of labor in the matching process, to 0.6, the central value of estimates in Petrongolo and Pissarides (2001). Further, I calculate the split of value added between labor and structures based on estimates of factor income for the U.S. economy by Valentinyi and Herrendorf (2008). In particular I set the share of land and structures in value added to 33.86%, 13.24%, 15.13%, and 19.95% in agricultural, manufacturing, construction and service sectors, respectively.[17]

The value for the Fréchet distribution shape parameter of consumer amenities, $\epsilon = 3.3$, is taken from the estimates in Monte et al. (2018). The sectoral Fréchet distribution shape parameters of productivities, θ_k, can be estimated from between country trade flows and observed trade barriers using equation (15).[18] I rely on the values calculated for the same country level trade flows in Krebs and Pflüger (2018b). Similarly, sectoral labor market frictions are taken from Carrère et al. (2015) who estimate them for 35 sectors based on time series employment data from a sample of 25 OECD countries.

Finally, as explained above, in some instances the observed interregional trade imbalances can not be fully explained even by remitting all ($\Psi_n = 1$) or none ($\Psi_n = 0$) of the locally created rents to the national portfolio and in these cases an exogenous transfer D_n^{reg} is used to fit the model to the data. However, with labor mobility, this implies that a reduction in a county's population, while increasing the productivity and subsequently wages of the remaining workers can actually leave them worse off, as the exogenous transfer is split over a smaller number of workers and thus trigger even more workers to leave the county. To avoid this problem, I again follow Caliendo et al. (2018) and solve for a base scenario in which the exogenous parts of interregional deficit transfers are set to 0. All counterfactual scenarios below are calculated starting from this base scenario. Moreover, while the model

[17]In particular I use the income shares of labor, land and intermediates from their table 6 to calculate the shares of capital and labor in value added of the four sectors. I multiply these results with the shares of land and structures in capital from their table 2 under the assumption that these values remain the same with intermediates.

[18]Head and Mayer (2014) provide an excellent overview over different techniques for estimating the trade elasticities.

and calculations include international trade and third countries my motivation is to study disaggregate geographical effects and I hence mostly limit the presentation of my results to effects in Germany.

4 Results

4.1 National effects

Benchmark scenario Before turning to the effects of shocks to individual regions or sectors I establish a benchmark case to compare these results to. This benchmark represents a homogeneous productivity shock affecting all counties in Germany equally. Such a shock is modeled by a uniform increase in T_{nk} in all industries k in all German counties $n \in N^G$. The resulting, national welfare and employment effects are presented in terms of elasticities calculated by dividing the change in the respective variable by the relative size of the shock. Throughout the paper all effects are calculated based on 10 percent shocks, that is by setting the respective $\hat{T}_{nk}$ to 1.1.[19] This magnitude is close to observed annual changes of the technology parameter in US states and sectors over a 5 year period.[20]

The resulting national German welfare and employment elasticities are

$$\frac{\hat{U}^G - 1}{0.1} = 1.24 \quad \text{and} \quad \frac{\hat{\chi}^G - 1}{0.1} = 0.32.$$

Thus, a uniform increase in the German productivity level of 1% increases average welfare by 1.24% and the national employment rate by 0.32% or by 0.3 percentage points based on the initial German employment rate. The results of this aggregate shock, however, mask a vast heterogeneity of effects when actual shocks occur in a sectorally or regionally disaggregated manner. Of course, when one looks at regional German productivity shocks affecting all sectors in one county, sectoral shocks affecting one industry in all counties or region and sector specific shocks one would naturally expect the response of *national* variables to vary substantially due to the different sizes of the shocked sectors and counties.[21] Berlin, for example, as the largest German county is about 100 times larger in terms of population than

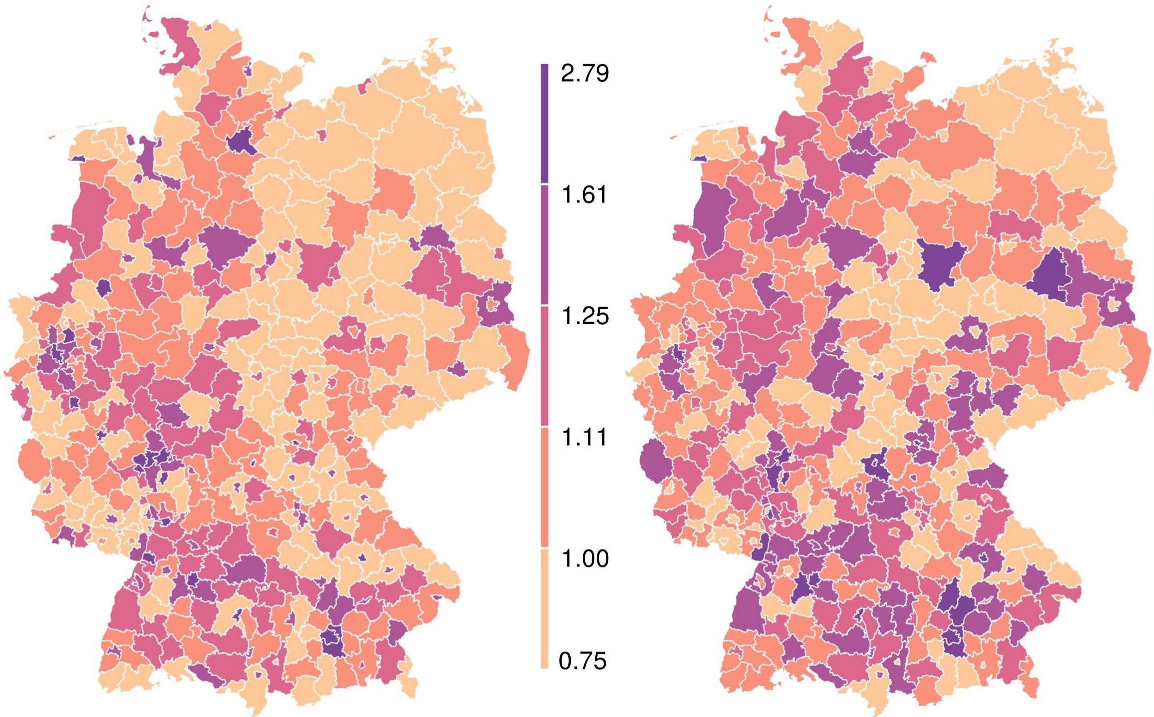
[19] Of course, as the model accounts for all non-linear general equilibrium effects, the calculated elasticities vary with the size of the shock. However, this is not problematic as non-linearities are small at the size of shocks considered here.

[20] Caliendo et al. (2018) calculate the average annual growth of the productivity parameter across US sectors and regions at 10.9% over the period 2002-2007, and the median over the period 2002-2007 and 2007-2012 at 8.4%.

[21] Regional productivity shocks are modelled by increasing T_{nk} for all industries k of one particular county $n \in N^G$, sectoral German shocks by increasing all T_{nk} for one sector k in all German counties $n \in N^G$, and region and sector specific shocks by changing individual T_{nk}.

the smallest county and thus shocks to it would certainly have a larger effect on the German economy as a whole. Hence to make the effects of disaggregated shocks comparable across experiments and to the results from the aggregate shock presented above, I follow Caliendo et al. (2018) and calculate elasticities for constant national magnitude shocks. Specifically, I not only divide the national welfare and employment changes of subsequent shocks by the size of the shock (0.1 in all instances) but also by the share of the German population directly affected, that is λ_n in the case of regional shocks. Intuitively, this implies that all elasticities presented below originate from productivity shocks that would be indistinguishable to an observer that only possesses aggregate national data.

Disaggregate shocks Turning to productivity shocks in individual regions a large heterogeneity of effects emerges. Figure 3 depicts this heterogeneity combining the results of 402 separate regional productivity shocks. Specifically, each county is colored according to the national German welfare or employment elasticity resulting from a productivity shock in that particular county. Hence, shocks in counties with a darker color have - accounting for county size - a large effect on national welfare and employment, respectively.



(a) welfare elasticity

(b) employment elasticity

Figure 3: National welfare and employment elasticities of regional shocks

The magnitude of welfare elasticities is, differences in modelling notwithstanding, similar to the results for U.S. states in Caliendo et al. (2018) and differs substantially across counties with a range from 0.76 to 2.78. This implies that predicting the effects of regional shocks based upon average effects of changes in a Germany wide measure of productivity can be deeply misleading. In particular the map shows that productivity shocks in Germany have the strongest national welfare effect if they take place in and around cities in the south and west of the country, especially Munich, Stuttgart, Frankfurt and Düsseldorf and that shocks in counties in former East Germany, in contrast, have a much milder effect.[22] This result is not as intuitive as it might seem. As my model captures the complete input-output network in Germany, a productivity shock to a smaller intermediate producer could, for example, lead to a larger national effect than a shock to a city that produces and consumes final goods. Counties with strong welfare elasticities are thus not only very productive but must also generate large spillovers to other locations in Germany through trade linkages. Turning to aggregate employment elasticities the observed heterogeneity across counties is even stronger with a range from 0.11 to 0.62.

