# Three essays on the causes and consequences of spatial inequality

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# Abstract

In this dissertation, I examine the causes and consequences of spatial inequality. Furthermore, I present the most current knowledge on how quantitative spatial models can serve as a tool to analyze the distribution of economic activity across space. In a collection of research papers, I investigate in particular (i) how market integration and fiscal policy shape the spatial allocation of economic activity, and (ii) how urbanization affects wage inequality. The first and second essays are joint works with Tobias Seidel and Jens Suedekum.

In the first essay, we use a quantitative model to study the implications of European integration for welfare and migration flows. The model suggests that the dismantling of trade barriers in Europe has led to moderate welfare gains and a more homogeneous spatial distribution of economic activity. We also look ahead in time and evaluate different scenarios for the Brexit. We find moderate welfare losses for the UK and continental Europe. In the most unfavorable scenario, about 500,000 people would leave the UK in the long run.

The second essay evaluates the importance of governmental activity for the spatial distribution of economic activity. We use a general equilibrium model with fiscal equalization to show that regional transfers are quantitatively important for understanding the spatial allocation of economic activity. Using data from Germany, we show that the abolition of fiscal equalization would lead to a welfare gain implying sizeable migration responses of individuals.

In the third essay, I identify the role of urbanization for wage inequality. A decomposition of the change in wage inequality suggests that urbanization has contributed about one-third to the growth of wage inequality in (West) Germany between 1985 and 2009.

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To my family.

# Contents

# Introduction

How and why does economic activity differ across space? For most of human history, people moved to seek a better life. Today, more than 50 percent of the worldwide population lives in cities. This figure will increase to 66 percent by 2050 according to the United Nations (2014). It is important to understand the underlying economic mechanisms of this trend. Policy makers, for example, need to consider the mobility response of economic agents when they invest in public infrastructure or redistribute income from rich to poor regions. Quantitative spatial models that include free mobility of workers between locations allow us to address this issue.[1] In this dissertation, I contribute to the understanding of the causes and consequences of spatial inequality in three ways.

The first chapter of this thesis is a joint work with Tobias Seidel. We use a quantitative model to study the implications of European integration for welfare and migration flows across 1,318 regions. The model shows that an increase of trade barriers to the level of 1957 reduces welfare by about 1-2 percent on average, depending on the presumed trade elasticity. However, remote regions may face initial welfare losses of up to 4 percent, causing an estimated migration of about 8 million individuals to the European core. Hence, the dismantling of trade barriers in Europe has led to a more homogeneous spatial distribution of economic activity. We also look ahead in time and evaluate different scenarios for the Brexit. We find moderate welfare losses of 0.44 percent for the UK in the most pessimistic scenario while continental Europe's welfare declines by 0.18 percent. In the most unfavorable scenario, about 500,000 people would leave the UK in the long run.

The second chapter of this thesis is a joint work with Tobias Seidel and Jens Suedekum. We use a general equilibrium model with fiscal equalization to show that regional transfers are quantitatively important for understanding the spatial allocation of economic activity. We find that the abolition of fiscal equalization

[1] See for example, Allen and Arkolakis, 2014, Behrens, Mion, Murata, Suedekum, 2017, Redding, 2016.

in Germany leads to a moderate welfare gain of about 0.33 percent implying the migration of about 5 percent of the population in the long run. The rates of increase in average real gross domestic product (GDP) per capita and average labor productivity are more pronounced, at 5.8 percent and 9.2 percent respectively.

In the third chapter, I pursue two goals. First, I explore the link between urbanization and wage inequality by using administrative data from (West) Germany. Second, I study the relative importance of worker- and firm-specific dimensions—like the distribution of firm size, occupational structure, and job tasks —to precisely account for the composition of cities.

Urbanization has contributed about 30 percent to the growth of wage inequality. Up to one-half of the effect occurs because occupations or job tasks with a greater increase in wage inequality are more concentrated in larger locations. Firm size explains around one-third, while differences in the industry composition only account for around one-fourth of the location-inequality premium. Sorting of workers within those groups across locations only explains a small part. In sum, groups of workers with an initial unequal pay in the mid-1980s today face even higher inequality in larger cities compared to smaller cities. This effect varies across the wage distribution with large positive effects for high-wage workers. Thus, urbanization boosts higher within-group inequality and contributes to greater inequality especially among high-skilled workers in Germany.

# Chapter 1

# A spatial perspective on European integration: Heterogeneous welfare and migration effects from the Single Market and the Brexit

*We use a quantitative model to study the implications of European integration for welfare and migration flows across 1,318 regions. The model suggests that an increase of trade barriers to the level of 1957 reduces welfare by about 1-2 percent on average, depending on the presumed trade elasticity. However, remote regions may face initial welfare losses of up to 4 percent causing an estimated migration of about 8 million individuals to the European core. This implies that the dismantling of trade barriers in Europe has led to a more homogeneous spatial distribution of economic activity. With regard to the Brexit, we find moderate welfare losses for the UK of 0.44 percent in the most pessimistic scenario while continental Europe's welfare declines by 0.18 percent. In the most unfavorable scenario, about 500,000 people would leave the UK in the long run.*

## 1.1 Introduction

We know at least since the times of Adam Smith and David Ricardo that the integration of markets promises welfare gains for all participating countries. However,

the spatial dimension of these welfare gains within countries and the associated migration patterns are less understood. Recent developments of rigorous quantitative models that incorporate regions and free mobility of workers between locations (e.g. Allen and Arkolakis, 2014, Behrens, Mion, Murata, Suedekum, 2017, Redding, 2016) allow us to address this topic. In this paper, we take a closer look at European integration by applying the spatial perspective. Which regions did benefit most from the dismantling of trade barriers and what migration pattern did these heterogeneous welfare effects cause? Addressing these questions aims at a better understanding of the spatial allocation of economic activity in Europe.

We combine a unique data set on inter-regional trade flows in Europe with a quantitative spatial model and analyze two events in the integration process of Europe. First, we raise trade costs to the level before the Common Market was established in 1957. According to Levchenko and Zhang (2012), trade costs in the European Union were about 45 percent higher in the 1960s compared to the 2000s. As substantial trade cost reductions took place with the founding of the European Community in 1957, we run our counterfactual with 60 percent higher trade costs across national borders. Second, we estimate welfare changes and implied migration flows for regions within the UK and in other European countries after the Brexit. Following Dhingra et al. (2016), we distinguish between an *optimistic* scenario where trade costs increase by about 3.7 percent and a *pessimistic* scenario with a 13.9 percent increase in trade barriers. These counterfactuals inform us about the magnitude of effects and – more importantly – about (relative) winners and losers across 1,318 NUTS-3 regions.

The model predicts moderate welfare losses of 1-2 percent when we withdraw the market integration steps since the introduction of the European Community in 1957. These welfare effects are distributed very heterogeneously across regions. The periphery experiences welfare losses that are up to six times larger than those in some core regions, so migration is triggered from remote locations to the European center. In our baseline scenario, the model suggests overall migration of 8.1 million individuals or 1.6 percent of the European population. In alternative scenarios, these figures rise to 11.4 million or 2.3 percent, respectively. European integration has therefore contributed to a more homogeneous distribution of economic activity.

The Brexit is associated with an increase of trade costs between the UK and the rest of Europe at national borders. As trade frictions between intra-national regions and across all other national borders remain unchanged, the model predicts only small welfare effects ranging between -0.2 and -0.44 percent for the UK in the

pessimistic scenario. The EU, in contrast, is much less affected with welfare losses being only half of those in the UK on average. These heterogeneous effects trigger migration of up to one million individuals in the most unfavorable scenario and with free migration across European regions. In that case, more than 500,000 individuals from the UK would relocate to the European Union. If migration is only allowed within UK boundaries, only 14,000 to 53,000 people migrate to equalize welfare differences within the country. In all scenarios, Scotland faces the largest losses in terms of welfare and hence the largest outmigration of people.

It is well understood that single-sector models like the one we use generate moderate welfare effects of trade liberalization. Implementing many sectors that use other sectors' output as intermediate inputs in their own production process magnifies welfare effects substantially – in Costinot and Rodriguez-Clare (2014) on average by a factor of six. We do not put too much emphasis on the *level* of welfare changes, but rather stress the heterogeneity across European regions triggering national and international migration. This establishes a main difference from the quantitative international trade literature (see Costinot and Rodriguez-Clare, 2014). As migration decisions are determined by *relative* welfare effects, we think that the model's prediction on migration flows is less sensitive to modelling decisions in this direction.

We build our analysis on recent work by Allen and Arkolakis (2014) employing an Armington trade model with perfect competition at the local level and heterogeneous goods across regions. Individuals are mobile across locations. Higher density causes both a positive production externality and a negative congestion externality ensuring stability and uniqueness of the migration equilibrium under certain parameter conditions. As trade is costly, geography matters for the attractiveness of locations. In the periphery, for example, distances to trading partners are larger on average implying higher price indices there compared to centrally-located regions. With a negative distance elasticity of trade flows exceeding unity, it is immediate (and well known from the gravity literature) that responses of trade flows to trade shocks are increasing in distance. This is the underlying force behind heterogeneous welfare effects of market integration across Europe and the implied migration pattern.

Our paper relates to a number of literatures. First, our paper adds to a recent and growing literature that extends quantitative trade models with factor mobility and exogenous local characteristics (e.g. Allen and Arkolakis, 2014, Bartelme, 2015, Behrens, Mion, Murata, Suedekum, 2017, Caliendo, Parro, Rossi-Hansberg and Sartre, 2014, Monte, Redding and Rossi-Hansberg, 2015, and Redding, 2016). We

apply this framework to the European context requiring inter-regional trade data that have not been used at this scale previously. This allows us to provide novel insights about the regional variation in welfare and migration effects in Europe.

Second, our paper contributes to the quantitative international trade literature focussing on regional economic integration. In a recent study, Levchenko and Zhang (2012) apply a multi-sector Ricardian model to explore the welfare implications of European trade integration. Corcos, Del Gatto, Mion and Ottaviano (2012) examine welfare effects of intra-EU-15 trade integration in a monopolistic-competition model with endogenous markups. Apart from building on a different methodological framework, our work deviates as we focus at heterogeneous implications at a more disaggregated regional level and account for both inter-regional and international migration flows.

Third, we contribute to the debate on the economic consequences of a withdrawal of the United Kingdom from the European Union. To the best of our knowledge, we are only aware of one paper by Dhingra et al. (2016) quantifying welfare effects of the Brexit. In contrast to their paper, our approach allows us to highlight welfare changes at the regional level *within* the UK and derive migration responses.

The paper is organized as follows. We first introduce the model in section 1.2. Section 1.3 discusses quantification and the data we use. We discuss counterfactuals in section 1.4 before offering concluding remarks in section 1.5.

## 1.2 A quantitative spatial model

We consider an economy with a continuum of locations $i \in S$ and $\bar{L}$ mobile workers.[1] Each location produces one unique variety of a good under perfect competition like in Armington (1969) or Anderson (1979). Goods can be shipped to other locations at iceberg costs such that $\tau(i, s) \geq 1$ units have to be sent from $i$ for one unit to arrive in $s$.[2] Intra-regional trade costs, $\tau(i, i)$, are normalized to unity. Further, locations differ from each other with regard to productivity $A(i)$, amenities $u(i)$ and remoteness being determined by bilateral trade costs with their trade partners.

[1]The continuum of locations is only for generalization. Later in the analysis we will only rely on a discrete number of locations.

[2]We assume that the triangle inequality holds for any $\tau(i, s)$, i.e. $\tau(i, s) < \tau(i, k)\tau(k, s)$ for any $i$, $s$ and $k$.

### 1.2.1 Preferences

Workers have identical preferences over the continuum of varieties that can be substituted with each other with a constant elasticity of substitution $\sigma > 1$. They also care about the utility derived from a local consumption amenity such that

$$W(i) = \left( \int_{s \in S} q(s,i)^{\frac{\sigma-1}{\sigma}} ds \right)^{\frac{\sigma}{\sigma-1}} u(i), \tag{1.1}$$

where $q(s,i)$ denotes consumption of the variety in location $i$ that is produced in $s$.[3] Welfare is increasing in both the quantity consumed and the number of differentiated varieties as well as in local amenities $u(i)$. Maximizing utility subject to income yields individual demand for a variety from $s$ in location $i$

$$q(s,i) = w(i)p(s,i)^{-\sigma} P(i)^{\sigma-1}, \tag{1.2}$$

where $w(i)$ is the nominal wage paid in $i$, $p(s,i)$ denotes the consumer price in $i$ and $P(i)$ represents the price index.

### 1.2.2 Profit maximization and inter-regional trade

With labor as the only factor of production and provided that perfect competition on the product market equates prices to marginal costs, we obtain consumer prices as $p(s,i) = \tau(s,i)w(s)/A(s)$, where, $A(s)$ denotes location-specific labor productivity. With these ingredients at hand, we are able to derive a gravity equation for bilateral trade flows between locations. Letting $X(i,s)$ be the value of shipments from $i$ to $s$, we have

$$X(i,s) = \left( \frac{\tau(i,s)w(i)}{A(i)P(s)} \right)^{1-\sigma} w(s)L(s), \tag{1.3}$$

where $1-\sigma$ is the trade elasticity of the CES demand system and $P(i)$ is the CES price index:

$$P(i) = \left[ \int_{s \in S} \tau(s,i)^{1-\sigma} A(s)^{\sigma-1} w(s)^{1-\sigma} ds \right]^{\frac{1}{1-\sigma}}. \tag{1.4}$$

[3] Allen and Arkolakis (2014) demonstrate that it is straightforward to introduce locational preferences into the utility function. This only affects the elasticity of amenities with respect to population as discussed below.

### 1.2.3 Agglomeration and dispersion forces

Local productivities and amenities are determined by an exogenous component, $\bar{A}(i)$ and $\bar{u}(i)$, and an endogenous part dependent on a location's population. The composite productivity level is given by

$$A(i) = \bar{A}(i)L(i)^{\alpha}, \tag{1.5}$$

where $\alpha \geq 0$ represents the elasticity of productivity with respect to population density. This formalization is a short cut for agglomeration externalities like knowledge spillovers or labor-market pooling that increase firm productivity in location $i$.[4] In contrast, higher population density also causes congestion externalities rendering a location less attractive. Local amenities are defined as

$$u(i) = \bar{u}(i)L(i)^{\beta}, \tag{1.6}$$

with $\beta \leq 0$ capturing the idea of a negative congestion externality.

### 1.2.4 Equilibrium

We use the following equilibrium conditions to solve the model:

1. **Labor market clearing.** This implies

$$\int_{s \in S} L(s)ds = \bar{L}. \tag{1.7}$$

2. **Goods market clearing.** In equilibrium, the aggregate value of the good sold to all destinations is equal to total income, so

$$w(i)L(i) = \int_{s \in S} X(i,s)ds \quad \forall i \in S. \tag{1.8}$$

3. **Welfare equalization.** Free mobility of labor ensures that welfare is equalized across all locations. Using insights from above, we can express welfare in location $i$ as a function of the location-specific amenity and real wages,

$$W(i) = \frac{w(i)}{P(i)}u(i). \tag{1.9}$$

[4]See Combes and Gobillon (2015) for a recent overview of the empirical literature on agglomeration economies.