The same heterogeneity of effects also exists when shocks affect a single sector in all German counties. Figure 4 shows the results of such shocks, with welfare elasticities ranging from 0.26 for shocks in the textiles sector to 4.19 for shocks in mining and quarrying. Again, employment elasticities are smaller, but their relative spread larger, ranging from 0.04 to 2.94.

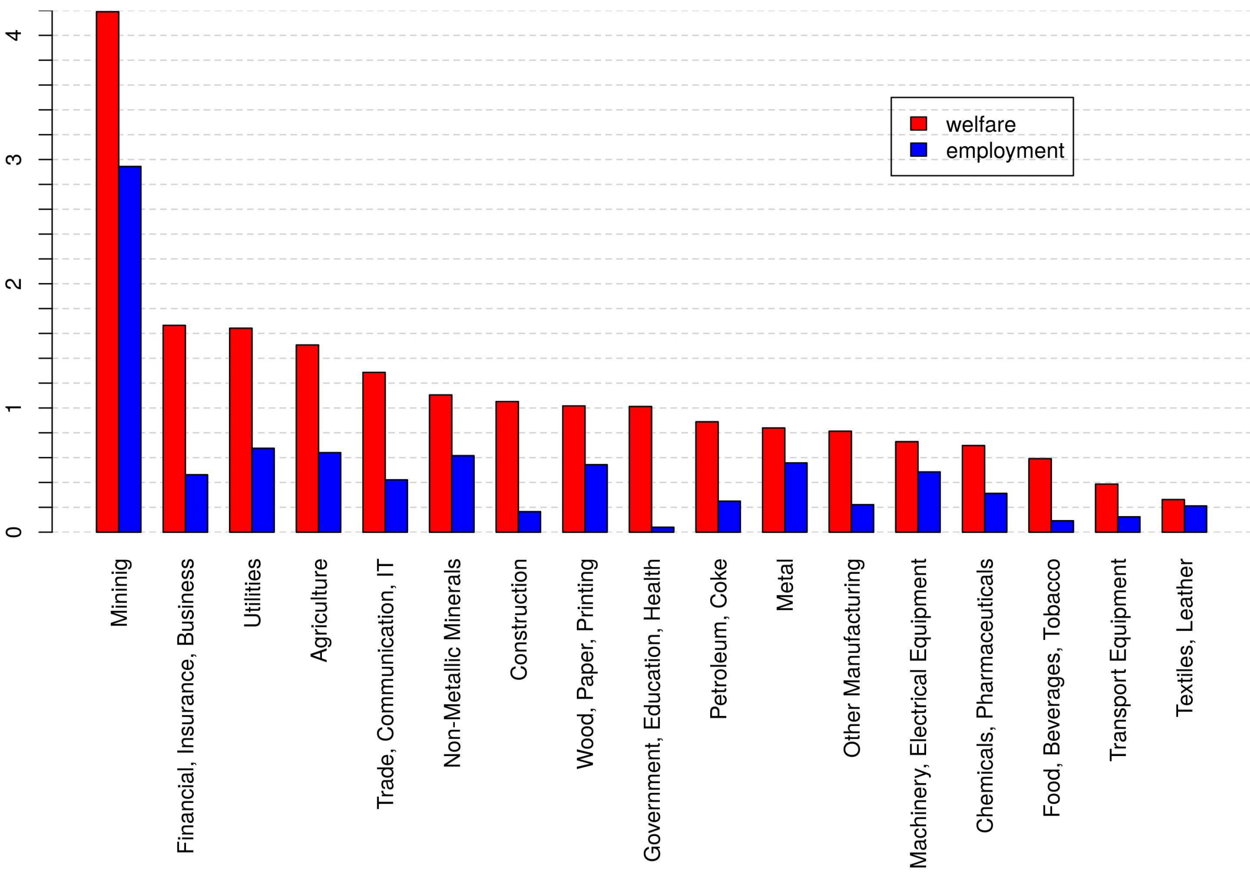


Figure 4: National welfare and employment elasticities of sectoral shocks

The results in figure 3 and 4 reveal a second important implication of my analysis. While

[22]The location of all counties referenced by name here can be found in figure B.1(a) in appendix B.

there is a correlation between national welfare and employment elasticities, this correlation is far from perfect with a Spearman's rank correlation coefficient of 0.61 for regional and 0.65 for sectoral shocks.[23] This is mirrored in the fact that figures 3(a) and (b) show both, counties in which a productivity shock has a strong effect on the average national welfare but not on national employment rates and vice versa. Importantly, and in contrast to Caliendo et al. (2018) my findings show that increasing average welfare and increasing the employment rate are not synonymous goals for policy makers.

4.2 Regional effects

Delving deeper. Having quantified the large differences in both national welfare and employment elasticities I now aim to identify the drivers of this heterogeneity in the complex interregional trade network and the strength of migration linkages. Before turning to the general results the interplay of effects is best explained by looking in detail at a single one of the 402 regional experiments that were summed up in figure 3 above.

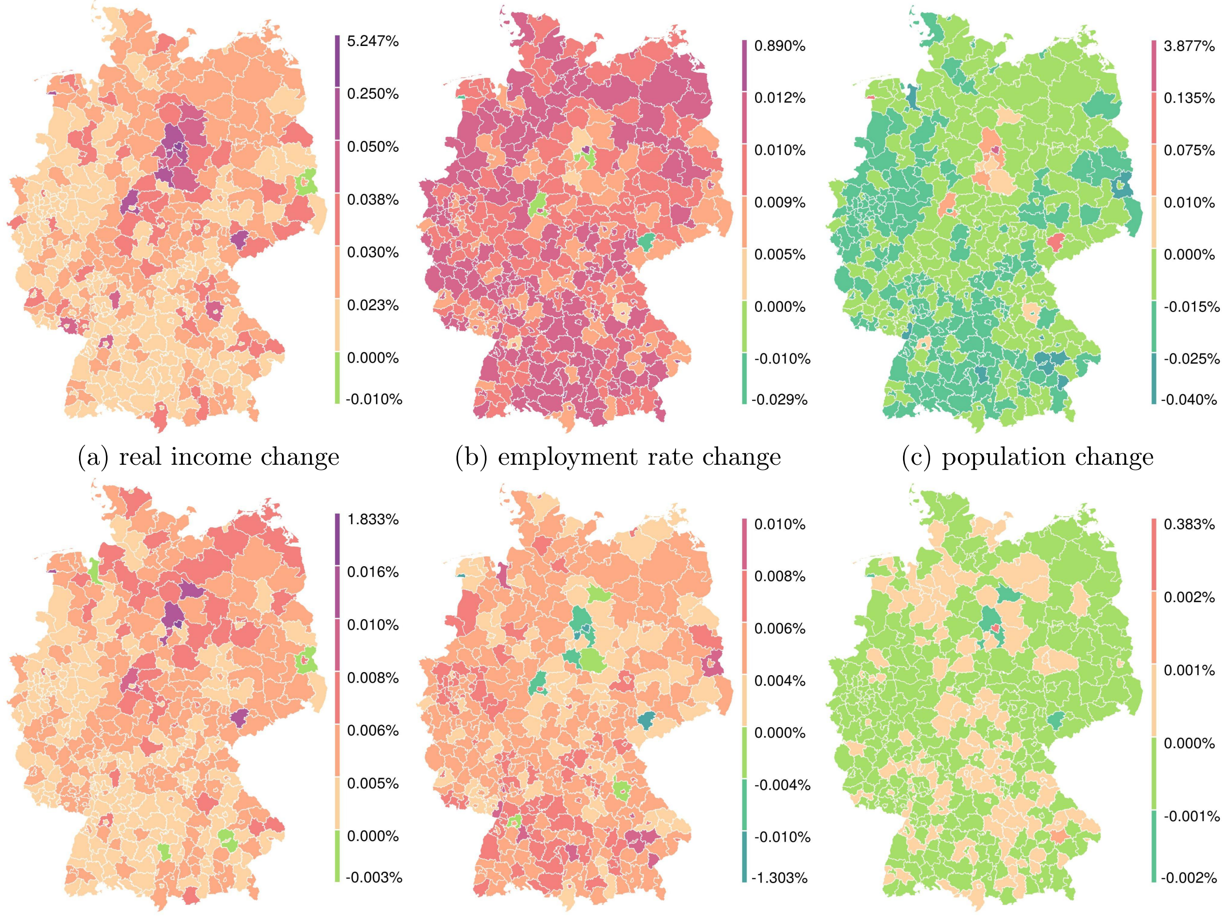
Figure 5, as an example, shows the effects of a 10 percent technology shock across all sectors in Wolfsburg, which has a relatively strong national welfare elasticity of 1.16 but a low national employment elasticity of 0.23 (cf. figure 3). Since the city is home to the car producer Volkswagen and therefore also hosts the by far largest single production plant in Germany with more than 50,000 workers, it is tightly integrated into the German production network and serves as an ideal laboratory.