Remote locations are characterized by a higher price index which has to be compensated by higher nominal wages and/or higher amenities than in centrally-located places for $W(i)$ to be equalized across all $i \in S$.

We derive a system of equations that allows us to (i) determine exogenous productivities and amenities and (ii) solve for endogenous wages and labor allocation across regions in the counterfactual analysis. Combining (1.3) and (1.9) with (1.8), we get

$$W^{\sigma-1} L(i)^{1-\alpha(\sigma-1)} w(i)^{\sigma} = \int_S \tau(i,s)^{1-\sigma} \bar{A}(i)^{\sigma-1} \bar{u}(s)^{\sigma-1} L(s)^{1+\beta(\sigma-1)} w(s)^{\sigma} ds \quad (1.10)$$

Second, combining utility, (1.9), with the price index (1.4) delivers

$$W^{\sigma-1} L(i)^{\beta(1-\sigma)} w(i)^{1-\sigma} = \int_S \tau(s,i)^{1-\sigma} \bar{A}(s)^{\sigma-1} \bar{u}(i)^{\sigma-1} L(s)^{\alpha(\sigma-1)} w(s)^{1-\sigma} ds, \quad (1.11)$$

where (1.5) and (1.6) have been substituted for composite productivities and amenities. Feeding the system of equations with information on bilateral trade costs, wages and population delivers solutions for exogenous productivities and amenities up to a constant with $W^{\sigma-1}$ as the eigenvalue of the system.[5] Allen and Arkolakis (2014) show that there is a unique and stable equilibrium if $\alpha + \beta \leq 0$.

## 1.3 Quantification

Quantifying the model requires estimates for bilateral trade costs $\tau(i,s)$, exogenous productivities $\bar{A}(i)$ and exogenous amenities $\bar{u}(i)$. We discuss identification, data sources and results for these steps sequentially in the following two subsections. The basic geographic unit is the third level of administrative division called the Nomenclature of Territorial Units for Statistics (NUTS-3). NUTS-3 regions are jurisdictional entities whose average population usually ranges between 150,000 and 800,000 people.[6] We choose the aggregation level of locations in a way to justify the assumption of no commuting and no spillovers between locations. The analysis contains information for 26 EU countries plus Norway in 2010 which leaves us with 1,318 European regions.

[5] Allen and Arkolakis (2014) show how this system of equations can be translated into a single nonlinear equation system. We follow their procedure in solving and quantifying the model.

[6] The principles and characteristics of the nomenclature of territorial units for statistics are available at http://ec.europa.eu/eurostat/web/nuts/principles-and-characteristics.

### 1.3.1 Parametrization of trade costs

To the best of our knowledge, there is no data set that contains information on inter-regional trade flows between *all* European NUTS-3 regions. However, German authorities provide information on a subset of inter-regional trade flows comprising information on the annual volume of intra-German and European shipments (in metric tons) that went through German territory in 2010. The data come from the Forecast of Nationwide Transport Relations in Germany 2030 (Verkehrsverflechtungsprognose 2030, henceforth VVP) provided by the Clearing House of Transport Data at the Institute of Transport Research of the German Aerospace Center.[7] The dataset allows us to differentiate by mode of transportation (road, rail, water) and by product category. We do not rely on transportation by mode, however, and aggregate shipments over all transport modes at the first level of the NST2007 classification.[8]

Table 1.1 provides an overview of the VVP-data coverage by comparing the reported aggregated trade volumes at the country level to those in COMTRADE.[9] First, we observe that about 87 percent of trade flows refer to intra-German transactions that are not covered by COMTRADE. Trade of German regions with other European regions makes up about 9 percent leaving about 4 percent of the overall volume as transit shipments. Second, we aggregate up trade volumes between regions in Germany and the 28 European countries that are member of the European Union (EU) plus Iceland, Liechtenstein, Norway and Switzerland that are members of the European Free Trade Association (EFTA). COMTRADE covers 98 percent of the volumes reported in the VVP-dataset for 2010 indicating high quality of the regional trade data we use. With regard to bilateral trade flows between the set of European economies without Germany, however, the VVP-dataset covers only 12 percent of the COMTRADE volume. This makes sense as VVP only reports those trade flows between European countries that transit through Germany. In the case of Spain and France, for instance, it is hard to imagine that goods should be shipped via Germany. If there is a systematically lower coverage of trade flows for more distant locations, estimates of distance elasticities could be biased. We there-

[7]The data can be accessed via http://daten.clearingstelle-verkehr.de/276/.

[8]NST is the abbreviation for Nomenclature uniforme des marchandises pour les statistiques de transport. This system represents a standard classification for transport statistics for goods transported by road, rail, inland waterways and sea (maritime) at the European level since 2008 and is based on the classifications of products by activity (CPA).

[9]Notice that COMTRADE data are only available at the country level, but contain both volume and value information at the product level.

Table 1.1: Aggregate trade volumes: COMTRADE vs. VVP

| | *COMTRADE* | *VVP* |
|---|---|---|
| Germany - Rest of Europe | 279.39 | 285.49 |
| Rest of Europe - Rest of Europe | 1,175.18 | 145.30 |
| Germany - Germany | - | 2,854.82 |

*Notes:* This table reports aggregate trade volumes in million metric tons. Column 2 reveals data from COMTRADE. Column 3 presents trade volumes from the Forecast of Nationwide Transport Relations in Germany 2030 (VVP). Both columns refer to the year 2010.

fore focus on inter-regional trade flows where a German region is either an exporter or an importer. We relegate further details on this dataset to Appendix 1.A.

As the regional trade data only contain information on volumes, we need to obtain values to apply the gravity equation. To this end, we define the ratio of values and quantities based on trade data from COMTRADE for the same set of countries and 2-digit product categories in 2010 to compute trade values. With this information at hand, we run a standard gravity regression to uncover the distance elasticity of trade flows. We follow the standard procedure in the gravity literature (see, e.g., Head and Mayer, 2014, for an overview) by estimating (1.3) with importer and exporter fixed effects to control for multilateral resistance. We proxy bilateral trade costs by distance according to

$$\tau(i,s) = dist(i,s)^{\theta}\tilde{\epsilon}(i,s), \tag{1.12}$$

where $\tilde{\epsilon}(i,s)$ is the error term. GIS software delivers Euclidian distances $dist(i,s)$ between the centroids of locations $i$ and $s$, so we end up with a $1,318 \times 1,318$ matrix. Log-linearizing (1.3) and substituting for the parametrization of trade costs yields the following gravity equation for the value of bilateral trade flows from $i$ to $s$:

$$\log X(i,s) = \delta(i) + \gamma(s) - (\sigma-1)\theta \log dist(i,s) + (1-\sigma)\beta'\mathbf{M} + \log \epsilon(i,s), \tag{1.13}$$

where $\delta(i)$ and $\gamma(s)$ are exporter and importer fixed effects that control for wages, productivity, population and the CES price index.[10] $\mathbf{M}$ collects standard bilateral control variables from the gravity literature like common border, language or contiguity and $\log \epsilon(i,s) = (1-\sigma)\log \tilde{\epsilon}(i,s)$.

[10] As the data distinguishes between product groups, we add product fixed effects in the estimation.

Table 1.2: Estimated distance elasticities

| | volumes | | values | |
|---|---|---|---|---|
| log(distance) | -1.21*** | -1.15*** | -1.24*** | -1.17*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| language | | 0.04 | | 0.02 |
| | | (0.021) | | (0.019) |
| contiguity | | -0.14*** | | -0.17*** |
| | | (0.008) | | (0.008) |
| border | | -1.05*** | | -1.18*** |
| | | (0.011) | | (0.010) |
| Constant | 18.50*** | 20.20*** | 4.32*** | 6.30*** |
| | (0.030) | (0.043) | (0.026) | (0.038) |
| Exporter FE | ✓ | ✓ | ✓ | ✓ |
| Importer FE | ✓ | ✓ | ✓ | ✓ |
| Product FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,772,302 | 1,772,302 | 2,228,320 | 2,228,320 |
| $R^2$ | 0.71 | 0.72 | 0.37 | 0.38 |

*Notes*: Columns 1 and 2 use the original volume data from VVP. Columns 3 and 4 are based on trade values where we have used the simple average of unit values per 2-digit product group. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.2 summarizes the regression output. Columns 3 to 4 build on bilateral trade values as the dependent variable where the latter specification adds commonly-used non-geographic covariates like language, contiguity and border. Following Nitsch and Wolf (2013), we also explore results for volumes instead of values as the dependent variable in Columns 1 and 2. Although this deviates from the theoretical model, it can be argued that trade values are proportional to trade volumes so the results are insightful for robustness reasons. Further, exporter and product-specific dummy variables account for the exporter- and product-specific price per ton that converts volume of exports into values.

The estimated coefficients on log distance are remarkably similar and range between $-1.15$ and $-1.24$, independent of using values or volumes. Moreover, the estimates are all statistically different from zero at the 1-percent level. Comparing our findings to those in the gravity literature establishes further credibility. Head and Mayer (2014) summarize that estimates of the trade-distance elasticity parameter in typical gravity equations cluster around -1.1 with a standard deviation of 0.41.

### 1.3.2 Identifying location fundamentals

A second piece of information that is unobservable from data, but required for quantification of the model, are values of exogenous productivities $\bar{A}(i)$ and amenities $\bar{u}(i)$. To uncover these model parameters, we feed estimated trade costs together with information on population $L(i)$ and wages $w(i)$ (proxied by GDP per capita) into (1.10) and (1.11). Both variables are provided by Eurostat at the NUTS-3 regional level. We divide total population of each region in 2010 by the area of that region and normalize both the population density and wages to have a mean of one.[11]

We use the structure of the model to solve for the overall productivity $A(i)$ and amenity $u(i)$ level. Then we use (1.6) and (1.5) to identify $\bar{A}(i)$ and amenity $\bar{u}(i)$ for all possible combinations of $\alpha$ and $\beta$. In the baseline, we follow Allen and Arkolakis (2014) in choosing $\alpha = 0.1$ and $\beta = -0.3$. These values can be justified as follows: Rosenthal and Strange (2004) highlight empirical evidence for positive productivity externalities with respect to population density of close to 10 percent. The value for $\beta$ can be retrieved from expenditure share data on housing. Allen and Arkolakis (2014) demonstrate that the model is isomorphic to a class of theories where workers spend a constant share $1 - \delta$ of their income on differentiated goods and $\delta$ on local non-tradable goods (e.g. housing) with $\beta = -\delta/(1 - \delta)$. According to Eurostat, average expenditure on housing amounted to 24.2 percent in the EU (28 countries) in 2010 justifying the chosen value for $\beta$.[12] In the baseline scenario, we choose $\sigma = 9$, which is in line with the preferred trade elasticity of 8 in Eaton and Kortum (2002). As a sensitivity check, we use $\sigma = 5$ implying a trade elasticity of 4 as suggested by Simonovska and Waugh (2014). Additionally, we calculate the model for a wider range of spillover parameters for sensitivity.

Figure 1.1 illustrates the distribution of exogenous productivities (Panel (a)) and amenities (Panel (b)) across European regions in the baseline case. Locations with high per-capita income have higher values of exogenous productivity, like in central Europe and Scandinavia. Eastern Europe features comparably low levels of exogenous productivity. The picture changes when we take a look at exogenous amenities. Technically speaking, the model predicts higher values of $\bar{u}(i)$ for locations with lower income to rationalize the location choice of people living there. This

[11] See Allen and Arkolakis (2014) for details.

[12] We use information on the final consumption expenditure of households by consumption purpose (COICOP 3 digit) from Eurostat with the code: nama_10_co3_p3.

is why Eastern European regions show darker colors (i.e. higher values) of $\bar{u}(i)$ in Panel (b) of Figure 1.1.

Combining our estimates for trade costs, exogenous productivities and amenities with wages, it is instructive to take a look at the implied price index in each location. Figure 1.2 illustrates the resulting geographic variation. The figure shows that our specification of trade costs as a constant elasticity function of distance leads to concentric circles around the geographic center of Europe. Intuitively, remote locations like Greece, Portugal or Finland have the highest price index so we can use $P(i)$ as a proxy for remoteness below.

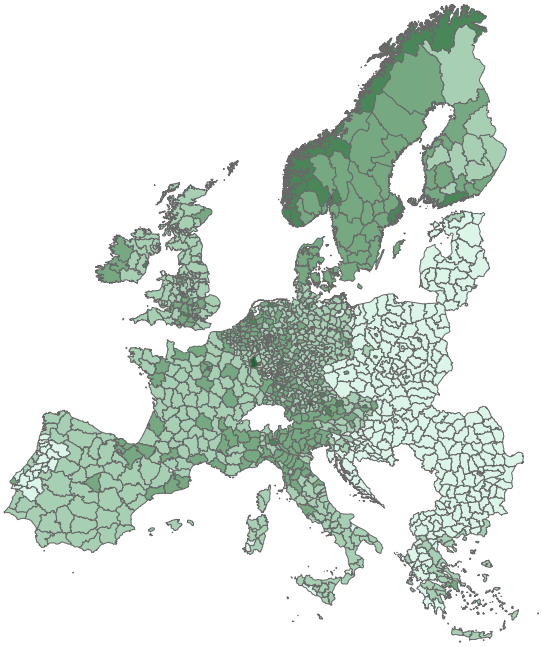
## 1.4 Counterfactuals

Based on the fundamentals of the model, we proceed by studying two major events of European integration. First, we withdraw the market integration steps since the foundation of the European Community in 1957 including the establishment of the Common and the Single Market. Second, we look ahead in time and evaluate different scenarios for the Brexit. Apart from overall effects on welfare and migration, we are particularly interested in the differences in welfare responses across regions and their implied migration flows that shape the economic landscape of Europe in the long run. As we have quantified the model based on data from 2010, we evaluate previous episodes of trade liberalization by simulating a situation prior to the respective reduction in trade costs. This means, we *raise* trade barriers to the level before the European Community was founded and compare this outcome to the status quo. Moreover, we keep the number of countries fixed. One might object that it is unnecessary to "replicate" the past as we can simply take a look at historical data. The rigidity of the model, however, allows us to abstract from other factors that have shaped the development of the local economy over time (e.g. technological change, population growth or changes in preferences) and simply focus on the implications of changes in trade costs. With regard to the Brexit, of course, we make statements about a trade shock that lies ahead of the baseline year 2010.