The change in expected welfare ($\hat{U}_n - 1$) from the 10 percent shock is 0.043 percent. As explained above, population mobility and heterogeneous amenities ensure that this effect is equal across all German counties and for the country as a whole. However, expected or average real income changes ($\hat{v}_n/\hat{P}_n - 1$) vary substantially across counties as shown in figure 5(a). In fact, despite the intra-country viewpoint, the realized real income gains dissipate only very modestly throughout the economy with the second largest relative real income increase only about one twentieth of that in Wolfsburg.

The map also illustrates the great strength of the underlying data set which captures Wolfsburg's economic ties: counties that profit the strongest are either geographically close to Wolfsburg or have important supply and demand linkages. For example, the three strong beneficiaries Emden in the far northwest, county Kassel ("Landkreis Kassel") to the southwest and Zwickau to the southeast of Wolfsburg all host further large VW production plants.[24] Moreover, it can be clearly seen how the positive effects in these counties "spill over" to their

[23] I use rank correlations to account for the outlying result in the mining sector. Standard correlation coefficients are 0.62 and 0.93, respectively with the latter dropping to 0.62 when ignoring the mining sector.

[24] The location of all counties referenced by name here can be found in figure B.1(b) in appendix B.



(a) real income change (b) employment rate change (c) population change

(d) expansion effect (e) mobility effect (f) composition effect

Figure 5: Effects of regional shock in Wolfsburg

closest neighbors. Finally, counties with relatively strong increases in real income further to the south west and south are home to various automotive suppliers. Overall, this shows that the geographic dissipation of real income gains closely follows a counties trade linkages.

Interestingly, the changes in disaggregate employment rates $(\hat{\chi}_n - 1)$ shown in 5(b) are more complex in nature. The employment rate in Wolfsburg increases by 0.89% but results in other counties are much milder ranging from -0.029% to 0.012%. Moreover, negative employment rate changes occur only in counties with close economic ties to Wolfsburg, despite these counties simultaneously winning both in terms of real income and average welfare. On the other hand, even some counties with hardly any real income gains, such as in the southwest of Germany, can increase their employment rates relatively strongly.

This pattern can in part be explained by population mobility. Importantly, real income increases do not necessarily imply an increase in population. Instead, Figure 5(c) shows that as implied by equilibrium condition (26) only counties in which expected real income increases faster than the national average see positive population changes $(\hat{\lambda}_n - 1)$. In the case of Wolfsburg the 10% technology shock leads to a population gain of 3.88%. In accordance with the small real income changes only a handful of other counties experiences population gains of more than 0.01%. Similarly, losses are generally small in magnitude with only some larger changes occurring, for example, in the area northwest of Munich, where the VW competitor BMW has its headquarter.

The effect of worker mobility on employment rates stems from the induced shifts in *per capita* fixed factor endowments across counties and sets this model apart from previous quantitative studies. Specifically, a larger potential work force increases the likeliness of a match for each open vacancy and, thus, leads to a higher ratio of actual workers to land in the production process. In turn, the marginal production and hence value of each worker decreases and firms spend less on opening vacancies per worker, thereby decreasing the employment rate.

Employment change decomposition. I offer a unique strategy to derive the magnitude of this mobility effect on the employment rate. In particular, I decompose the employment rate given in equation (30) into

$$\hat{\chi}_n = \left(\frac{\hat{w}_n}{\hat{P}_n}|_{\hat{\lambda}=1}\right)^{\iota} \frac{\left(\frac{\hat{w}_n}{\hat{P}_n}\right)^{\iota}}{\left(\frac{\hat{w}_n}{\hat{P}_n}|_{\hat{\lambda}=1}\right)^{\iota}} \frac{\frac{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{H}R_{nk}}{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{H}R_{nk}\tilde{\mu}_{nk}}}{\frac{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{H}R'_{nk}\tilde{\mu}_{nk}}{\sum_{k=1}^{K}\tilde{\beta}_{nk}^{H}R'_{nk}}},$$

where $|\hat{\lambda} = 1$ refers to changes in a counterfactual scenario in which the same shock occurs, but population is assumed to be immobile. In this paper, the use of a general equilibrium quantitative model comes with the great benefit that I can directly undertake this counterfactual. This is done by solving the equilibrium conditions (27) - (29) under the assumption that $\lambda_n = \lambda'_n$ and thus $\hat{\lambda}_n = 1$ for all n. The first term of the equation captures the effect of changes in productivity and economic expansion (or decline) on the employment rate that would have occurred under population immobility. The second term then measures further changes in the employment rate that stem from the movement of workers and the final term quantifies the effect of changes in the sectoral composition discussed above.

The bottom half of figure 5 shows this decomposition of the employment rate effect. Panels d, and e, reveal that in northern and eastern counties increases in the employment rate are mainly due to economic expansion, whereas in southern and eastern counties they are mostly driven by the mobility effect, that is by the increased scarcity of workers caused by migration. This effect is also the major explanation for the low gains or even losses of the counties with the closest economic ties to Wolfsburg. In Wolfsburg itself the expansion effect raises the employment rate by 1.83% and the population increase of 3.88% reduces it by -1.3%.

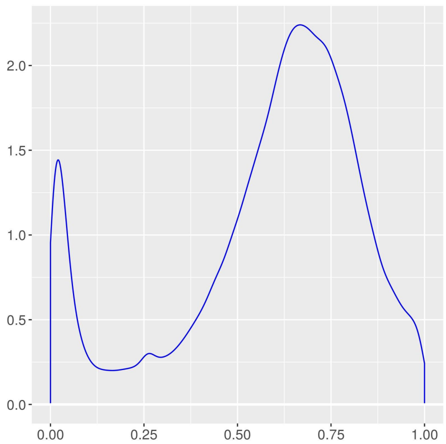
Finally, for the Wolfsburg shock the magnitude of the composition effect is much milder staying below an absolute 0.001% change in almost all counties. Nevertheless, in Wolfsburg itself it increases the employment rate by 0.38% and is thus responsible for more than one third of the total effect. The observed positive effect in Wolfsburg is inline with expectations: the high specialization on car manufacturing in Wolfsburg suggests that the county's firms have made productivity draws and face transport costs that allow them to outbid a large share of competitors in the transport equipment sector. This, however, also implies that for Wolfsburg the potential for further market gain from the increase in productivity through the shock is smaller in this sector compared to the others. Consequently, I observe that the *relative* share of transport equipment in the production of Wolfsburg is reduced by the shock. As transport equipment has the second lowest matching efficiency $\tilde{\mu}_{nk}$ the redistribution of workers between sectors explains the positive composition effect. Similarly, the only other positive composition effect above 0.001% is found in Dingolfing, which is home to the BMW headquarter. Here the increased productivity of the competitor VW decreases the relative focus of the county on the transport equipment sector exerting a positive force on the employment rate. In contrast the counties with suppliers and production plants connected to VW in Wolfsburg increase their share in this sector and thus experience losses from the composition effect.

Over all counties the average magnitudes of the mobility and composition effect relative to the average expansion effect are 0.89 and 0.13, respectively. This indicator for the importance of the three effects can also be calculated for their effect on the aggregate, national employment elasticities discussed in section 4.1. In case of the Wolfsburg shock this elasticity was 0.23 and it decomposes into an expansion effect of 0.17, a mobility effect of 0.03 and a composition effect of 0.02. As each increase in population must go along with a decrease somewhere else, the importance of the population effect for the national employment rate is reduced. In fact, the magnitude of the mobility effect relative to the expansion effect drops substantially to 0.17, whereas it remains about the same for the composition effect at 0.13. Despite the differences in their strength, all three effects clearly matter substantially in determining the effect of shocks on the German employment rate.

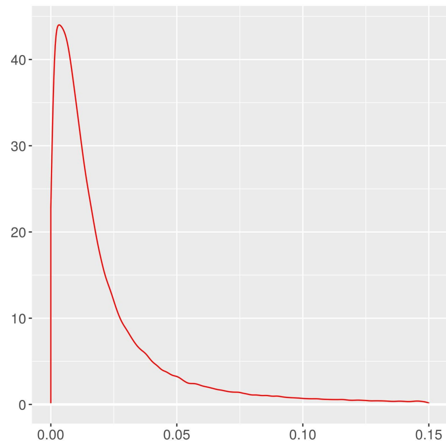
Regional shocks. The same decomposition of employment effects can be performed for all 402 different regional shocks. On average, for the national employment rate, the size of the mobility and composition effect is equal to 3.64% and 1.48% of the expansion effect with maxima across regional experiments of 50% and 12.61%, respectively.[25] I also perform the decomposition for local employment effects, that is for each of the 402 regional shocks I obtain 402 local employment effects and decompose them into the expansion, mobility and composition effect. To measure the importance of mobility and structural transformation on the employment rate I calculate the size of the (absolute) mobility effect and the (absolute) composition effect relative to all three effects combined. Figure 6 depicts the density distri-

[25] All 402 results are provided in a supplementary appendix available online.

butions of these two measures. Clearly, the role of the composition effect is minimal in most counties and for most shocks. Its size relative to the sum of employment effects is usually only a few percent. In contrast, population mobility matters greatly. It is responsible for around 70 percent of the total employment effects in a large share of counties for a large number of shocks. This points to a much more efficient adaptation of local labor markets to shocks than what is generally presumed for Germany.[26]



(a) Size of mobility effect relative to all effects



(b) Size of composition effect relative to all effects

Figure 6: Decomposition of employment effects of regional shocks

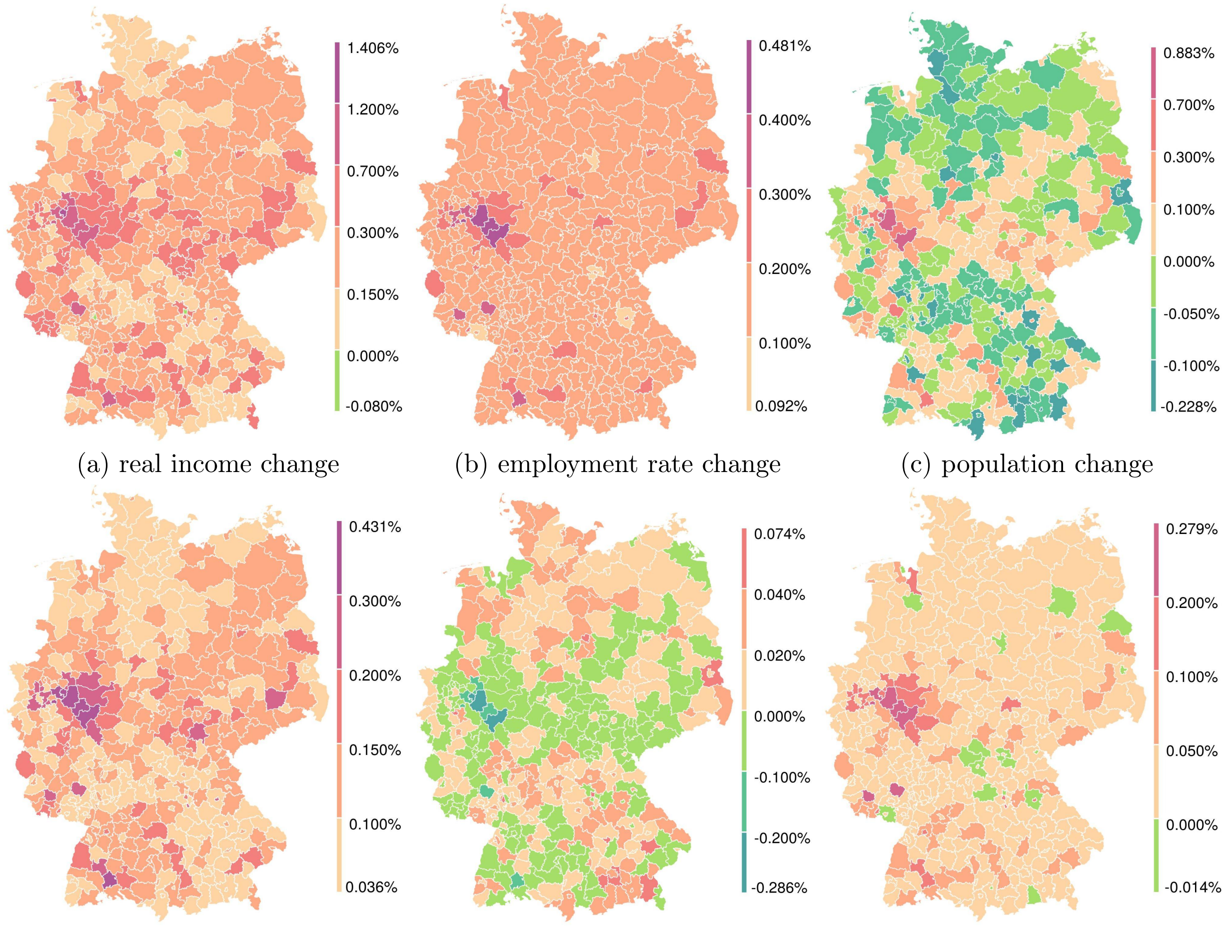
Interestingly, the relative size of the mobility effect exhibits a bi-modal distribution, that is, there is also a sizable fraction of counties that are affected relatively little by population mobility. The explanation for this lies with the structure of German counties that, in most cases, are either a single densely populated city or a less dense rural county. In the former locations the strain on the fixed factor is already high and additional population inflow quickly reduces the value of workers and their employment rate. In contrast even larger inflows to less densely populated locations with a high endowment with the fixed factor per capita will not influence the employment rate greatly.

In summary, whereas the dissipation of real income gains from a regional technological shock are strongly connected to the economic ties between counties, the employment effects are more difficult to predict. They depend, firstly, on these same economic ties but, secondly, also on the strength with which the ensuing migration influences worker productivity. This in turn hinges on fixed factor endowments. Thirdly, mobility effects are more important for regional employment changes than for national employment effects where positive and negative forces interact. Lastly, while the sectoral composition of each region's workforce plays a minor role in general, it is of greater importance in some select regions where shocks imply large structural transformation. However, this does not mean that the composition

[26]This result is also obtained - albeit in a different model focusing on commuting - by Krebs and Pflüger (2018a).

effect can be neglected in general. Indeed, it can become more important when shocks favor one particular sector over the others. I turn to this type of sectoral shocks next.

Sectoral shocks Instead of affecting a singular region, many types of productivity shocks affect a specific sector in the whole country. Recent examples for this in Germany include the emergence of electric cars, the regulatory end of nuclear power, or tighter emission standards for diesel cars. This section looks at these types of shocks and how the resulting effects differ from those of regional shocks. Again, it is helpful to begin with a specific shock as an example. In particular, figure 7 shows the disaggregate effects of a 10% technology shock in the German metal industry. Again, mobility ensures that the resulting welfare gain of 0.22% is identical across Germany. However, as before, real income gains are very heterogeneous. They are strongest in the Ruhr-area in the west of Germany where the metal industry is traditionally located and in some further clusters in the south west of the country. Employment rate changes are positive for all counties. In contrast, three counties ("Wolfsburg", "Ludwigshafen am Rhein", and "Erlangen") lose real income, albeit only slightly.



(a) real income change (b) employment rate change (c) population change

(d) expansion effect (e) mobility effect (f) composition effect

Figure 7: Effects of a nation wide shock in the metal sector

As all counties that produce in the metal industry see a direct positive effect from the technological shock, real income gains are regionally less concentrated than in the example of the cross-sector shock in Wolfsburg. Consequently, positive and negative population changes are more balanced, with 166 counties gaining and 236 losing population versus 14 and 388 in the previously considered case. Moreover, the relative spread of population changes is also smaller. As a result the importance of the mobility effect for regional employment rates drops. Across all counties the average magnitude of the mobility effect relative to the average magnitude of the expansion effect is now 0.22 compared to 0.89 in the Wolfsburg scenario.

At the same time, as the metal industry has the fourth highest matching efficiency, the technology shock is likely to lead to a positive composition effect. However, as can bee seen in figure 7(f) there can be exceptions. Firstly, a negative composition effect can occur if a county's production is in relative terms shifted away from industries with even higher matching efficiency. Secondly, indirect effects can, through terms of trade changes and factor movements, lead a county to focus its relative production away from the metal sector despite the technological improvement. Across all counties the average magnitude of the composition effects relative to the average magnitude of the expansion effect is now 0.26 and thus twice as high as in the Wolfsburg scenario.

Again, one can also assess the role of the three effects in forming the national employment elasticity. For the shock in the metal sector the latter is equal to 0.557, with an expansion effect of 0.446, a mobility effect of -0.002 and a composition effect of 0.079. Clearly, as positive and negative mobility effects are more balanced now, the influence of mobility on the national employment rate is reduced to almost 0. On the other hand, the composition effect is still about 17.8% as large as the expansion effect. Table A.3 in the appendix shows the same decomposition for all 17 possible sectoral shocks. On average across counterfactual scenarios the magnitude of the mobility effect is 1.14% that of the expansion effect. In contrast the composition effect influences the national employment rate change on average 11.23% as strongly as the expansion effect, with a maximum of 53.82% for a shock to the textiles and leather industry.

5 Conclusion

This paper quantified the surprisingly large heterogeneity of real income and employment effects across German counties in response to standardized local and sectoral productivity shocks. Local employment elasticities vary by a factor of 3.6 and real income elasticities by a factor of 2.3 depending on where a productivity shock takes place geographically. Using a quantitative model with imperfect mobility, land as a fixed factor and sector-specific labor market frictions, I identify the sources of this heterogeneity in Germany's complex interregional linkages. An outstanding data set of interregional shipments in Germany provides the unique opportunity to capture the true interregional trade structure. Based on this, I find that the spatial dissipation of real income effects in response to a local productivity shock closely follows the treated county's trade network.

In contrast, the heterogeneity of employment rate changes is driven by more complex effects. To see this, I make use of my quantitative modelling approach to decompose employment rate changes into an expansion effect directly resulting from increased productivity, a mobility effect driven by worker migration in and out of local labor markets, and a composition effect that captures the restructuring of county level productivity across sectors with varying labor market frictions that I prove to exist using unemployment and vacancy data from the German federal institute of employment research.