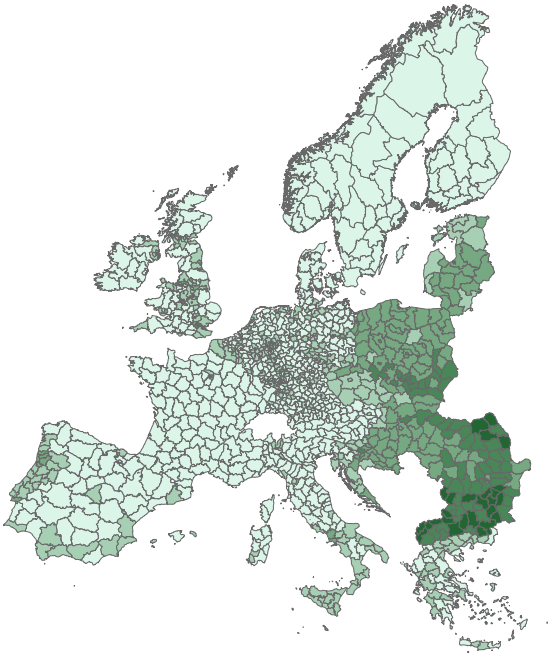
It is noteworthy that changes of trade costs have a specific flavor in our model. Trade integration is associated with lower barriers across national borders while bilateral trade costs do not change *within* countries. This is one of the novel aspects of quantitative spatial models allowing us to also study differential responses of border regions compared to non-border regions. We proceed in the standard way by using the estimated primitives of the model jointly with counterfactual trade costs

Figure 1.1: Estimated exogenous productivities and amenities

(a) Exogenous productivities



(b) Exogenous amenities



*Notes:* This figure plots the exogenous productivity $\bar{A}(i)$ and amenity $\bar{u}(i)$ for $\alpha = 0.1$ and $\tilde{\beta} = -0.3$. A darker shading indicates higher values.

Figure 1.2: Estimated Price Index

*Notes:* This figure plots the estimated price index $P(i)$ for $\alpha = 0.1$ and $\beta = -0.3$. A darker shading indicates higher values.

to solve for wages and population density. Relating these values to observed data on wages and population in 2010 allows us to compute welfare changes and implied migration flows as a response to these hypothetical trade shocks.

### 1.4.1 Reversing the Common and Single Market

The introduction of the Common Market in 1957 and the Single Market in 1992 were two important steps towards a reduction of trade barriers within the European Union. Levchenko and Zhang (2012) have estimated that trade costs within Western Europe were about 45 percent higher in the 1960s compared to the 2000s. As trade barriers were substantially reduced in the 1950s already, Levchenko and Zhang (2012) admit that their estimate understates the overall difference in trade costs from before European integration to the present. Nevertheless, we use these estimates as a helpful point of departure and suppose that trade costs in the 1950s were about 60

percent higher than in 2010.[13] Then the model informs us about changes in welfare and population density. Of course, we ignore changes in exogenous productivities and amenities over time and only let changes in trade barriers drive welfare changes and migration according to the model.

We simulate the model for three different mobility scenarios: no labor mobility, intranational labor mobility, and international (within Europe) labor mobility. Table 1.3 reports welfare changes by country in Columns 1 to 3 in the absence of labor mobility and implied changes in population in Columns 4 to 6 when workers can freely choose their place of residence. Note that the average welfare changes in Column 1 are realized for all regions within a country when labor is allowed to move within national boundaries. In our benchmark specification, the model predicts an average welfare loss of 1.1 percent. However, the regional differences are enormous. Looking at average welfare changes by country, it is immediate that countries that are located in the periphery of Europe lose most while those in the center lose least. To name a few examples, Greece (-3.1 percent), Finland (-2.8 percent) or Portugal (-2.7 percent) lose more than Belgium (-0.8 percent), Germany (-0.8 percent) or France (-0.9 percent). At the regional level, these disparities become even more pronounced. The largest loss is observed in Greece with nearly 4 percent while the region with the lowest welfare loss of 0.59 percent is located in Germany – in the centre of Europe.

If we allow people to migrate to those places that offer the highest welfare level, we observe from Columns 4 to 6 that migration would take place from the periphery to the core. There are only 6 out of 27 countries that experience immigration, namely Belgium, Germany, France, Luxembourg, the Netherlands and the United Kingdom. Greece is predicted to lose nearly 6 percent of its population as a response to this trade shock in the long run, some Greek regions even up to 8 percent. Corresponding to the welfare results, the region with the largest inflow of people can be found in Germany where the population is predicted to increase by 1.53 percent. Translating these figures to absolute migration flows delivers a value of 8.12 million individuals or 1.6 percent of the European population that would change their region of residence as a response to this trade shock.

[13] We have also derived results for trade costs changes of 50 percent and 100 percent, respectively, to assess the sensitivity of results. The overall welfare change increases by a factor of 1.8 when we increase trade costs changes from 50 to 100 percent.

Table 1.3: Welfare change and implied migration flows

| | No mobility | | | International mobility | | |
|---|---|---|---|---|---|---|
| *Country* | $\Delta W(i)$ | *min* | *max* | $\Delta L(i)$ | *min* | *max* |
| Austria | -1.44 | -1.57 | -1.07 | -0.79 | -1.39 | 0.09 |
| Belgium | -0.78 | -0.79 | -0.77 | 0.97 | 0.92 | 1.00 |
| Bulgaria | -2.78 | -3.07 | -2.49 | -5.14 | -5.83 | -4.14 |
| Croatia | -1.74 | -2.14 | -1.58 | -2.06 | -3.11 | -1.44 |
| Czech Republic | -1.32 | -1.60 | -1.11 | -0.76 | -1.50 | -0.02 |
| Denmark | -1.42 | -1.52 | -1.24 | -0.88 | -1.27 | -0.43 |
| Estonia | -2.69 | -2.83 | -2.50 | -4.73 | -5.19 | -4.20 |
| Finland | -2.84 | -3.70 | -2.43 | -5.70 | -7.76 | -4.00 |
| France | -0.90 | -1.57 | -0.73 | 0.03 | -1.41 | 1.12 |
| Germany | -0.76 | -0.99 | -0.59 | 0.96 | 0.31 | 1.53 |
| Greece | -3.13 | -3.82 | -2.72 | -5.89 | -8.03 | -4.81 |
| Hungary | -1.84 | -2.09 | -1.62 | -2.26 | -2.98 | -1.55 |
| Ireland | -1.52 | -1.76 | -1.48 | -1.62 | -2.02 | -1.18 |
| Italy | -1.69 | -2.75 | -1.17 | -2.04 | -4.90 | -0.20 |
| Latvia | -2.42 | -2.64 | -2.23 | -4.07 | -4.62 | -3.40 |
| Lithuania | -2.27 | -2.46 | -2.10 | -3.52 | -4.09 | -3.02 |
| Luxembourg | -0.81 | -0.80 | -0.80 | 0.90 | 0.90 | 0.90 |
| Netherlands | -0.83 | -0.93 | -0.76 | 0.80 | 0.50 | 1.01 |
| Norway | -1.97 | -3.97 | -1.65 | -3.57 | -8.53 | -1.69 |
| Poland | -1.70 | -2.14 | -1.34 | -1.90 | -3.12 | -0.74 |
| Portugal | -2.67 | -3.02 | -2.36 | -4.63 | -5.70 | -3.76 |
| Romania | -2.71 | -3.00 | -2.17 | -4.37 | -5.63 | -3.18 |
| Slovakia | -1.72 | -1.97 | -1.58 | -1.96 | -2.62 | -1.44 |
| Slovenia | -1.56 | -1.61 | -1.47 | -1.36 | -1.54 | -1.11 |
| Spain | -2.75 | -3.03 | -1.75 | -3.51 | -5.71 | -1.96 |
| Sweden | -1.99 | -3.35 | -1.52 | -3.12 | -6.73 | -1.28 |
| United Kingdom | -0.96 | -1.57 | -0.75 | 0.19 | -1.45 | 1.04 |

*Notes:* This table reports percentage change in welfare and population in response to a 60 percent increase of trade costs between European countries. Columns 1-3 assume no labor mobility and report average welfare changes per country as well as minimum and maximum values across regions. Column 4 reports the percentage change in population when we allow for labor to move freely across all locations. Columns 5 and 6 show the minimum and maximum population change in a region per country.

To better understand the importance of location fundamentals for the change in welfare, we derive conditional correlations from a simple regression of the form

$$\Delta W(i) = \beta_0 + \beta_1 L_0(i) + \beta_2 \bar{A}(i) + \beta_3 \bar{u}(i) + \beta_4 P_0(i) + \beta_5 border + \epsilon(i). \qquad (1.14)$$

$\Delta W(i)$ denotes the percentage change in welfare for the scenario without labor mobility, $L_0(i)$ and $P_0(i)$ reflect population density and the price index in location $i$ prior to the change in trade costs. The latter can be interpreted as a measure of remoteness as regions located in the periphery are characterized by higher average trade costs and thus higher values of $P_0(i)$. Exogenous productivities, $\bar{A}(i)$, exogenous amenities, $\bar{u}(i)$, and a dummy variable equal to one for all regions adjacent to a national border complete the list of covariates. $\epsilon(i)$ reflects a stochastic error term. We run two versions of the above specification, one without and one with country fixed effects, to explore the relevance of unobserved country characteristics. It is immediate from Table 1.4 that remoteness, as proxied by the price index, turns out to play the most important role. Also the border dummy turns out significant. In contrast, the estimates for initial population density or exogenous productivity are not statistically different from zero. As $\Delta W(i)$ is negative for all locations, we can infer that a higher initial price index leads to stronger negative responses to increases in trade costs. *border* exerts the same impact qualitatively.

$P_0(i)$ and *border* represent measures for remoteness at the European and the national level, respectively, so the estimation results indicate that regions are affected differently by a common trade cost shock. Although trade barriers are only raised at national borders in this counterfactual exercise, regions in the European periphery (those with a higher price index) lose more if the trade elasticity exceeds minus one. This is a standard insight from international trade theory (see, e.g. Anderson and van Wincoop, 2003). A similar argument can be made with respect to a region's location within a country. If located close to a national border, raising trade barriers at the border increases the remoteness of this location relative to other non-border locations in the same country. This is why, controlling for overall remoteness through $P_0(i)$, *border* comes out with a negative sign.

To get a feeling for the sensitivity of the results, we repeat the counterfactual exercise for alternative values of $\sigma$, $\alpha$, and $\beta$ and compute associated welfare changes and implied overall migration flows in millions and in percent of the European population. We compare $\sigma = 9$, which is in line with the preferred trade elasticity of 8 in Eaton and Kortum (2002), with $\sigma = 5$ implying a trade elasticity of 4 as suggested by Simonovska and Waugh (2014). Further, we

Table 1.4: Welfare change and location characteristics

| | (1) | (2) |
|---|---|---|
| initial pop. density | 0.027 | -0.002 |
| | (0.027) | (0.007) |
| exog. productivity | 0.214 | 0.070 |
| | (0.159) | (0.054) |
| exog. amenity | -0.330*** | -0.031 |
| | (0.186) | (0.058) |
| initial price index | -3.330*** | -3.816*** |
| | (1.06) | (0.171) |
| border region dummy | -0.414*** | -0.069*** |
| | (0.13) | (0.024) |
| Country FE | ✗ | ✓ |
| $R^2$ | 0.85 | 0.98 |
| Observations | 1,318 | 1,318 |

*Notes*: This table reports OLS estimates of welfare changes in percent, $\Delta W(i)$, without labor mobility on a region's characteristics. Clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

double the productivity elasticity $\alpha$ and reduce the congestion elasticity $\beta$ to -0.6. As shown by Allen and Arkolakis (2014), the model can be straightforwardly extended to account for heterogeneous locational preferences of workers where $\beta = \beta_0 - 1/\theta$. Setting the Frechet shape parameter $\theta = 3$, as suggested by Bryan and Morten (2014) and used in Redding (2016), and keeping the baseline congestion elasticity at $\beta_0 = -0.3$ we arrive at a value of approximately -0.6.

Table 1.5 provides an overview of results. We observe that reducing $\sigma$ from a value of 9 to 5 roughly doubles welfare responses – from our baseline scenario of -1.11 percent (row 1) to -2.08 percent (row 5). Intuitively, a lower elasticity of substitution implies that consumers do not respond as elastically to changes in relative prices by substituting expensive goods. As a consequence, higher trade costs lead to larger changes in the overall price index and thus in welfare. Notice, however, that the ranking of welfare losses across regions is not affected. Migration flows respond less sensitively to reductions in $\sigma$ than welfare. Nevertheless, overall migration is predicted to rise by around 40 percent compared to the benchmark.

Accounting for locational preferences (higher value of $\beta$) or a higher productivity elasticity $\alpha$ does not lead to major changes in welfare responses. However, migration is naturally affected a lot. If individuals have preferences to reside in certain locations, they are more reluctant to move in response to exogenous shocks. Thus

Table 1.5: Sensitivity: Welfare and European migration

| $\sigma$ | $\alpha$ | $\beta$ | $\hat{W}$ *(in percent)* | $\hat{L}$ *(in millions)* | $\hat{L}$ *(in percent)* |
|---|---|---|---|---|---|
| 9 | 0.1 | -0.3 | -1.11 | 8.12 | 1.60 |
| 9 | 0.1 | -0.6 | -1.16 | 4.17 | 0.82 |
| 9 | 0.2 | -0.3 | -1.06 | 11.30 | 2.23 |
| 9 | 0.2 | -0.6 | -1.15 | 4.88 | 0.96 |
| 5 | 0.1 | -0.3 | -2.08 | 11.41 | 2.25 |
| 5 | 0.1 | -0.6 | -2.18 | 6.64 | 1.31 |
| 5 | 0.2 | -0.3 | -2.00 | 14.18 | 2.80 |
| 5 | 0.2 | -0.6 | -2.15 | 7.49 | 1.48 |

*Notes:* This table reports welfare changes and migration (in millions and in percent of the total population) for different parameter values of $\sigma$, $\alpha$ and $\beta$ when trade costs are increased by 60 percent between countries.

raising $\beta$ nearly halves migration flows to about 4 million individuals. The opposite happens, of course, if the positive agglomeration externality rises. In that case, wages respond more elastically to every additional immigrant rendering the location more attractive for other individuals from other locations. Comparing rows 1 and 3 reveals that overall European migration increases by about 40 percent. Interestingly, if we combine both effects (as shown in row 4), migration remains substantially lower than in the baseline scenario.

As regions are affected to different extents, we finally examine how an increase in trade barriers at national borders affect the distribution of local GDP. Table 1.6 summarizes three different measures of inequality, namely variance, Gini-index, and Theil-index, before the trade cost shock and after the shock with intranational labor mobility and international labor mobility. We observe that the inequality measures increase by 0.54 percent, 0.02 percent and 0.11 percent, respectively, if workers can freely migrate within national borders. Allowing for international migration raises inequality by a factor of 4-8. The variance is now predicted to increase by 2.2 percent, the Gini-index rises by 0.16 percent while the Theil-index goes up by 0.4 percent. In sum, the numbers suggest that trade integration in Europe has led to a more equal distribution of economic activity across regions.