I find that population mobility reduces the magnitude of local employment rate responses to county level productivity shocks by a striking 70 percent on average. In contrast, the composition effect has a much milder influence on employment elasticities, except for in a handful of counties where it can reach a maximum magnitude of 20.9 percent compared to all employment effects combined. Responses in the national employment rates are shown to be less dependent on mobility, as the employment effect of worker in- and outflows in individual counties partially cancel out.

For productivity shocks affecting individual sectors across all regions the composition effect is substantially magnified as workers all across Germany are shifted into the treated sector implying a large restructuring. However, as all locations experience at least a small productivity boost from such a shock, the incentive to migrate and hence the strength of the mobility effect is reduced compared to the scenario of a productivity shock in a single region.

Moreover, I derive in line with recent real world observations that real income and employment effects, while correlated, do not move in unison. In fact, the combined mobility and composition effect can even be quantitatively large enough to overcome the expansion effect and thus lead to employment and real income effects of opposite sign. This is crucial for regional policymakers who have an interest in both outcome variables.

Finally, while I have focused on technology shocks and developments in Germany the model also delivers results for third countries and is apt to determine the effects of a range of further shocks such as reductions in trade barriers or changes in international and interregional deficit transfers. I leave such questions for future research.

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Appendix: Shocking Germany - A spatial analysis of German regional labor markets

A Tables

Table A.1: Countries in the sample

ISO3	Name	ISO3	Name	ISO3	Name
AUS	Australia	FRA	France	MLT	Malta
AUT	Austria	GBR	Great Britain	NLD	Netherlands
BEL	Belgium	GRC	Greece	NOR	Norway
BGR	Bulgaria	HRV	Croatia	POL	Poland
BRA	Brazil	HUN	Hungary	PRT	Portugal
CAN	Canada	IDN	Indonesia	ROU	Roumania
CHE	Switzerland	IND	India	RUS	Russia
CHN	China	IRL	Ireland	SVK	Slovakia
CYP	Cyprus	ITA	Italy	SVN	Slovenia
CZE	Czech Republic	JPN	Japan	SWE	Sweden
DEU	Germany	KOR	Korea	TUR	Turkey
DNK	Denmark	LTU	Lithuania	TWN	Taiwan
ESP	Spain	LUX	Luxembourg	USA	United States
EST	Estonia	LVA	Latvia	ROW	Rest of World
FIN	Finland	MEX	Mexico		

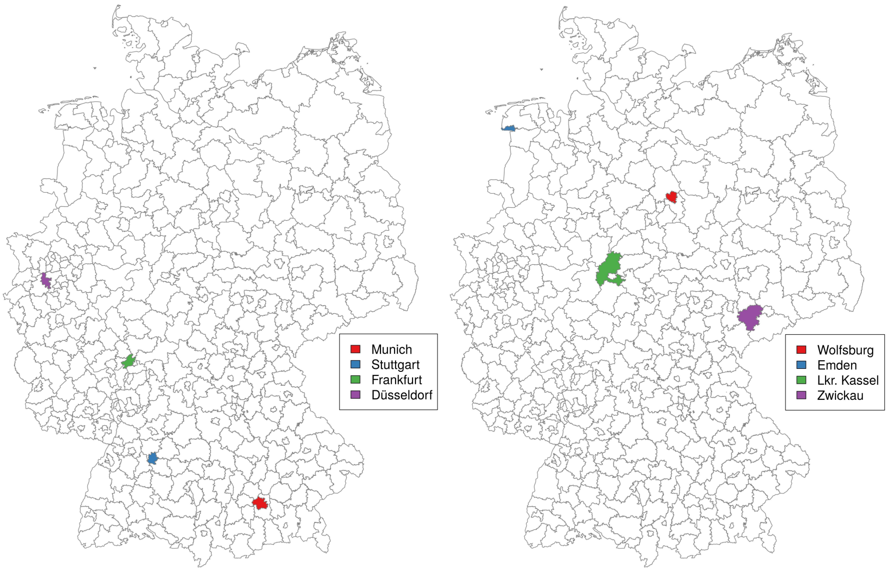
Table A.2: List of sectors

#	Description
1	Agriculture
2	Mininig
3	Food, Beverages, Tobacco
4	Textiles, Leather
5	Wood, Paper, Printing
6	Petroleum, Coke
7	Chemicals, Pharmaceuticals
8	Non-Metallic Minerals
9	Metal
10	Machinery, Electrical Equipment
11	Transport Equipment
12	Other Manufacturing
13	Utilities
14	Construction
15	Trade, Communication, IT
16	Financial, Insurance, Business
17	Government, Education, Health

Table A.3: Decomposition of national employment rate elasticities of sectoral shocks

	Total	Expansion	Mobility	Composition
Agriculture	0.640	0.721	-0.008	-0.039
Mininig	2.944	3.009	0.001	-0.017
Food, Beverages, Tobacco	0.091	0.104	-0.002	-0.009
Textiles, Leather	0.211	0.132	-0.001	0.071
Wood, Paper, Printing	0.543	0.425	-0.003	0.086
Petroleum, Coke	0.249	0.264	-0.002	-0.009
Chemicals, Pharmaceuticals	0.312	0.349	-0.001	-0.026
Non-Metallic Minerals	0.615	0.437	-0.002	0.127
Metal	0.557	0.446	-0.002	0.079
Machinery, Electrical Equipment	0.485	0.457	-0.000	0.019
Transport Equipment	0.123	0.146	-0.001	-0.019
Other Manufacturing	0.221	0.315	-0.002	-0.070
Utilities	0.675	0.662	0.001	0.007
Construction	0.165	0.163	0.002	-0.001
Trade, Communication, IT	0.421	0.437	-0.000	-0.010
Financial, Insurance, Business	0.462	0.466	0.000	-0.003
Government, Education, Health	0.039	0.036	0.004	0.000

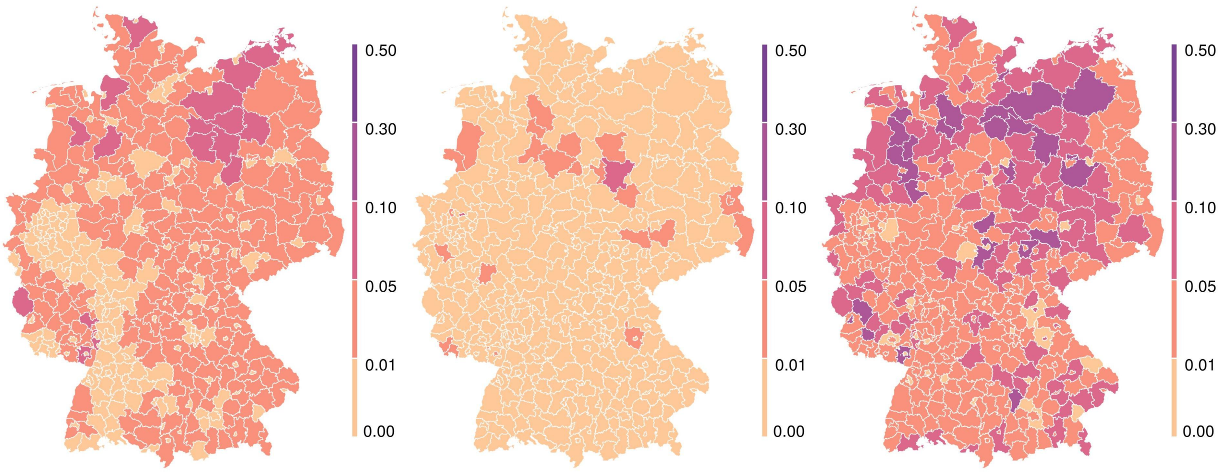
B County reference



(a) (b)

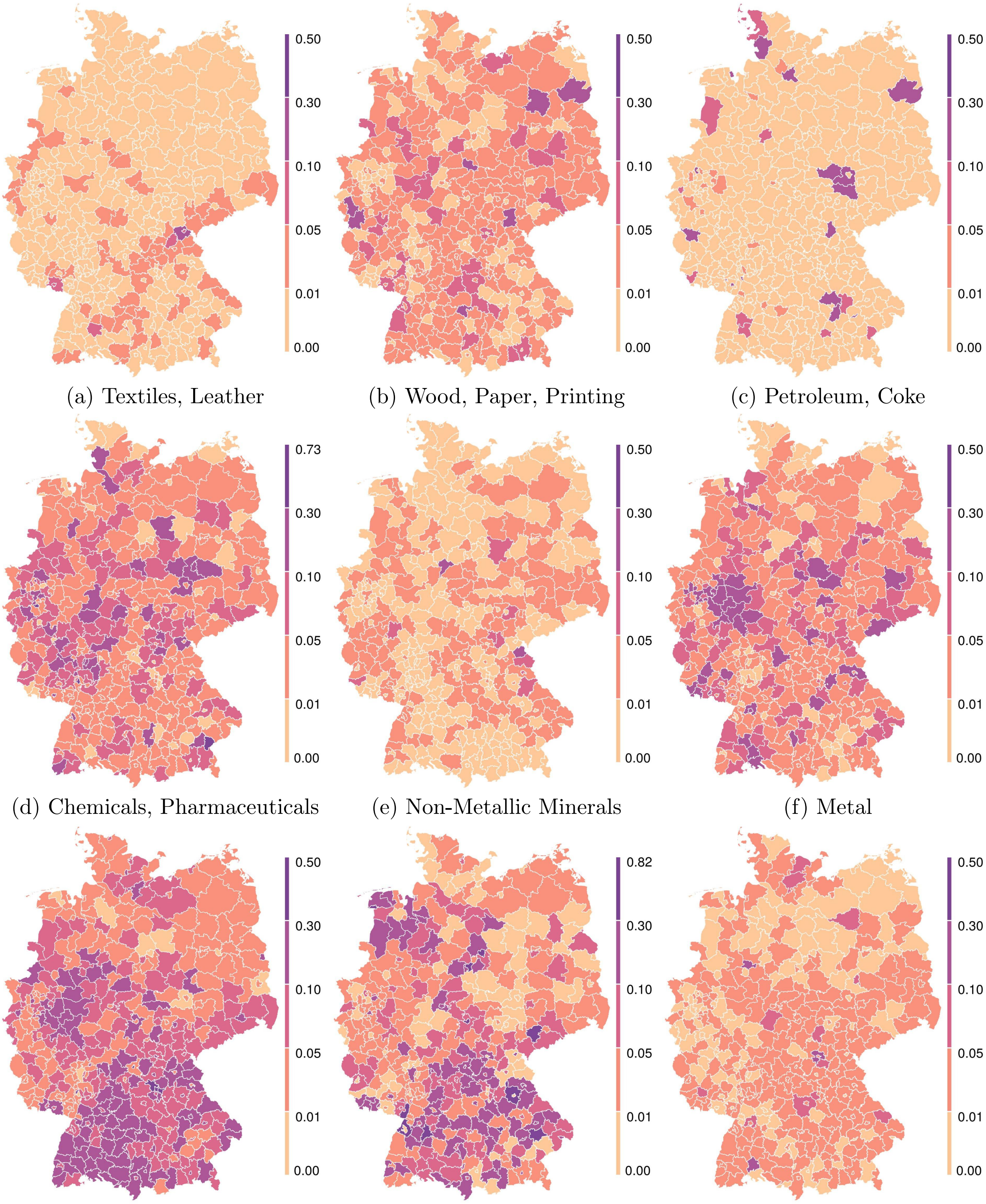
Figure B.1: County reference

C Initial production structure



(a) Agriculture (b) Mininig (c) Food, Beverages, Tobacco

Figure C.1: Sectoral shares in county revenue (1)

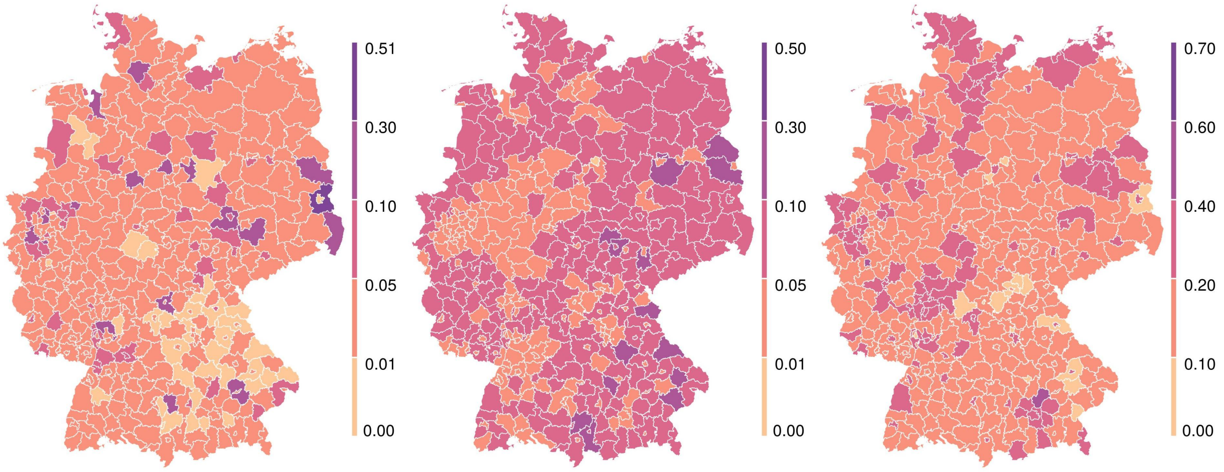


(a) Textiles, Leather (b) Wood, Paper, Printing (c) Petroleum, Coke

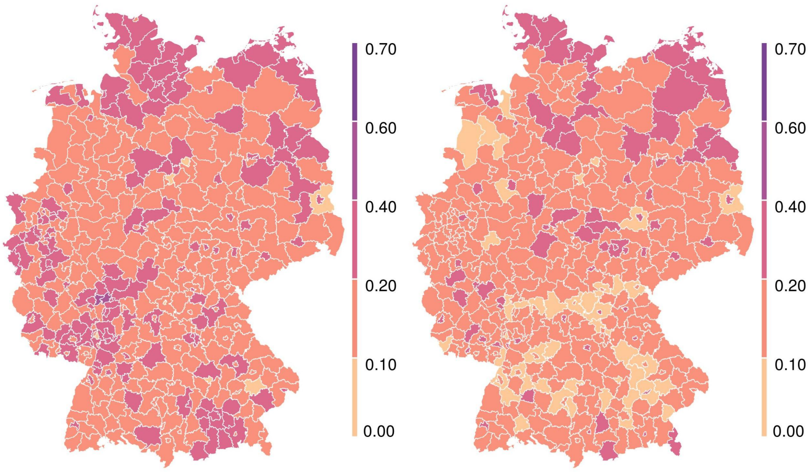
(d) Chemicals, Pharmaceuticals (e) Non-Metallic Minerals (f) Metal

(g) Machinery, Electrical Eq. (h) Transport Equipment (i) Other Manufacturing

Figure C.2: Sectoral shares in county revenue (2)



(a) Utilities (b) Construction (c) Trade, Communication, IT



(d) Financial, Insurance, Business (e) Government, Education, Health

Figure C.3: Sectoral shares in county revenue (3)

D Data

D.1 WIOD data

The raw WIOT-data. For each combination of countries and sectors the world input output table (WIOT) in the WIOD contains an entry $X_{ni,jk}$ for the value of flows from industry k in supplier country i to industry j in destination country n, including within country flows $X_{ii,jk}$. It also provides the values of flows from industry k in country i to country n that end up as final consumption by households $X_{ni,Ck}$, final consumption by non-profit organizations $X_{ni,Pk}$, government spending $X_{ni,Gk}$, investments $X_{ni,Ik}$ and inventory changes $X_{ni,Qk}$. All entries in these raw data (and in the following) are in value terms at current prices.

Inventory changes. Of course, inventory changes can be negative and sometimes they are significantly large. If final demand were simply calculated by summing over consumption, investment, government spending and inventory changes it would turn out to be negative in some cases. To reconcile the real world data with the static model that has no room for inventories I follow Costinot and Rodríguez-Clare (2014) and split the vector of inventory changes into a vector with all positive changes $X_{ni,Qk+}$ and one with all negative changes $X_{ni,Qk-}$ and treat them as follows. Positive inventory changes are directly included in final demand as are final consumption, government spending and investments, i.e. the build-up of inventory is treated as if it were consumed in the current period. Formally, final demand in country n for goods from industry k in country i, $X_{ni,Fk}$, is thus defined as $X_{ni,Fk} = X_{ni,Ck} + X_{ni,Pk} + X_{ni,Gk} + X_{ni,Ik} + X_{ni,Qk+}$. Negative inventory changes, in contrast, are treated as if they were produced (and consumed) in the current period. To do this, the output vector can not simply be increased by the respective (absolute) value of inventory changes because the production of the inventory in the last period also required intermediates and, thus, had a larger overall effect. To see how to calculate the necessary changes consider N countries and K sectors in matrix notation. X is the original $(N \cdot K) \times 1$-vector of total outputs, A the $(N \cdot K) \times (N \cdot K)$-matrix of input coefficients, F the $(N \cdot K) \times 1$-vector of final demand including positive inventory changes and Inv the $(N \cdot K) \times 1$-vector of negative inventory changes. Then the total output can be calculated as the sum of intermediate flows, final demand, and inventory changes as $X = AX + F + Inv$. The goal is to calculate the new level X_{new} for which the final demand vector is unchanged but inventory changes Inv are set to 0, i.e. the total output if the negative inventory changes had been produced in the current period. Rearranging terms gives $X_{new} = (E - A)^{-1}F$ where E is the unit matrix. The new input output matrix is obtained by combining intermediate good flows AX_{new} and the unchanged final demand vector F.