Table 1.6: Reversing European integration: Inequality of local GDP

| | $Var$ | $\Delta Var(\%)$ | $Gini$ | $\Delta Gini(\%)$ | $Theil$ | $\Delta Theil(\%)$ |
|---|---|---|---|---|---|---|
| before the shock | 49.75 | | 0.81 | | 1.71 | |
| after the shock, intranational mobility | 50.02 | 0.54 | 0.81 | 0.02 | 1.71 | 0.11 |
| after the shock, international mobility | 50.84 | 2.18 | 0.81 | 0.16 | 1.72 | 0.42 |

*Notes:* This table reports the level and percentage changes of inequality statistics of local gross domestic product (GDP).

### 1.4.2 The Brexit

Turning from a historical event to the present, we use the model to study the implications of the Brexit for regional welfare and migration in both the UK and continental Europe. In 2013, Britain's prime minister David Cameron announced to hold a referendum about membership in the European Union. Three years later, 51.9 percent of voters supported a withdrawal from the EU inducing prime minister Cameron to step back.[14] While the conditions of Brexit will be negotiated in the near future, it is expected that UK's access to the Single Market will be restricted implying higher trade frictions between the UK and the rest of the EU.

We consider two scenarios of how trade costs change after the Brexit following Dhingra et al. (2016). In the *optimistic* scenario we assume that the UK would face one quarter of the tariff-equivalent of non-tariff barriers between the USA and the EU. Berden et al. (2013) have estimated this value at 14.7 percent. This delivers a total trade cost increase of $\Delta\tau(i,s)_{EU-UK} = 0.25 \times NTB_{EU-USA} = 0.25 \times 14.7 = 3.67$ percent.

The *pessimistic* scenario presumes that international trade takes place under the regulations of the World Trade Organization. Both the UK and the EU will then apply their most favoured nation tariff (MFN) on imports. Adding 75 percent of the tariff equivalent of non-tariff barriers between the EU and the USA, we get a total trade cost increase of $\Delta\tau(i,s)_{EU-UK} = 0.75 \times NTB_{EU-USA} + MFN_{EU-UK} = 0.75 \times 14.7 + ((3.09 + 2.6)/2) = 13.87$ percent. It is noteworthy that we raise trade costs between regions located in the UK and those in other EU countries while intranational trade costs remain identical everywhere.

[14]See Dhingra et al. (2016) for a more detailed exposition.

If we allow labor mobility within the UK and within the rest of Europe separately, the model predicts that welfare in the UK declines by 0.23 percent in the pessimistic scenario and by 0.06 percent in the optimistic case. Continental Europe is affected less with changes of -0.09 percent and -0.03 percent, respectively. If we reduce the elasticity of substitution to $\sigma = 5$, the welfare effects roughly double. More precisely, welfare is predicted to decline in the UK by 0.44 percent and 0.12 percent in the pessimistic and optimistic case, respectively. The figures for continental Europe are 0.18 percent and 0.05 percent. These numbers are fairly small, but in line with single-sector trade models predicting only moderate welfare changes in response to trade costs.[15] Dhingra et al. (2016) find welfare losses of 1.28 percent and 2.61 percent in the pessimistic and the optimistic scenario, respectively, employing a multi-sector Armington trade model à la Costinot and Rodriguez-Clare (2014). While it is well understood that introducing multiple sectors and intermediate goods magnifies welfare effects, our focus is on heterogeneous effects across regions and their implied migration consequences. Moreover, in Dhingra et al. (2016) the change in welfare is mainly due to the assumption that intra-EU trade barriers decline by 5.7-10.5 percent in the next decade. If we allowed for this effect in addition, our welfare responses would increase by a factor of two in the pessimistic and five in the optimistic scenario.

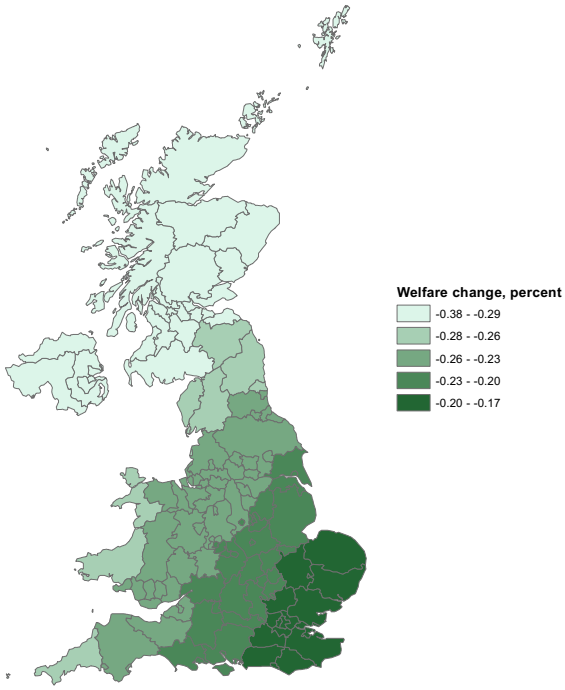
Panel (a) of Figure 1.3 offers a graphical illustration of changes in welfare in the *pessimistic* scenario when labor is assumed to be immobile. This would be the initial shock and is instructive to evaluate to what extent locations are affected differently. We observe that Scotland experiences the largest initial welfare loss of about 0.3 to 0.38 percent while welfare declines by only 0.17 to 0.21 percent in the London area. In the rest of Europe, regions in the vicinity of the UK like Belgium or the Netherlands face the lowest welfare losses of about 0.02 percent. Similar effects occur in Ireland.

Panel (b) of Figure 1.3 shows percentage changes of population based on free mobility within the UK and within continental Europe (plus Ireland), respectively. Corresponding to the welfare results, Scotland experiences the largest decline in population of up to 0.88 percent. In contrast, the south of England gains up to 0.27 percent. Intuitively, Scotland suffers from its remote position relative to the geographic center of Europe and there are no regions in the North that could serve as substitute trade partners. Looking at migration responses in continental Europe, it is astonishing that a similar pattern leads to higher densities in the core (like

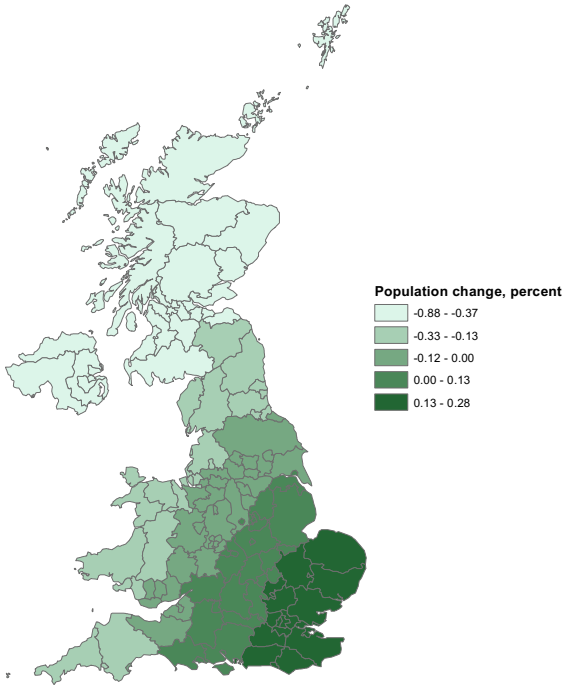
[15] See the survey by Costinot and Rodriguez-Clare (2014).

Figure 1.3: Estimated welfare and population changes in percent

(a) Welfare




(b) Population




*Notes:* This figure plots the percentage change in welfare in Panel (a) and population density in Panel (b) after the Brexit in the pessimistic scenario where trade costs between the UK and the EU increase by 13.9 percent for EU-UK trade flows.

Belgium, the Netherlands, parts of Germany and France) at the expense of the periphery. Population is predicted to increase by about 0.16 to 0.5 percent in this greater area.

As the above results relate only to the scenario where labor can migrate within the UK or within the rest of Europe, we are also interested in migration patterns with free mobility across Europe. We therefore compute migration flows both in total and as a share of the population in the UK and in the rest of Europe, respectively, rather than relative to each NUTS3-region. We observe from Table 1.7 that total migration *within* the UK amounts to about 52,000 individuals or 0.08 percent of the population if we consider the pessimistic scenario with a baseline value of $\sigma = 9$ (row 1). The corresponding figures for the EU are 451,000 or 0.1 percent of the population. In sum, the Brexit causes migration of about 500,000 individuals. If migration remains free across UK-EU boundaries, the model predicts that 366,000 individuals would relocate to another region. As the UK experiences a larger welfare loss than the EU, all relocation takes place across the Channel to settle in the EU. As the Brexit affects regions heterogeneously, as shown above, an additional 348,000 Europeans change location within the other European countries – which is less than the corresponding number in the *within*-scenario. These figures make up 0.58 percent of the British population and 0.08 percent of the population in the other European countries. Reducing the elasticity of substitution to $\sigma = 5$ raises migration to about 700,000 or by roughly 40 percent with internal migration and to more than one million migrants in total if we impose a lower elasticity of substitution of $\sigma = 5$. In the latter case, more than 530,000 people or 0.86 percent of the British population would leave the UK to settle in the rest of Europe.

Turning to the more favorable optimistic scenario where trade costs only increase by 3.7 percent, overall migration sums up to values between 136,000 (only 14,000 within the UK) and 193,000 (20,000 within the UK) if labor mobility is ruled out between the UK and the EU. If we relax this assumption, overall migration adds up to 275,000 in the case of $\sigma = 5$ implying an emigration of 142,000 people from the UK.

Table 1.7: Sensitivity: Migration flows

| | | UK | | EU | |
|---|---|---|---|---|---|
| Scenario | $\sigma$ | in thousands | in percent | in thousands | in percent |
| | | | Within | | |
| | 9 | 52.64 | 0.08 | 451.19 | 0.10 |
| | 5 | 75.45 | 0.12 | 634.00 | 0.14 |
| *Pessimistic* | | | Free | | |
| | 9 | 366.29 | 0.58 | 348.60 | 0.08 |
| | 5 | 537.87 | 0.86 | 478.61 | 0.11 |
| | | | Within | | |
| | 9 | 14.07 | 0.02 | 122.21 | 0.03 |
| | 5 | 20.19 | 0.03 | 172.51 | 0.04 |
| *Optimistic* | | | Free | | |
| | 9 | 97.19 | 0.15 | 95.69 | 0.02 |
| | 5 | 142.57 | 0.23 | 132.41 | 0.03 |

*Notes:* This table reports the number of migrants in thousands and in percent of the overall population in the UK and the EU, respectively, as a response to the Brexit. We distinguish two scenarios (*pessimistic* and *optimistic*) and two values for the elasticity of substitution ($\sigma = 9$ and $\sigma = 5$). For the optimistic scenario we assume trade costs for EU-UK trade flows to increase by 3.7 percent; for the pessimistic scenario by 13.9 percent. We further distinguish between migration *Within* the UK and the EU and *Free* migration across all countries. Agglomeration and congestion elasticities are set to $\alpha = 0.1$ and $\beta = -0.3$.

## 1.5 Conclusions

This paper has analyzed welfare and migration consequences of European integration using a quantitative spatial general equilibrium model similar to Allen and Arkolakis (2014). Based on a unique dataset on inter-regional trade flows in Europe, we were able to quantify the model for 1,318 European regions in 2010 to study the heterogeneous effects of trade integration across regions.

If we raise trade costs to a level before the foundation of the European Community in 1957, welfare declines by about 1-2 percent on average. However, some remote locations face welfare losses of up to 4 percent. This sets off migration from the periphery to the center of about 8-11 million people, depending on the specifica-

tion. We thus conclude that European market integration has contributed to a more equal distribution of economic activity, that is less density in the core of Europe.

Turning to the present debate of UK's withdrawal from the European Union, the Brexit, we find that Scottish regions would expect the largest welfare losses while the south of England experiences the lowest losses. Since we employ a single-sector model, welfare losses are moderate with 0.44 percent in the most unfavorable scenario. Nevertheless, as the UK is affected more severely by the Brexit than the rest of Europe, free mobility across the Channel could imply emigration of more than 500,000 people from the UK to settle other parts of Europe. This is equivalent to nearly one percent of the British population.

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# Appendix

## 1.A European regional trade data

The trade flow matrix comes from the Forecast of Nationwide Transport Relations in Germany 2030 (Verkehrsverflechtungsprognose 2030, VVP). It covers trade flows (in metric tons) that either have a German NUTS3-region as origin or destination or serve as a transit region for intra-European trade of regions outside of Germany. The data distinguish between the mode of transport, namely road, rail and water, and product groups according to NST-2007. For rail and water, the data come from the German Federal Statistical Office and for road from the Federal Motor Transport Authority (Kraftfahrtbundesamt).

Table 1.A.1: Aggregate trade volumes per product category: Comtrade vs. VVP

| | *Between Germany - Rest of Europe* | | *Between Rest of Europe* | | *Within Germany* |
|---|---|---|---|---|---|
| *Product category* | *COMTRADE* | *VVP* | *COMTRADE* | *VVP* | *VVP* |
| 10 | 14.57 | 14.46 | 106.16 | 15.29 | 155.71 |
| 21 | 0.82 | 0.88 | 21.80 | 3.18 | 29.19 |
| 22 | 0.32 | 0.87 | 104.16 | 0.49 | 12.45 |
| 23 | 12.79 | 0.24 | 98.09 | 0.14 | 1.63 |
| 31 | 0.13 | 1.67 | 12.98 | 1.40 | 15.83 |
| 32 | 0.96 | 0.52 | 2.82 | 0.05 | 5.60 |
| 33 | 39.53 | 35.38 | 93.85 | 1.85 | 867.64 |
| 40 | 35.94 | 24.36 | 122.19 | 13.29 | 279.69 |
| 50 | 1.79 | 2.81 | 6.88 | 3.33 | 10.60 |
| 60 | 26.02 | 23.86 | 78.27 | 14.10 | 112.22 |
| 71 | 0.72 | 1.41 | 6.68 | 0.50 | 10.24 |
| 72 | 17.14 | 11.05 | 148.13 | 5.46 | 128.10 |
| 80 | 42.65 | 29.47 | 131.50 | 8.18 | 136.19 |
| 90 | 21.51 | 20.73 | 51.11 | 9.14 | 280.01 |
| 100 | 29.08 | 25.20 | 91.92 | 15.07 | 167.88 |
| 110 | 8.70 | 8.82 | 24.90 | 7.88 | 47.93 |
| 120 | 9.32 | 12.00 | 23.18 | 5.88 | 68.60 |
| 130 | 1.99 | 3.16 | 7.89 | 1.20 | 12.00 |
| 140 | 15.42 | 12.96 | 42.64 | 6.82 | 251.62 |
| 150 | . | 1.29 | . | 2.38 | 29.93 |
| 160 | . | 5.59 | . | 6.06 | 68.55 |
| 170 | . | 1.27 | . | 2.98 | 32.89 |
| 180 | . | 10.66 | . | 6.99 | 83.95 |
| 190 | . | 36.82 | . | 13.65 | 46.35 |

*Notes:* This table reports aggregate trade volumes in million tons per product category. We compare values that come from COMTRADE with values from the Forecast of Nationwide Transport Relations in Germany 2030 (VVP).

For German locations trade flows are reported at the NUTS3-level. For other European countries, geographical units are more aggregated with a higher level of aggregation for more distant countries. For example, coverage for the Netherlands occurs at the NUTS2-level while Portugal has no regional breakdown (NUTS0). The data were collected in a project undertaken by Intraplan Consulting, Munich, in collaboration with BVU Consulting, Freiburg, for the Federal Ministry of Transport and Digital Infrastructure and is only available for 2010. The data are made available

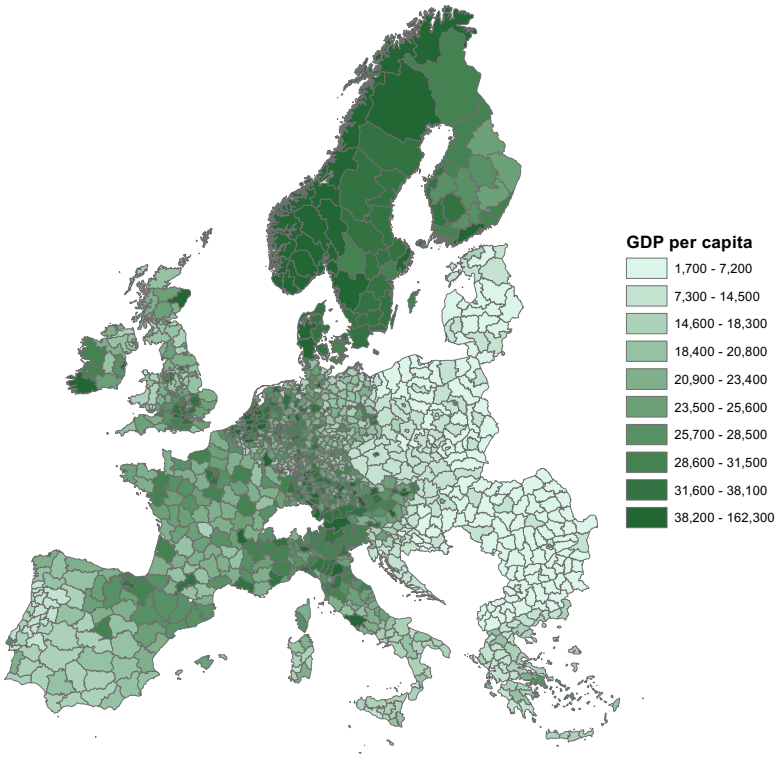
through the Institute for Transport Research of the German Aerospace Center under http://daten.clearingstelle-verkehr.de/276/.

## 1.B Data on local GDP and population

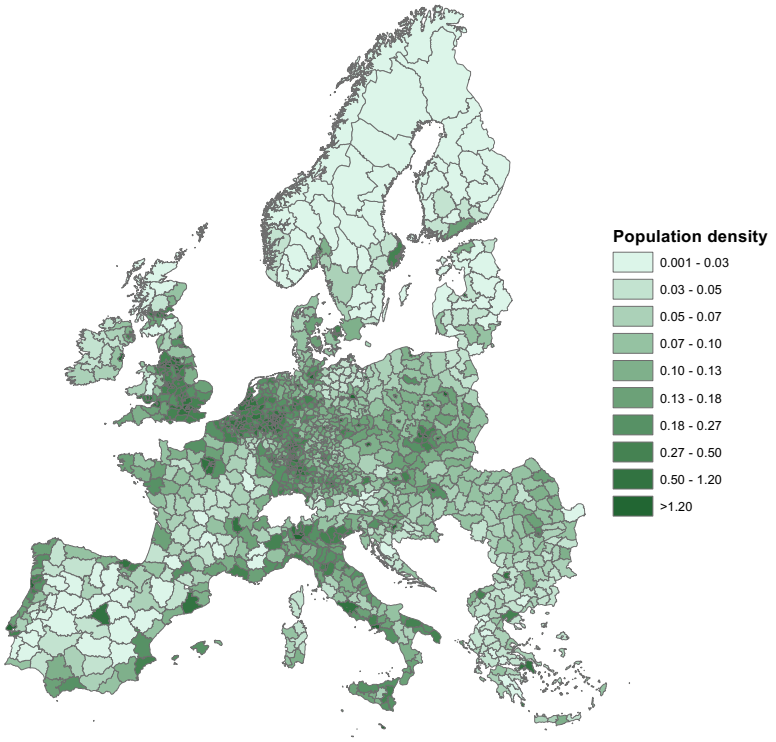
As the model requires data on local GDP and population (density) across European regions, we plot this information in two panels of Figure 1.B.1. Darker colors indicate higher values of income and population. The data are taken from the Statistical Office of the European Union (Eurostat) and can be accessed via http://ec.europa.eu/eurostat/data/database. We use information on the gross domestic product (GDP) at current market prices by NUTS 3 regions with the code: nama_10r_3gdp; on area by NUTS-3 region with the code: demo_r_d3area; and on the average annual population to calculate regional GDP data (thousand persons) by NUTS-3 regions with the code: nama_10r_3popgdp.

Figure 1.B.1: Distribution of GDP per capita and Population density in 2010

(a) GDP per capita




(b) Population density




*Notes:* This figure plots the quantiles of the GDP per capita distribution in Panel (a) and of the population density distribution in Panel (b) for the year 2010. A darker shading indicates higher values.

# Chapter 2

# Fiscal redistribution in the spatial economy

*We use a general equilibrium model with fiscal equalization to show that regional transfers are quantitatively important for understanding the spatial allocation of economic activity. We find that the abolishment of fiscal equalization in Germany would lead to a moderate welfare gain of about 0.33 percent implying migration of about 5 percent of the population in the long run. The increases in average real GDP per capita and average labor productivity are more pronounced at 5.8 percent and 9.2 percent, respectively.*

## 2.1 Introduction

Geography is important for the spatial allocation of economic activity. High consumption or production amenities and good access to trade partners (e.g. ports, railways, and highways) attract both workers and firms. Allen and Arkolakis (2014) have shown that geography explains between 20-70 percent of the variation in income across space in the US, depending on the choice of parameters. While these determinants are well understood, we aim at quantifying the importance of governmental activity in a spatial framework. As governments intervene in markets in a number of ways and for a number of reasons, we restrict governmental activity to taxation of income, the provision of local public goods, and the redistribution of resources across regions (fiscal equalization). The mobility response of workers to governmental intervention is important for local jurisdictions which try to attract economic resources, but also have to finance the provision of local public goods.

We build a multi-region general equilibrium model with income taxation, local public services and inter-regional transfers. A recipient region benefits from receiving transfers as local governments can raise the provision of local public services. On the contrary, donor regions experience welfare losses as public resources are not spent locally. These transfers stimulate labor migration to transfer recipients. At the aggregate level, we show that the introduction of a fiscal equalization scheme generally exhibits ambiguous welfare effects in the spatial economy. For example, higher relative local gross domestic product (GDP) of donors compared to recipients implies higher welfare gains when fiscal transfers are introduced. This is because a donor's transfer of one percent of local GDP translates into a higher *relative* subsidy for poorer recipients. In addition, geography matters for overall welfare effects. If resources are transferred from the core to the periphery, aggregate welfare declines as one unit of income buys less utility in locations with higher price indexes.

We proceed by assessing the role of fiscal transfers for the spatial allocation of economic activity and aggregate welfare for Germany. The largest European economy has established a fairly extensive system of fiscal equalization that raises financial capacity of some states from less than 50 percent to a level close to the mean. Using detailed information on inter-regional trade flows, income, population, tax rates and transfers for 411 districts in Germany in 2010, we show that inter-jurisdictional redistribution explains up to 31 percent of the spatial variation in income and is thus quantitatively of major importance for understanding the spatial economy. Moreover, we find that abolishing fiscal equalization between regions leads to welfare gains of 0.33 percent in the benchmark specification implying migration of about 4.6 million individuals or 5.7 percent of the population. The model predicts that the abolishment of transfers leads to outmigration in former recipient locations of up to one third of the initial population while former donors expect a pronounced inflow of migrants.

Our paper relates to a number of literatures. First, our paper adds to a recent and growing literature that extends quantitative trade models with factor mobility and exogenous local characteristics (e.g. Allen and Arkolakis, 2014, Bartelme, 2015, Behrens, Mion, Murata, Suedekum, 2017, Caliendo, Parro, Rossi-Hansberg and Sartre, 2014, Monte, Redding and Rossi-Hansberg, 2015, and Redding, 2016). Similar to Fajgelbaum, Morales, Suarez Surrato and Zidar (2016), we incorporate taxation and local public services into this class of models while explicitly allowing for inter-jurisdictional fiscal equalization. This allows us to quantify the role of fiscal equalization for the regional variation in welfare and migration.

Second, we contribute to the public finance literature on fiscal equalization (Boadway and Flatters, 1982, Watson, 1986), the role of federal taxation for the spatial allocation of economic activity (Albouy, 2009), and factor mobility in response to tax changes (Bartik, 1991, Moretti and Wilson, 2015). We add to this literature by quantifying a structural model. Albouy (2012) and Tombe and Winter (2017) undertake a similar exercise to ours for Canada, albeit with a different type of model.

Third, fiscal equalization can be regarded as one form of place-based policies as those jurisdictions with high tax income per capita (i.e. high fiscal capacity) are obliged to transfer resources to locations with lower fiscal capacity. The paper is therefore related to recent work in this area by Kline and Moretti (2014), Busso, Gregory and Kline (2013), Ehrlich and Seidel (2016), or Gottlieb and Glaeser (2008). We deviate from this work by evaluating fiscal equalization as one particular form of place-based policies.

The paper is organized as follows. We first introduce the model in section 2.2 and discuss underlying determinants of welfare effects of inter-regional transfers. Section 2.3 quantifies the model for Germany, derives the importance of fiscal equalization for the spatial allocation of economic activity and analyzes the welfare implications of abandoning transfers. Section 2.4 concludes.

## 2.2 A quantitative geography model with fiscal equalization

We consider an economy with $N$ regions and $\bar{L}$ mobile workers. Local governments collect income taxes to provide public services and reallocate resources across locations.

### 2.2.1 Production technologies

Each region $i \in N$ produces a unique variety of a differentiated good under perfect competition and assembles a final good $Q(i)$ from a continuum of varieties according to a CES-aggregator such that

$$Q(i) = \left[ \int_N q(n,i)^{\frac{\sigma-1}{\sigma}} dn \right]^{\frac{\sigma}{\sigma-1}}. \tag{2.1}$$

$q(n,i)$ denotes the quantity of the variety produced in location $n$ and used for assembly in location $i$ and $\sigma > 1$ represents the elasticity of substitution between varieties. The price of the final good in $i$ is determined by the prices of varieties, $p(n,i)$, such that

$$P(i) = \left[\int_N p(n,i)^{1-\sigma} dn\right]^{\frac{1}{1-\sigma}}.$$

The final good is assembled locally at zero cost and not traded. Importantly, $Q(i)$ can be used by consumers for private consumption $C(i)$ and by local governments to provide public services $G(i)$. Thus, we have $Q(i) = C(i) + G(i)$.

Varieties require labor as the sole input in the production process and cause costs of transportation when traded between regions. We follow the standard iceberg notion such that $\tau(i,n) \geq 1$ units of a good have to be sent from location $i$ for one unit to arrive in location $n$. We set intra-regional trade costs to zero, so $\tau(i,i) = 1$. Finally, locations may differ with regard to labor productivity $A(i)$.

### 2.2.2 Taxes, public spending, and fiscal equalization

The public sector taxes labor income to provide public services $G(i)$ and to reallocate resources across locations. Total tax revenues in region $n$ are then given by $t(i)w(i)L(i)$, where $w(i)$ describes the wage rate. The tax rate $t(i)$ can be understood as a location-specific average tax rate on local income comprising different types of taxes. This notion provides sufficient flexibility for the empirical analysis and follows the observation that local governments possess at least some degree of tax authority.

Without inter-regional transfers, the public budget constraint is given by $G(i) = t(i)w(i)L(i)$. Considering fiscal equalization, however, every region either receives resources from other locations or transfers own income to recipients. We relate these resources relative to local GDP, so recipients receive $\theta(i)w(i)L(i)$ as overall subsidies where $\theta(i) > 0$ denotes the subsidy rate. For donor regions, $\theta(i) < 0$ so we refer to it as the transfer rate. Importantly, as overall transfers are related to local GDP, $\theta(i)$ is only equal in absolute terms between donors and recipients if local income is identical. If, as usual, donors have higher income, a transfer rate of one percent implies a higher subsidy rate in the destination region as recipients have a lower per-capita income, are less densely populated or both.

### 2.2.3 Preferences

Having introduced the technologies for final good production and public services, we are ready to turn to the specification of workers' utility. Individuals in location $i$ derive utility from publicly provided services, their net real wage income spent on private consumption, and a location-specific amenity $u(i)$ such that

$$W(i) = u(i) \left[ \frac{G(i)}{P(i)L(i)^{\eta}} \right]^{\gamma} \left[ (1 - t(i)) \frac{w(i)}{P(i)} \right]^{1-\gamma}. \tag{2.2}$$

We allow for different degrees of rivalry in the consumption of $G(i)$ governed by $\eta \in [0; 1]$. When $\eta = 0$, $G(i)$ is a pure public good. When $\eta = 1$, $G(i)/L(i)$ represents per-capita transfers in location $i$. The parameter $\gamma$ describes the relative importance of private consumption and publicly provided services. The amenity $u(i)$ captures, for example, temperature or scenery, but also house prices (as a disamenity) or the rate at which local governments transform public spending into public goods (see Fajgelbaum et al., 2016). Transferring income to another region decreases welfare of donors through lower provision of public services while recipients experience higher welfare due to transfers.

Combining individual demand and public demand for the variety from location $i$ in location $n$, we obtain aggregate demand

$$q(i, n) = \frac{p(i, n)^{-\sigma}}{P(n)^{1-\sigma}} E(n),$$

where $E(n) = (1 + \theta(n))w(n)L(n)$ represents the sum of private and public income including transfers that is available for expenditures in location $n$.