Consumption and intermediate goods shares. The final input-output table allows to derive two (country level) parameters of the model. Firstly, the share that industry k has in the consumption of country n can be calculated by dividing expenditures on industry k by total demand of country n to get $\delta^k_{nC} = \sum_i X_{ni,Fk} / \sum_k \sum_i X_{ni,Fk}$. Similarly, the share that industry k has in the intermediate demand of industry j in country n as $\delta^k_{nj} = \sum_i X_{ni,jk} / \sum_k \sum_i X_{ni,jk}$.

Bilateral trade flows. The adjusted input output matrix also serves to calculate for each industry k the trade flow X_{nik} between any supplying country i to any destination country n. These bilateral trade flows are obtained by summing over all uses of k (intermediate use in all industries and final demand) in its destination country, $X_{nik} = \sum_j X_{ni,jk} + X_{ni,Fk}$. When looking at the data, several of these bilateral trade flows are zero due to the high level of sectoral and geographical disaggregation. For trade between any two countries in any industry to become 0 in the Eaton-Kortum model trade costs between those two countries have to be infinitely high. This leads to two complications. Firstly, it can no longer hold true that direct trade between those countries is cheaper than trade via some partner country (with non-infinite trade costs) and I must, therefore, assume that such trade without modification is prohibited. Secondly, for any shock to trade barriers d_{nik} the relative change of the infinite trade barriers $\hat{d}_{nik}$ has to be defined as 1.

Country production and spending. The value of country i's total production in industry k, i.e. the revenue of firms in industry k, can be obtained by summing over all importing countries n, such that $X_{ik} = \sum_n X_{nik}$. The value of total production (revenue) in country i is then given by summing these across all industries, $R_i = \sum_k X_{ik}$. Summing across exporting countries i gives country n's total spending in industry k, $E_{nk} = \sum_i X_{nik}$. Then summing over the spending in each industry gives country n's total spending $E_n = \sum_k E_{nk}$.

Bilateral trade shares. The share π_{nik} that country i has in country n's spending in industry k can be calculated by dividing industry k flows from i to n, X_{nik}, by country n's total industry spending E_{nk}. Hence, these bilateral trade shares are, $\pi_{nik} = X_{nik}/E_{nk}$.

D.2 County revenue data

Sectorally disaggregated revenue data for Germany is, unfortunately, only published at the state and not at the county level. Therefore, in the mining and manufacturing sectors, where such information is available, I rely on sectoral county level employment data from the German federal and regional statistical offices to split sectoral state revenues across individual counties based on each county's share in its state's total sector employment. In a few cases with low firm numbers county sector level employment data is censored for anonymity reasons. In these cases I use the residual state sector revenues, that is, after subtracting calculated revenues from counties with employment data, and split them across the remaining counties with censored employment data according to firm numbers.[27]

In the agriculture, construction and service sectors no geographically disaggregated employment or firm data is available. In these sectors I proxy for county shares in the German total revenue with value added shares for which disaggregated data exists.[28] For the sector

[27]In this process I account for the employment in some very large or small firms via secondary sources (annual reports, etc.) to avoid larger distortions from the assumption of an average revenue per firm.

[28]German and state sectoral data for revenue, employment and firm number can be found in tables 42271-0002 and 42271-0011 from www-genesis.destatis.de. Regional data for employment and firm number is

"Utilities" value added data at the county level is only available as a total combined with the mining sector. To split the value added I begin by using the sectorally more disaggregated state data to calculate the state's share of value added in revenue in the mining sector.[29] Applying this state share to the county level mining revenue data derived above allows to approximate county level value added in the mining sector. Finally, subtracting this value from the aggregate utilities and mining value added from the data, gives the county level value added in the "Utilities" sector. I then proceed as with the other non-manufacturing sectors above and use the share of each counties sectoral value added in the national value added of the "Utilities" sector to proxy for the county's share in total German revenue in the "Utilities" sector.

Lastly, I scale sectoral revenues across all counties such that the resulting aggregate German sectoral revenues match the values reported in the WIOD.

D.3 County trade data

Raw Data. For county level trade in the mining and manufacturing sectors I rely on data provided by Schubert et al. (2014) as part of the official "Forecast of nationwide transport relations in Germany 2030" on behalf of the German ministry of transport and digital infrastructure ("Bundesministerium für Verkehr und digitale Infrastruktur"). The data set gives the total shipments in tons by water, train or truck for 2010 between German counties and their partners, disaggregated along 25 product categories.[30] The trade partner can be either a further German county (including the county itself), one of 32 third countries (of which 25 are also in the WIOD Database), or a major German or international port. The latter two appear as origin or destination whenever the actual origin or final destination is unknown or not in the explicit country sample, e.g. shipments to and from Japan. Moreover, the data thus differentiates between shipments to/from, e.g.Hamburg and Hamburg port.

The data on rail and river transport is based on data sets from the federal statistical office specially compiled to publicly unavailable levels of spatial and sectoral disaggregation. Data on truck shipments relies, firstly, on a similar special report at the county level prepared by the department of motor vehicles ("Kraftfahrtbundesamt") from a monthly .5% mandatory sample of German registered trucks with a gross vehicle weight rating above 3.5 tons and secondly, on complementary NUTS-3 level shipment data for foreign owned trucks from Eurostat.

available in table 001-51-4, and value added data in table 426-71-4-B from www.regionalstatistik.de.

[29]Sectorally disaggregated value added data at the state level is available in table 8211-0002 from www-genesis.destatis.de.

[30]The full matching between sectors of all classifications used by the different data sources to the final 17 sectors can be found in a supplementary appendix available online.

Of the 25 product categories 18 can be directly matched to my agriculture, mining and manufacturing industries 1 to 12.[31] Three categories have no match in my data ("mail", "moving items, not-for-market items", "Equipment and material for transportation, packaging") and are dropped. The remaining three categories refer to "mixed", "unknown" and "other" goods and I use those to scale trade in all other sectors for the respective pair of trade partners.[32] Finally, while the category "Secondary raw materials; municipal wastes and other wastes" would match to sector 13 ("Utilities") of this paper, it only makes up for a small share of trade in the sector. The much larger share of electricity, gas and steam supply, as well as water treatment, collection and supply is (mostly) not captured by the shipment data which does not contain information on pipeline or power line "transport". Consequently, I do not use the category to proxy for the geographical trade structure of the "Utilities" sector. Instead I drop the category from the shipment data set and treat the "Utilities" sector as the other service sectors below.

Value flows. I am interested in the sectoral trade values between German counties, and between German counties and third countries. Unfortunately, data is only available in terms of shipped tons and not value. I address this problem differently depending on the trade partners. For flows from foreign countries to German counties in the sectors with available shipment data (1 to 12) I calculate the counties share in the total sectoral weight exported from the third country to Germany. I then use these shares together with the value of the trade flow between the two countries as reported in the WIOD to calculate the value of the bilateral flow. Hence, the value flow X_{nik} from third country i to a German county n in sector k is given by $X_{nik} = (W_{nik}/\sum_{n \in N^G} W_{nik}) X_{Gik}^{WIOD}$, where W_{nik} is the respective weight flow and X_{Gik} the value of total German imports from country i in sector k as calculated from the WIOD. If third country i is listed in the WIOD data but not explicitly listed in the shipment data I calculate weight shares by using the combined shipments that originate in one of the countries not in the WIOD or that appear in the data to originate in a major port.

There are two cases in which the WIOD reports flows from a foreign country to Germany despite zero flows in the shipment data. This is the case for exports from Ireland to Germany in industries 4 ("textiles and leather") and 8 ("metal") and I split these imports evenly across all German counties.

For German counties as exporters I proceed similarly: the data includes shipments within the county and hence the sum of all sectoral shipments originating in a German county represents total sectoral production weight of that county. Consequently, for exports from

[31] See the supplementary online appendix.

[32] Some select importer-exporter pairs only have shipments in the category "unknown". In these cases I assume that these shipments consist of the exporter's average export mix.

German counties to any partner I can use the share of the weight of the respective exports in total sectoral production weight to calculate the value of the flow from the sectoral county revenues. Mathematically, $X_{nik} = \frac{W_{nik}S_{nk}^{WIOD}}{\sum_n W_{nik}S_{nk}^{WIOD}} R_{ik}$, where R_{ik} is county i's revenue in sector k and S_{nk} a scale factor. The latter becomes necessary to ensure that the resulting aggregate flows from Germany to any third country as well as total inner German trade flows match the WIOD flows. In particular it scales relative export weights to each country-sector across all German counties until the aggregate German bilateral flow with the partner in each sector matches the value reported in the WIOD. Hence, for value flows X_{nik} from a German county i to a third country n in sector k the scale factor is chosen such that $X_{nGk}^{WIOD} = \sum_{i \in N^G} X_{nik}$, where X_{nGk}^{WIOD} is the WIOD trade flow from Germany to country n in sector k. Similarly, for value flows X_{nik} from a German county i to another county n in sector k the scale factor is chosen such that $X_{GGk}^{WIOD} = \sum_{i \in N^G} \sum_{n \in N^G} X_{nik}$, where X_{GGk}^{WIOD} is Germany's own trade in sector k as given by the WIOD.

For a few county-country trade partners and sectors there are weight flows in the shipment data despite the exporter having zero revenue in the respective industry, or weight flows between countries despite the WIOD reporting zero trade. These errors are likely to stem from classification and matching problems since shipment data is classified along product categories whereas WIOD and county revenue data is based on industry categories. This can, for example, lead to a situation where leather industry exports are coded as automotive products (leather car seats) and exports are measured in a sector in which nothing is produced according to the revenue data. In such cases, to remain matched to the WIOD, I rely on the revenue data and set shipment weights to zero.[33]

For utilities, construction and service sectors for which there is no shipment data, I obtain county exports to foreign countries by splitting the WIOD total German exports across counties according to each county's share in the respective sectors national revenue.

To obtain values for trade flows in the above sectors when a German county is an importer I must first calculate county sectoral demands (consumption and intermediate). To do so the sectoral German demand from the WIOD is split across counties according to their share in total German value added. The value added in turn is calculated in two separate groups. For agriculture, mining, utilities, construction and service sectors I use the sectoral German wide value added share from the WIOD to calculate county value added from county revenues. For the remaining sectors I rely on county level aggregate manufacturing value added from the data to first calculate an average value added share for the manufacturing sector as a whole in each county. I then scale the relative share of value added to remaining revenue across

[33] In four county-sectors the shipment data shows exports but no "own trade". This can not concur with the model assumptions and in these cases I set the share of own trade $\pi_n nk$ to 5%, which is at the lower end of all observed values in other county-sectors.

all German counties in each sector until the aggregate German value matches the sectoral value added share reported in the WIOD. Finally, sectoral German demand from the WIOD is split across counties according to the counties value added share in total German value added.

Intermediate demand at the county level can subsequently be calculated using the sectoral county revenues together with the derived value added shares and the national sectoral intermediate demand shares of each industry from the WIOD. Together with the consumption demand this allows to calculate county level demand for utilities, construction and service sectors. Trade flows between counties in these sectors are then calculated by assuming that this demand is satisfied across all counties according to their revenue share in the respective industry. Hence, for any pair of German counties n and i, $X_{nik} = \frac{R_{ik}}{\sum_{i \in N^G} R_{ik}} X_{GGk} \frac{X_{nk}^D}{\sum_{n \in N^G} X_{nk}^D}$, where X_{nk}^D is county n's total demand of industry k goods.

Having derived all bilateral trade flows and all sectoral county revenues I can calculate each county's trade deficit and supply with goods from each sector. Finally, I scale relative sectoral consumption and sectoral intermediate demand shares such that sectoral demand matches sectoral supply. This implies that in counties with a relatively high supply of e.g. "Transport Equipment" goods both relative intermediate usage and relative consumption of such goods will be larger.

The result is thus a data set containing information on revenues and trade among 442 locations (402 German counties, 39 other countries and a modeled ROW) in 17 sectors.

Concluding remarks

This thesis contributes to the literature predicting the effects of a proposed transatlantic trade and investment partnership between the European Union and the United States. It is unique in its analysis of land and housing as a key factor driving the obtained low welfare results as well as in its regional viewpoint that determines that all German counties would benefit - albeit very little - from a TTIP.

In a more general context this thesis provides a quantification of the heterogeneity of German regions, as well as of the differences in their responses to both aggregate and local shocks. It identifies and quantifies different mechanism that drive the varying responses with a particular focus on local labor markets.

To explain the sources of heterogeneity it develops a unique data set of goods shipments between German counties and uses it together with further data sets to construct a full interregional input-output table for Germany embedded into an international input-output table. Analysing the resulting trade and production structure and using it to simulate the effects of economic shocks several key variables and mechanisms explaining the observed heterogeneity emerge.

First, the sectoral composition of a county's production is important in explaining its trade linkages with other locations as different sectors show vastly differing patterns of agglomeration across space. Changes in the sectoral composition of production can also explain some of the variance in employment responses to shocks but play a more important role when shocks are sectoral compared to regional in nature.

Population mobility and commuting are a second important margin of adjustment to shocks and play a crucial role in propagating shocks across local labor markets. Migration between regions reduces the magnitude of (un)employment rate responses of local labor market shocks by about 70 percent. A counties openness to commute also turns out to be an important predictor of the strength of employment responses across local labor markets. A more open local labor market can attract a larger number of workers in the form of commuters without increasing the strain on a local fixed factor such as land and housing.

The endowment with land and the size of its share in total expenditure are the third key element driving the heterogeneity across local labor markets. The lower the endowment and the more important land is in demand the stronger is its role as a congestion force. Subsequently, it reduces the magnitude of migration and therefore also increases the importance of commuting as and adjustment mechanism. In reverse, when the power of housing to act as a congestion force is reduced due to a lower share of housing in total expenditure, migration and ensuing general equilibrium effects become more important making an ex-ante prediction of resulting changes more difficult.

Finally, this thesis opens up many opportunities to answer further pressing questions. For one, the derived interregional input-output table and the constructed models are suited to analyse a range of further specific shocks such as, for example, the British exit from the European Union or the accession of new member states. Moreover, obtaining similar interregional trade data for several years to construct a time series of interregional input-output tables for Germany would open up the possibility to test the predictions of the model simulations and thus greatly benefit the quantitative literature as a whole. Such questions, however, are beyond the scope of this thesis and must be left for exciting future research.

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Deutschsprachige Zusammenfassung

Diese Dissertationsschrift befasst sich mit der ökonomischen Bedeutung von Regionen innerhalb Deutschlands. Regionen sind dabei aus zweierlei Sicht ein wichtiges Untersuchungsobjekt. Dies gilt zum Einen, da makroökonomische Schocks über Regionen Hinweg zu substantiell unterschiedlichen Effekten führen. Dringliche Themen wie die Robotisierung und die Verwendung künstlicher Intelligenz, der Brexit, oder US-amerikanische Zölle werden Würzburg anders Beeinflussen als Berlin und implizieren somit unterschiedliche Interessen bei der jeweiligen Bevölkerung, den jeweiligen Firmen und Politikern. Zum Anderen können regionale ökonomische Schocks wie Erfindungen, Insolvenzen, oder die Ansiedlung eines bedeutenden Betriebs durch Handel und „input-output“ Verbindungen zu Schocks von makroökonomischer Bedeutung anwachsen. Allerdings sind regionale Heterogenitäten innerhalb Deutschlands und die komplizierten Netzwerke verschiedenster Art zwischen Regionen weder gut dokumentiert noch ausreichenden verstanden. Dies gilt insbesondere auch für lokale Arbeitsmärkte welche ein Kerninteressen der Regionalpolitik darstellen und ebenfalls von bedeutenden Heterogenitäten geprägt sind. Die vorliegende Arbeit analysiert und quantifiziert das regionale Produktions- und Handelsnetzwerk innerhalb Deutschlands und untersucht welche Aspekte für die beobachteten breiten Unterschiede bei der Anpassung lokaler Arbeitsmärkte an ökonomische Schocks verantwortlich sind.

Der erste Aufsatz, *„How deep is your love? A quantitative spatial analysis of the transatlantic trade partnership“*, setzt sich dabei mit der Prognose von Effekten eines konkreten Schocks in Form des vorgeschlagenen transatlantischen Freihandelsabkommens (TTIP) auseinander. Die Arbeit findet einerseits nur mäßige Wohlfahrtseffekte, sowohl für die Vereinigten Staaten als auch für die Europäische Union und Drittstaaten, andererseits zeigt sie, dass alle Landkreise in Deutschland Wohlfahrtsgewinne erzielen und es somit zumindest regional keine Verlierer des Abkommens geben würde.

Der zweite Aufsatz, *„RIOTs in Germany - Constructing an interregional input-output table for Germany“*, nutzt einen einzigartigen Datensatz von Gütersendungen per LKW, Zug oder Schiff zwischen allen 402 deutschen Landkreisen im Jahr 2010 um, mit Hilfe weiterer Daten, eine interregionale input-output Tabelle für Deutschland zu erstellen und die Verflechtungen lokaler Märkte zu untersuchen.

Der dritte Aufsatz, „*On the Road (Again): Commuting and Local Employment Elasticities in Germany*“, analysiert die Bedeutung des Pendelns für lokale Arbeitsmärkte. Es zeigt sich dabei, dass Pendelströme eine zentrale Marge bei der Anpassung an lokale Schocks darstellen und dass deutsche Arbeitsmärkte wesentlich flexibler und anpassungsfähiger sind als weitläufig angenommen.

Der vierte Aufsatz, „*Shocking Germany - A spatial analysis of German regional labor markets*“, integriert Arbeitslosigkeit in die zur Prognose lokaler Schocks verwendeten quantitativen Modelle. Dadurch kann er den Effekte von durch Schocks ausgelöster Migration innerhalb Deutschland auf lokale Arbeitsmärkte quantifizieren. Es zeigt sich, dass die Änderung lokaler Arbeitslosigkeitsraten als Antwort auf lokale Produktivitätsschocks durch Migration im Durchschnitt um 70 Prozent gedämpft wird. Strukturelle Anpassung führen langfristig zu einer im Vergleich wesentliche geringeren Änderung dieser Raten.

Lebenslauf

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