### 2.2.4 Profit maximization and inter-regional trade

As each location produces a unique variety of a composite good under perfect competition, profit-maximizing behavior equates prices to marginal production and transport costs. Consumers in location $j$ have to pay $p(i, j) = \tau(i, j)w(i)/A(i)$ for a good produced in location $i$ where, recall, $A(i)$ denotes location-specific labor productivity. Combining prices and aggregate demand delivers sales from $i$ to $j$,

$$X(i, j) = \left( \frac{\tau(i, j)w(i)}{A(i)P(j)} \right)^{1-\sigma} E(j), \tag{2.3}$$

where $P(j)$ is the CES price index:

$$P(j) = \left[ \int_N \left( \frac{\tau(n,j)w(n)}{A(n)} \right)^{1-\sigma} dn \right]^{\frac{1}{1-\sigma}}. \tag{2.4}$$

As long as there is no free trade and productivity of labor is not equalized across locations, prices will differ.

### 2.2.5 Agglomeration and dispersion forces

Importantly, both location-specific productivities and amenities depend on the number of workers in a region. Thus, migration between regions gives rise to externalities that shape the spatial economy. In particular, we impose that

$$A(i) = \bar{A}(i)L(i)^{\alpha} \tag{2.5}$$

and

$$u(i) = \bar{u}(i)L(i)^{\beta} \tag{2.6}$$

Both productivities and amenities contain exogenous components, $\bar{A}(i)$ and $\bar{u}(i)$, and endogenous parts that are determined by population density in that location. We restrict parameters to empirically relevant values: $\alpha \geq 0$ implies that local productivity increases in population while $\beta \leq 0$ captures the notion of negative externalities (e.g. due to congestion).

### 2.2.6 Equilibrium

We use the following equilibrium conditions to solve the model:

1. **Labor market clearing.** This requires

$$\int_N L(n)dn = \bar{L} \tag{2.7}$$

2. **Goods market clearing with income transfers.** Total labor income in region $i$, $w(i)L(i)$, has to equal total sales of region $i's$ product in all locations $n \in N$. This delivers

$$w(i)L(i) = \int_N X(i,n)dn, \tag{2.8}$$

where $X(i,n)$ accounts for transfers according to (2.3).[1]

3. **Balanced public budget.** Each government spends its available budget entirely on the provision of local public services, so

$$[t(i) + \theta(i)]\, w(i)L(i) = G(i). \tag{2.9}$$

Further, total paid transfers have to equal the sum of total received transfers, so

$$\int_N \theta(i)w(i)L(i)dn = 0. \tag{2.10}$$

4. **Utility equalization.** Free mobility of labor ensures that utility is equalized across all locations.

We derive a system of equations that allows us to (i) determine exogenous productivities and amenities and (ii) solve for endogenous wages and labor allocation across regions in the counterfactual analysis. First, we combine utility, (2.2), and bilateral exports, (2.3), with goods-market clearing, (2.8), to get

$$\begin{aligned} L(i)^{1-\alpha(\sigma-1)}w(i)^{\sigma} =& W^{1-\sigma}\bar{A}(i)^{\sigma-1}\int_N \tau(i,n)^{1-\sigma}\bar{u}(n)^{\sigma-1}\Omega(n)^{\sigma-1} \\ & (1+\theta(n))\, w(n)^{\sigma}L(n)^{1+(\sigma-1)[\beta+\gamma(1-\eta)]}dn, \end{aligned} \tag{2.11}$$

where $\Omega(n) \equiv (t(n)+\theta(n))^{\gamma}(1-t(n))^{1-\gamma}$. Second, combining utility, (2.2), with the price index (2.4) delivers

$$\begin{aligned} w(i)^{1-\sigma}L(i)^{(1-\sigma)[\beta+\gamma(1-\eta)]} =& W^{1-\sigma}\Omega(i)^{\sigma-1}\bar{u}(i)^{\sigma-1} \\ & \int_N \tau(n,i)^{1-\sigma}\bar{A}(n)^{\sigma-1}w(n)^{1-\sigma}L(n)^{\alpha(\sigma-1)}dn. \end{aligned} \tag{2.12}$$

Similar to Allen and Arkolakis (2014), we are able to express the above system of two nonlinear integral equations as one equation providing a direct link between $w(i)$ and $L(i)$ for each location (see Appendix 2.A for details). We have

$$W(i)^{1-\sigma}A(i)^{1-\sigma}\Omega(i)^{\sigma-1}w(i)^{\sigma}L(i)^{1+\gamma(\sigma-1)(1-\eta)} = \phi w(i)^{1-\sigma}u(i)^{1-\sigma} \tag{2.13}$$

[1]Notice that inter-regional transfers imply trade imbalances in equilibrium. Donor regions produce more than they consume so they run a trade surplus. This phenomenon is well-understood from the international trade literature (see, e.g., Dekle, Eaton and Kortum, 2007). Total expenditures equal total imports, so $E(i) \equiv (1+\theta(i))w(i)L(i) = \int_N X(n,i)dn$. Comparing this expression with (2.8) shows that the difference between exports and imports is given by $-\theta(i)w(i)L(i)$, while $\int_N(-\theta(n)w(n)L(n))dn = 0$.

where $\phi > 0$ is some scalar. Plugging this relationship into (2.12) delivers

$$L(i)^{\tilde{\sigma}\lambda_1} = W(i)^{(1-\sigma)(1-\tilde{\sigma})}\bar{u}(i)^{(1-\tilde{\sigma})(\sigma-1)}\bar{A}(i)^{\tilde{\sigma}(\sigma-1)}\Omega(i)^{(1-\tilde{\sigma})(\sigma-1)} \tag{2.14}$$
$$\times \int_N W(n)^{(1-\sigma)\tilde{\sigma}}\tau(n,i)^{1-\sigma}\bar{u}(n)^{\tilde{\sigma}(\sigma-1)}\bar{A}(n)^{(1-\tilde{\sigma})(\sigma-1)}\Omega(n)^{\tilde{\sigma}(\sigma-1)}\left(L(n)^{\tilde{\sigma}\lambda_1}\right)^{\frac{\lambda_2}{\lambda_1}} dn,$$

where we have defined

$$\lambda_1 \equiv 1 - \alpha(\sigma-1) - (\beta + \gamma(1-\eta))\sigma$$
$$\lambda_2 \equiv 1 + \alpha\sigma + (\beta + \gamma(1-\eta))(\sigma-1)$$
$$\tilde{\sigma} \equiv \frac{\sigma-1}{2\sigma-1}.$$

Using data on tax rates, bilateral trade costs, wages, and population jointly with the equilibrium conditions allows us to solve the model for exogenous productivities $\bar{A}(i)$ and amenities $\bar{u}(i)$ up to a constant with $W^{\sigma-1}$ as the eigenvalue of the system. Following Allen and Arkolakis (2014), it can be shown that there is a unique and stable equilibrium if $\lambda_2/\lambda_1 \in [-1;1]$. Furthermore, the solution for the equilibrium distribution of labor can be obtained as the uniform limit of a simple iterative procedure according to (2.14) if $\lambda_2/\lambda_1 \in (-1;1]$. For $\alpha \in [0,1]$ and $\beta \in [-1,0]$, $\eta \in [0,1]$ and $\gamma \in [0,1]$, we see that $\lambda_2/\lambda_1 \in [-1;1]$ if and only if $\alpha+(\beta+(1-\eta)\gamma) \leq 0$. Intuitively, migration to location $i$ has to generate a larger reduction in amenity $u(i)$ than increase in productivity $A(i)$ to ensure that all regions are populated (given $\gamma$ and $\eta$).

### 2.2.7 Wages, population and welfare

Combining welfare (2.2) with (2.13) and taking logs yields

$$\lambda_1 \ln L(i) = C_L + \sigma \ln\bar{u}(i) + (\sigma-1)\ln\bar{A}(i) + \sigma\ln\Omega(i) - (2\sigma-1)\ln P(i) \tag{2.15}$$
$$\lambda_1 \ln w(i) = C_W - (1-\alpha(\sigma-1))\ln\bar{u}(i) - (\sigma-1)(\beta+\gamma(1-\eta))\ln\bar{A}(i) \tag{2.16}$$
$$- (1-\alpha(\sigma-1))\ln\Omega(i) + (1+(\sigma-1)(\beta-\alpha+\gamma(1-\eta)))\ln P(i),$$

where the constants $C_L$ and $C_W$ are determined by the wage normalization and labor-market clearing. We observe that higher provision of public services (as measured by $\Omega$) raises population density in that location as long as $\lambda_1 > 0$. With regard to wages, the effect of inter-regional transfers is generally ambiguous and depends on the sign of $1-\alpha(\sigma-1)$.

While it is immediate from (2.2) that transfers increase (decrease) welfare in recipient (donor) regions, the aggregate welfare effects of fiscal equalization are less straightforward. To better understand the driving mechanisms of aggregate welfare, we design a model economy with 100 locations and study (i) the role of income disparities between donor and recipient locations and (ii) the role of geography (i.e. trade costs). For the first exercise, we set trade costs to zero and split the economy into 50 donors and 50 recipients and impose a general tax rate on income for all locations. Further, we normalize the population of each region to unity. We then solve the model with different initial relative wages between donors and recipients. According to Panel (a) of Figure 2.1, the aggregate welfare gain of introducing a fiscal equalization scheme is zero if all regions are identical (relative initial GDP equal to one). This is intuitive as a transfer of one unit of income exerts the same marginal utility effect in absolute terms if regions are initially identical. Making donors relatively richer, that is moving right along the horizontal axis, leads to aggregate welfare gains. In contrast, making recipients richer, that is moving to the left, yields the opposite effect. As the transfer rate is kept constant, total transfers make up a larger share of recipients GDP if relative initial local GDP in donor regions is higher. Taking away one percent of income in rich donor regions raises expenditure by more than one percent in poorer recipient locations.

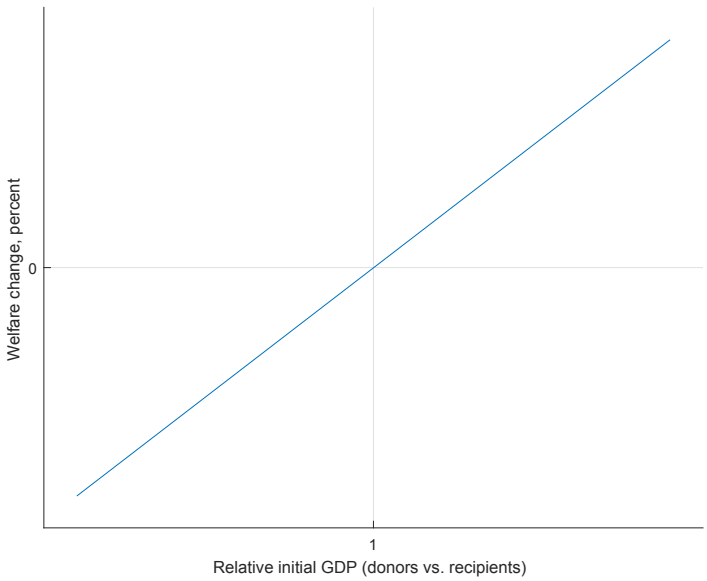
Second, we focus on the role of geography and keep relative initial GDP constant at a ratio of one. We allocate all regions on a line with donors in the center and recipients in the periphery. Setting trade costs to zero replicates the finding from Panel (a) that the introduction of a fiscal equalization scheme has no aggregate welfare implications at the margin. However, raising trade costs leads to higher price indexes in the periphery compared to the core, so transferring income to the periphery generates less utility there than in the core. Hence, fiscal equalization leads to an aggregate welfare loss. Panel (b) of Figure 2.1 illustrates that this effect gets stronger in the level of trade frictions, albeit at decreasing rates.

## 2.3 Quantification: Fiscal equalization in Germany

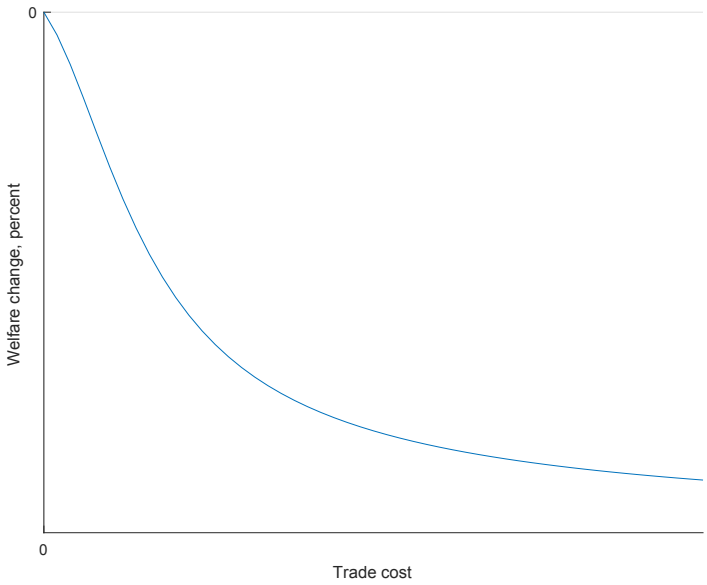
In this section, we bring the model to data, identify underlying parameters and quantify aggregate effects. Germany runs a pronounced fiscal equalization scheme and therefore serves as an appropriate candidate for this exercise. We start with an overview of the institutional setting before introducing the data and discussing

Figure 2.1: Aggregate welfare effects of fiscal equalization

(a) Income dispersion




(b) Geography




*Notes:* The Figure illustrates the welfare consequences of introducing a fiscal equalization scheme. Panel (a) shows the association between the percentage change in welfare and the relative initial GDP of donors versus recipients. Panel (b) plots the reaction of welfare when trade becomes more costly and recipient regions are located in the periphery.

identification. In the counterfactual analysis, we explore aggregate effects when abandoning the fiscal equalization scheme.

### 2.3.1 Institutional background

Political power in Germany is divided between the federal government and 16 state governments (Länder). Each of these authorities is autonomous and independent with respect to budgetary issues, but at the same time responsible for carrying out their tasks in an effective way. Each of the 16 state governments has to ensure that municipalities on its territory are equipped with the necessary financial means.

The federal government, the states, and the municipalities can set certain tax rates independently and keep (most of) the resulting tax revenues. The most important taxes with regard to revenue, however, are taxes that are *jointly* set by the federal government and the states implying a common tax schedule in all locations. The resulting revenues are shared between the two layers according to a specific formula. The most important joint taxes comprise income taxes, corporate taxes, and the value added tax (VAT). This implies that there is a common VAT rate and a common income tax schedule across states. As shown in Table 2.1, the latter accounted for 70.3 percent of overall tax revenues in 2010. The total sum of tax revenues summed up to 530.6 billion euros or 20.6 percent of GDP.[2]

Article 72 of the German Constitution postulates that the states have to provide "equivalent living conditions" in all regions. However, this principle conflicts with

Table 2.1: Tax revenues, 2010

| | in billion euros | in percent |
|---|---|---|
| joint | 372.9 | 70.3 |
| federal and tariffs | 97.8 | 18.4 |
| state | 12.1 | 2.3 |
| municipality | 47.8 | 9.0 |
| sum | 530.6 | 100 |

*Source*: German Statistical Office (2011).

[2]See German Statistical Office (2011).

uniform tax schedules and the fact that economic activity is unevenly distributed across the country. Based on the prior that all individuals have similar financial needs, installing equivalent living conditions can only be achieved by redistributing tax revenues from jurisdictions with higher financial capacity to those with lower tax revenues per capita.[3] This mechanism is referred to as the German *Länderfinanzausgleich (LFA)* - the formula-based federal fiscal equalization scheme. The LFA takes place in four steps: First, revenues of joint taxes are distributed among the federal level, the states (as a whole), and the municipalities (*vertical distribution*). For example, the federal government and the states receive 42.5 percent of income taxes each while the remaining 15 percent accrue to municipalities.[4] In a second step, the states' share of VAT revenue is assigned to each of the 16 states. 75 percent of the total amount is distributed according to population shares while 25 percent is dedicated to those jurisdictions with below-average per-capita tax revenues. This allocation mechanism already exerts a substantial equalizing effect. Comparing Columns 2 and 3 of Table 2.2 reveals that Thuringia, for example, climbs from 48.7 percent of average financial capacity (before VAT redistribution) to 88 percent (after VAT redistribution) while Bavaria's financial capacity is reduced from 129.3 to 115.6 percent.

Third, states with above-average financial capacity have to redistribute part of their tax income to those states below average. A progressive schedule ensures a further convergence to the mean of all 16 states (see Column 4). The fourth step involves transfers of the federal government to those states whose financial capacity per inhabitant falls short of 99.5 percent of the average. The respective transfers close 77.5 percent of this gap.[5]

Outside of the LFA-system, the federal government has transferred 10.3 billion euros of special supplementary grants to selected states that face exceptional tasks like investments in public infrastructure in the new Länder in 2010. Together with the LFA-transfers, the total sum amounts to about 26.5 billion euros or 5 percent of the overall tax revenue of Germany. Moreover, each state government runs an individual transfer scheme to allocate resources between state and municipalities. In the data section below, we go into more detail on how we have computed the tax revenue and the available budget for each German district.

[3]Financial capacity of a state is defined as the sum of its tax revenues plus 64 percent of the sum of the receipts of that state's municipalities relative to population.

[4]See Federal Ministry of Finance (2016) for further details.

[5]Federal Ministry of Finance (2015).

Table 2.2: Fiscal redistribution, 2010

| | Before VAT redistribution | After VAT redistribution | After fiscal equalization | After general suppl. federal grants |
|---|---|---|---|---|
| Bavaria | 129.3 | 115.6 | 105.5 | 105.5 |
| Baden-Württemberg | 117.2 | 109.5 | 103.8 | 103.8 |
| Berlin | 88.2 | 68.1 | 90.5 | 97.5 |
| Brandenburg | 61.8 | 90.6 | 96.3 | 98.8 |
| Bremen | 95.1 | 74.1 | 91.9 | 97.8 |
| Hamburg | 157.5 | 102.1 | 101.1 | 101.0 |
| Hesse | 127.4 | 116.0 | 105.7 | 105.6 |
| Lower Saxony | 85.7 | 97.6 | 98.8 | 99.3 |
| Mecklenburg Western Pomerania | 49.0 | 86.5 | 95.1 | 98.5 |
| North Rhine-Westphalia | 100.5 | 98.5 | 99.2 | 99.4 |
| Rhineland Palatinate | 97.4 | 95.5 | 97.8 | 99.1 |
| Saarland | 79.6 | 94.3 | 97.4 | 99.0 |
| Saxony | 50.3 | 88.3 | 95.6 | 98.6 |
| Saxony-Anhalt | 48.3 | 88.0 | 95.5 | 98.6 |
| Schleswig Holstein | 93.4 | 97.4 | 98.7 | 99.3 |
| Thuringia | 48.7 | 88.0 | 95.5 | 98.6 |
| Redistribution (in bn. euros) | 6.62 | 7.04 | 2.62 | |

*Source*: Federal Ministry of Finance (2015).

### 2.3.2 Data

Quantifying the model requires data on inter-regional trade flows, tax revenues per district, the distribution of tax income across regions, and data on population, labor income, and geographical information. Infrequent availability of inter-regional trade data restricts us to undertake the quantitative exercise for the year 2010.

**Tax data.** Information on the collection and distribution of taxes is provided by the Statistical Office in Germany.[6] The general challenge is to assign taxes to *one* local jurisdiction as required by the theoretical model although the German tax system consists of *three* main layers (federal, state, municipalities). Tax statistics

[6]The specific statistics are called Fachserie 14-4 (Steuerhaushalt) and Fachserie 14-10 (Realsteuervergleich), and Bruttoeinnahmen der Gemeinden (gross income of municipalities).

follow the latter logic such that information on tax revenues per location is not readily available.

First, we need to compute average tax rates in location $i$. As municipalities keep a certain fraction of value added taxes and income taxes, we are able to infer from local tax revenues and the distributional share the overall revenue of these taxes. Other types of taxes like business or property taxes can be taken directly as they are municipality taxes.[7] In sum, these directly assignable taxes make up about 73 percent of overall tax revenues in Germany. Aggregating these taxes at the district level allows us to compute each district's revenue share in each state and in Germany as a whole to assign the remaining state and federal taxes to the local jurisdiction. Relating each district's tax revenue to local GDP delivers the average tax rate $t(i)$.

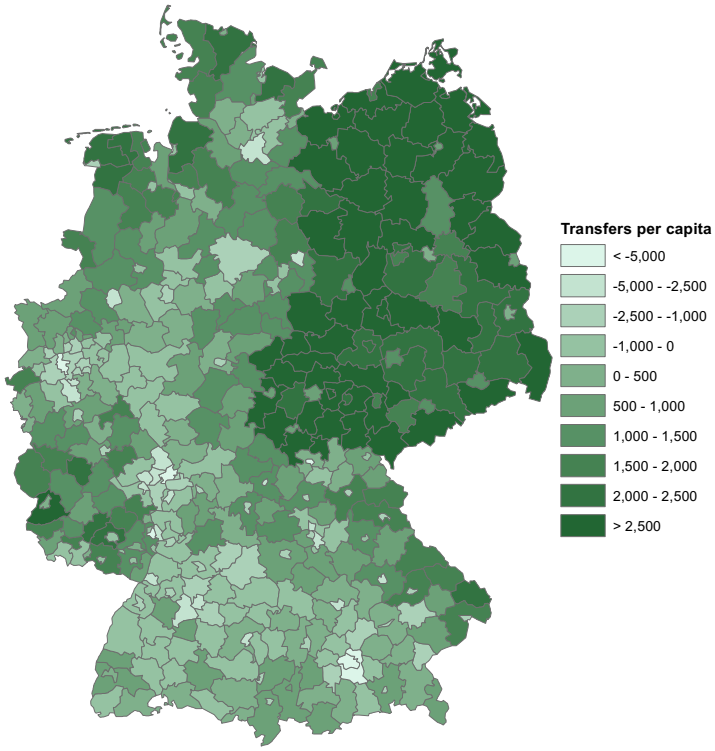
To obtain transfer rates $\theta(i)$, we compute tax revenues *after* redistribution. From municipalities' gross income statistics we take tax revenues and transfers received from other government layers making up about 20 percent of overall tax revenues in Germany. As we know overall tax revenues after redistribution for both the state and the federal level, we are able to compute the differences with regard to state and federal taxes to be allocated. In contrast to the first step above, we now allocate the remaining taxes according to population shares rather than tax revenue shares. Relating these numbers at the district level to local GDP yields the average tax rate *after* equalization, $t(i)+\theta(i)$. Using $t(i)$ from the previous exercise allows us to back out the transfer rate $\theta(i)$ for each region.

Recall, recipients receive $\theta(i)w(i)L(i)$ as overall subsidies with $\theta(i) > 0$. For donor regions, $\theta(i) < 0$ so we refer to it as the transfer rate. In sum, the mechanism of the LFA relates per-capita transfers to local GDP as illustrated in Figure 2.2. Districts in East Germany benefit most from fiscal redistribution with per-capita transfers of more than 3,000 euros per year in some parts. Notice that darker areas indicate recipients, bright areas donors. Transfers are mainly financed by rich jurisdictions in West Germany. Frankfurt leads the list with per-capita transfers of about 11,000 euros. Munich, as another example, pays about 5,700 euros per capita.

**Trade data.** We use information on trade flows from the Forecast of Nationwide Transport Relations in Germany 2030 (Verkehrsverflechtungsprognose 2030, henceforth VVP) provided by the Clearing House of Transport Data at the Institute of Transport Research of the German Aerospace Center.[8] The data contain bilateral trade volumes in metric tons between European regions where one German region

[7]Notice that the business tax has to be shared with the state the municipality is located in.
[8]The data can be accessed via http://daten.clearingstelle-verkehr.de/276/.

Figure 2.2: Per-capita transfers (in euros)




*Notes:* Darker areas indicate recipients, bright areas donors.

is either exporter, importer or part of the trade route of the product for the year 2010. To derive the trade elasticity, we restrict the data to Germany. In total we use trade flows between the 411 German regions.

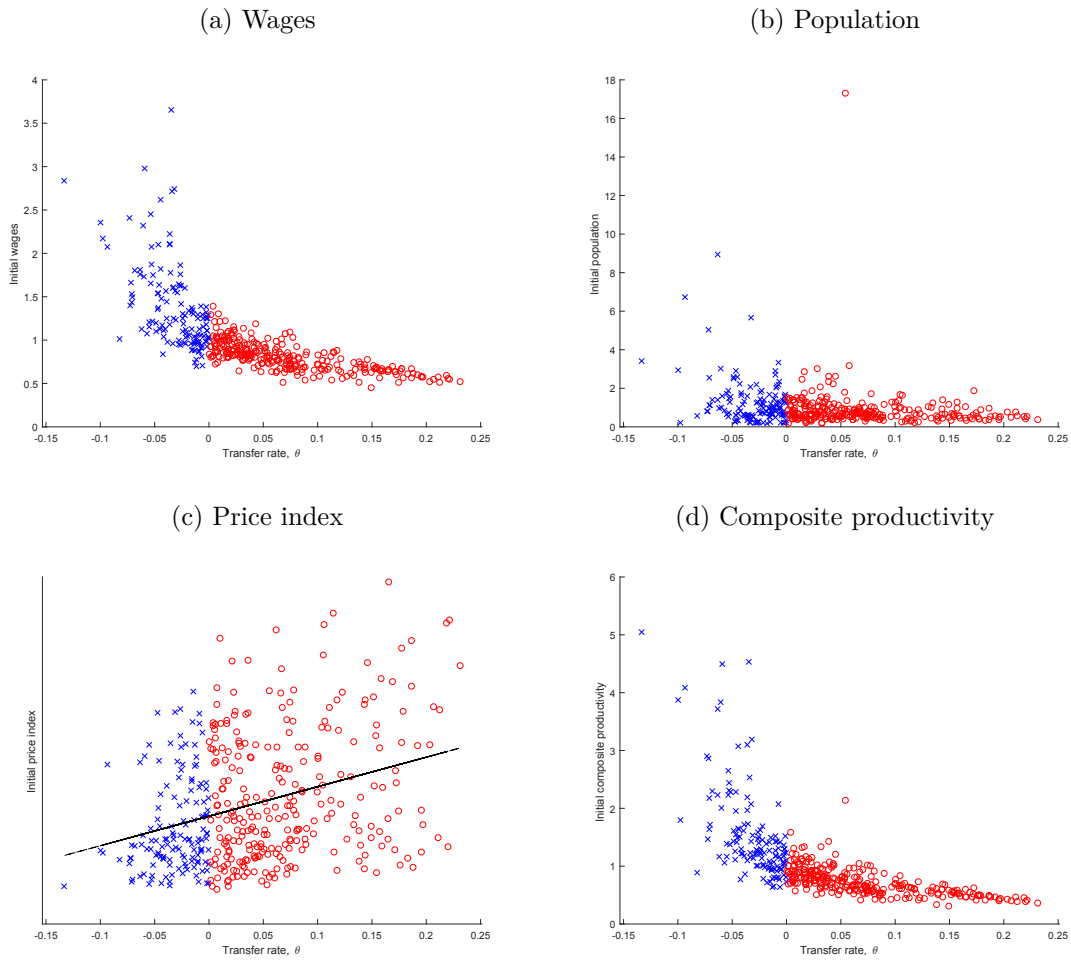
The data distinguish trade flows by transport mode (road, rail, water), so we aggregate over modes as we do not focus on differences in this dimension. Further, the model requires trade *values* rather than *volumes*. To convert volumes into values, we compute unit values from COMTRADE data that are available by product group at the aggregate national level. We take both a simple average of unit values by product group (to arrive at the two-digit level) and a weighted average where values serve as weights. Bilateral distances between regions' centroids are obtained using GIS software.

**Income and population.** Finally, we use data from Eurostat on GDP and population at the NUTS3-level and the ratio of both as a proxy for wages. We further normalize wages to have a mean of one without loss of generality.

Panels (a) and (b) of Figure 2.3 illustrate how wages and population relate to the transfer rate $\theta$. Locations with high per-capita income are net donors, that is $\theta(i) < 0$. Donors are indicated by blue crosses while red circles indicate recipient regions.

The picture establishes credibility in the plausibility of the computed transfer rate. More populated locations are on average net donors, whereas small and less densely populated locations are net recipients of the transfer system. Berlin sticks out as the location with the largest population. It receives transfers of 5.3 percent of its local GDP. Importantly, discrepancy between donors and recipients with respect to population and per-capita income implies that paid transfers are lower relative to local GDP than received transfers. The average level of $\theta$ is -0.03 for donors and 0.07 for recipients.

Figure 2.3: Relationship of wages, population, price index and productivity with the transfer rate




*Notes:* Panel (a) links wages to transfer rates $\theta(i)$. Panel (b) plots the relationship of population with the transfer rate $\theta(i)$. Panel (c) maps the level of the price index in relation with the transfer rate. In Panel (d), we have plotted the level of the estimated composite productivity $A(i)$. Notice that donors have a negative transfer rate $\theta < 0$ and are marked by crosses (in blue). Recipients are identified by positive transfer rates and are marked by circles (in red).

### 2.3.3 Identification and choice of parameters

In this subsection, we uncover bilateral trade costs $\tau(i,n)$, exogenous productivities $\bar{A}(i)$ and exogenous amenities $\bar{u}(i)$ and discuss the choice of additional model parameters.

**Trade costs.** We follow the standard procedure in the gravity literature (e.g. Head and Mayer, 2014) by estimating (2.3) with importer and exporter fixed effects to control for multilateral resistance. We proxy bilateral trade costs by the Euclidian distance $dist(i,n)$ between the centroids of locations $i$ and $n$ according to

$$\tau(i,n) = dist(i,n)^{\theta}\tilde{\epsilon}(i,n), \tag{2.17}$$

where $\tilde{\epsilon}(i,n)$ is the error term. Log-linearizing (2.3) and substituting for the parametrization of trade costs yields the following gravity equation for the value of bilateral trade flows from $i$ to $n$:

$$\log X(i,n) = \delta(i) + \gamma(n) - (\sigma-1)\theta \log dist(i,n) + (1-\sigma)\beta'\mathbf{M} + \log \epsilon(i,n), \tag{2.18}$$

where $\delta(i)$ and $\gamma(n)$ are exporter and importer fixed effects that control for wages, productivity, population and the CES price index.[9] $\mathbf{M}$ collects standard bilateral control variables from the gravity literature and $\log \epsilon(i,n) = (1-\sigma)\log \tilde{\epsilon}(i,n)$. Following Lameli, Nitsch, Suedekum, and Wolf (2015) we include a historical dialect similarity measure and dummy variables for adjacent regions and for regions located in different federal states.

Table 2.3 summarizes the regression output. Columns 3 to 4 build on bilateral trade values where the weighting relates to the unit values applied to the raw volume data. Following Nitsch and Wolf (2013), we also explore results for volumes instead of values as the dependent variable in Columns 1 and 2. Although this deviates from the theoretical model, it can be argued that trade values are proportional to trade volumes so the results are insightful for robustness reasons. Further, exporter and product-specific dummy variables account for the exporter- and product-specific price per ton that converts volume of exports into values.

In line with previous results of Lameli, Nitsch, Suedekum, and Wolf (2015) we find that distance, historical ties (as measured by dialect similarity), contiguity, and administrative borders affect trade flows between German regions. Cultural and geographical proximity have positive effects for trade between German regions. Fur-

[9] As the data distinguish between product groups, we add product fixed effects in the estimation.

thermore, the volume and value of trade flows falls with distance and administrative borders. Indeed, the point estimates on log distance range between $-0.93$ and $-1.26$. Moreover, they are statistically significant at the 1-percent level and compare nicely with standard estimates in the gravity literature. Given the estimated distance elasticity we parameterize trade costs according to $\tau(i,n)^{1-\sigma} = dist(i,n)^{-1.23}$. We are confident in this parametrization of trade costs as Head and Mayer (2014) summarize that estimates of the trade-distance elasticity parameter in typical gravity equations cluster around -1.1 with a standard deviation of 0.41.

Table 2.3: Estimated distance elasticities

| | volumes | | values | |
|---|---|---|---|---|
| log(distance) | -1.26*** | -0.98*** | -1.23*** | -0.93*** |
| | (0.002) | (0.004) | (0.003) | (0.005) |
| dialect sim. | | 0.23*** | | 0.24*** |
| | | (0.013) | | (0.015) |
| contiguity | | 0.52*** | | 0.58*** |
| | | (0.010) | | (0.011) |
| state border | | -0.46*** | | -0.46*** |
| | | (0.005) | | (0.006) |
| Exporter FE | ✓ | ✓ | ✓ | ✓ |
| Importer FE | ✓ | ✓ | ✓ | ✓ |
| Product FE | ✓ | ✓ | ✓ | ✓ |
| Constant | 3.10*** | 3.56*** | 17.5*** | 18.0*** |
| | (0.066) | (0.065) | (0.079) | (0.078) |
| Observations | 1,104,635 | 1,104,635 | 853,950 | 853,950 |
| $R^2$ | 0.41 | 0.41 | 0.70 | 0.70 |

*Notes*: Columns 1 and 2 use the original volume data from VVP. Columns 3 and 4 are based on trade values where we have used the simple average of unit values per 2-digit product group. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Exogenous amenities and productivities.** The values of exogenous productivities $\bar{A}(i)$ and amenities $\bar{u}(i)$ represent a second piece of information that is unobservable from data, but required for quantification of the model. To uncover these model parameters for 411 districts, we feed estimated trade costs together with information on population $L(i)$, wages $w(i)$ (proxied by GDP per capita), tax rates $t(i)$ and transfer rates $\theta(i)$ into (2.12) and (2.13) defining a system of $2 \times 411$ equations in $2 \times 411$ unknowns. Labor-market clearing pins down the equalized welfare level in this system.[10]

[10]Details on solving for exogenous amenities and productivities are provided in the online appendix of Allen and Arkolakis (2014).

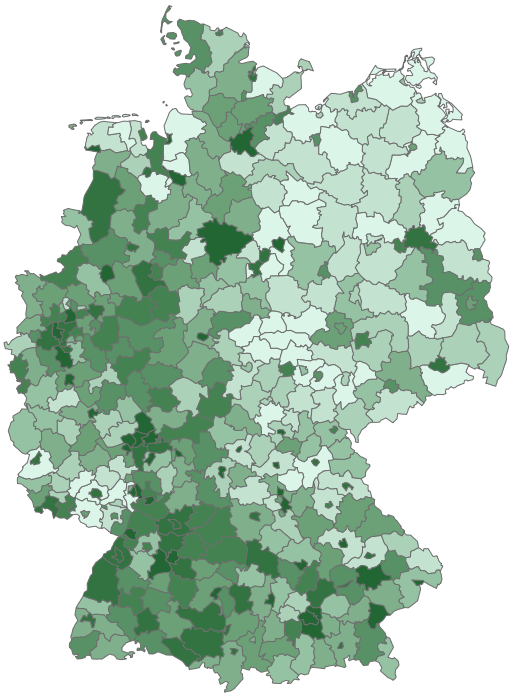
**Further parameters.** We finally need to choose the values of five additional parameters – $\alpha$, $\beta$, $\gamma$, $\sigma$ and $\eta$ – to derive values for $\bar{u}(i)$ and $\bar{A}(i)$. We motivate these values by estimates from the empirical literature. First, we set $\alpha = 0.1$ as Rosenthal and Strange (2004) show that productivity increases by up to 8 percent if population doubles. Second, our chosen value of $\beta = -2/3$ is derived as follows. Allen and Arkolakis (2014) show that their model is isomorphic to models where households spend a constant income share on housing, $\delta$, such that $-\beta_0 = -\delta/(1-\delta)$. According to Eurostat, average expenditure on housing amounted to 24.9 percent in Germany in 2010 leading to a value of $\beta_0$ of about one third.[11] In addition, $\beta$ can be understood to contain locational preferences of workers. If these preferences are distributed Frechet with shape parameter $k = 3$ as suggested by Bryan and Morten (2014), the overall value of $\beta$ can be written as $\beta = -\beta_0 - 1/\theta$, where $\beta_0$ is the baseline congestion elasticity. Third, we need a value for $\gamma$ governing the importance of public goods or transfers in the utility function. As the average tax rate amounts to about 25 percent, we choose $\gamma = 0.25$. In sum, these values ensure stability and uniqueness of the migration equilibrium as $\alpha+\beta+(1-\eta)\gamma \leq 0$. Fourth, the elasticity of substitution $\sigma$ plays a crucial role for quantifying welfare effects in trade models. We follow Simonovska and Waugh (2014) in choosing a value of five. Fifth, we assume that local governments provide pure public goods, so $\eta = 0$ in the baseline. We also study the other extreme of a pure private transfer when $\eta = 1$.

Figure 2.4 summarizes the pattern of exogenous productivities (Panel (a)) and exogenous amenities (Panel (b)). Locations with high per-capita income are characterized by higher values of exogenous productivity, like the south-west of Germany and bigger cities. Combining this information with location-specific population delivers composite productivity $A(i) = \bar{A}(i)L(i)^{\alpha}$ which is also higher in donor regions (see Panel (c) in Figure 2.3 above). Average labor productivity in donor regions is twice as high as in recipient locations. Turning to exogenous amenities, we observe from Panel (b) of Figure 2.4 that donor regions are also characterized by higher levels in this dimension. Combining these findings with location-specific population size (see Appendix 2.C.1) modifies this result because densely populated places suffer from negative congestion externalities. Finally, we observe from Panel (c) of Figure 2.3 that recipients are characterized by higher price indexes on average indicating that they are more remote than donor regions.

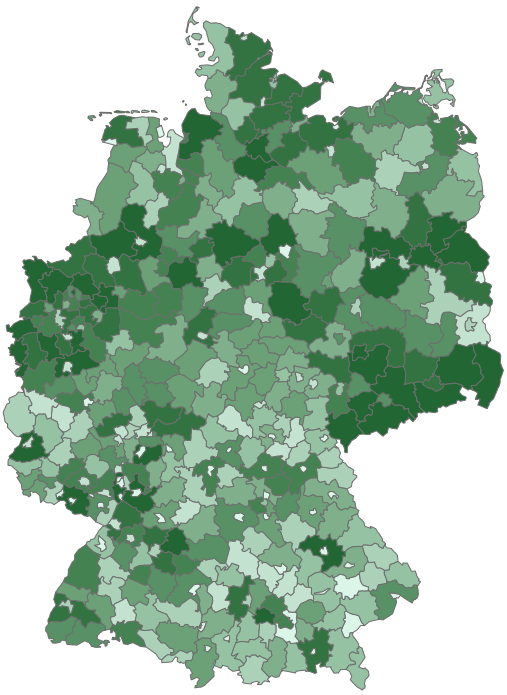
[11] We use information on the final consumption expenditure of households by consumption purpose (COICOP 3 digit) from Eurostat with the code: nama_10_co3_p3.

Figure 2.4: Estimated exogenous productivities and amenities

(a) Exogenous productivities



(b) Exogenous amenities



*Notes:* This figure plots the exogenous productivity $\bar{A}(i)$ and amenity $\bar{u}(i)$ for $\alpha = 0.1$, $\tilde{\beta} = -2/3$, $\gamma = 0.25$ and $\eta = 0$. A darker shading indicates higher values.

### 2.3.4 Importance of fiscal equalization

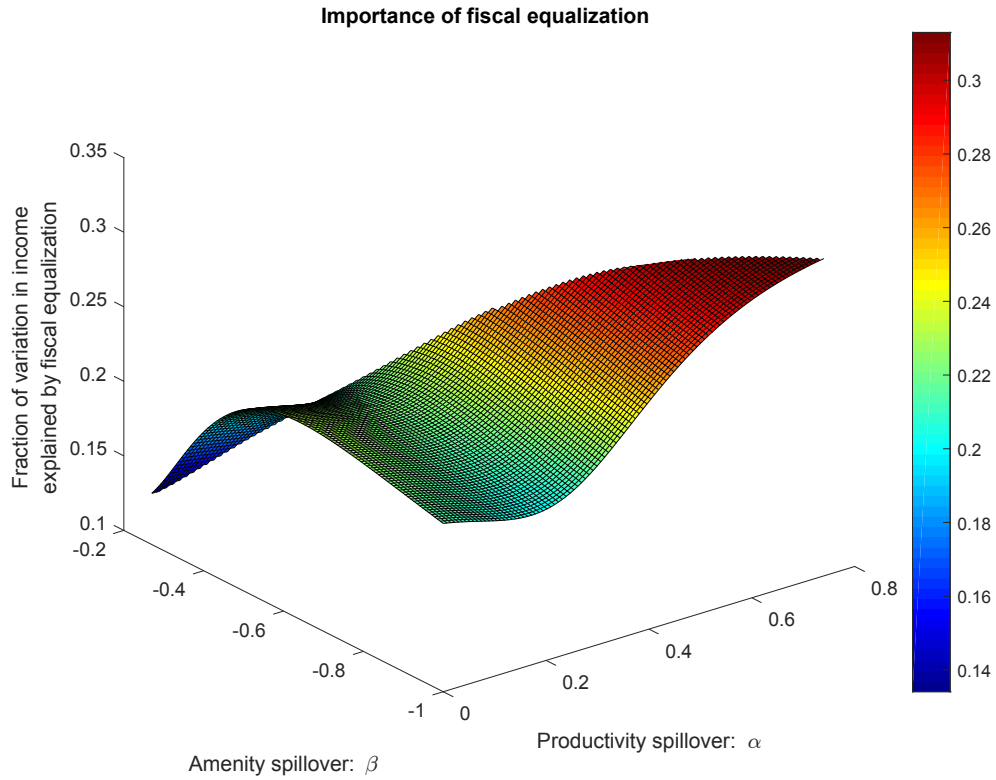
The model allows us to assess the importance of inter-regional transfers for the variation in local GDP. Combining (2.15) and (2.16) delivers a log-linear relationship between total income in location $i$ and exogenous productivities, exogenous amenities, the price index and fiscal equalization:

$$\frac{\lambda_1}{\sigma-1}\ln Y(i) = \frac{C_W + C_L}{\sigma-1} + (1-(\beta+\gamma(1-\eta)))\ln\bar{A}(i) + (1+\alpha)\ln\bar{u}(i) \\ - (2+\alpha-(\beta+\gamma(1-\eta)))\ln P(i) + (1+\alpha)\ln\Omega(i). \tag{2.19}$$

We apply a Shapley decomposition to (2.19) in order to determine the combined contribution of fiscal equalization ($\Omega$) to the spatial dispersion of income. Figure 2.5 reports the fraction of the spatial variation in income that is due to fiscal equalization rather than local characteristics or geographical location (that is $P$). For our baseline values $\gamma = 0.25$ and $\eta = 0$, we report the results of the decomposition for all combinations of $\alpha \in [0,1]$ and $\beta \in [-1,0]$ with a stable and unique equilibrium.

The decomposition suggests that at least 13 percent of the observed spatial variation in income is due to fiscal equalization. When the spillovers are such that $\alpha = 0.71$ and $\beta = -0.97$ fiscal equalization may account for up to 31 percent of the observed variation in income. In sum, the results indicate that the fiscal equalization scheme in Germany is important for the spatial variation in incomes across regions. Geographical location, in contrast, explains only a minor fraction of spatial income variation.

Figure 2.5: Fraction of Spatial Variation in Income due to Fiscal Equalization in Germany




*Notes:* This figure shows the fraction of the observed variation in income across regions in Germany in 2010 that is due to fiscal equalization. For $\gamma = 0.25$ and $\eta = 0$ we calculated the results of the decomposition for all combinations of $\alpha \in [0, 1]$ and $\beta \in [-1, 0]$ with a stable and unique equilibrium.

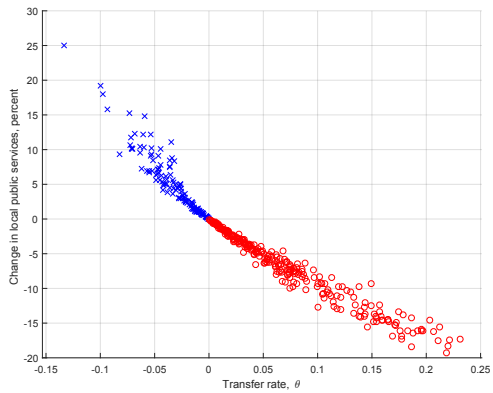
### 2.3.5 Abolishing the redistribution scheme

To assess aggregate effects of fiscal equalization, we run a counterfactual scenario where we set the transfer rates to zero in all regions, so $\theta(i) = 0$ for all $i \in N$, and compare the counterfactual equilibrium values of the model with those of the baseline scenario. On average, abandoning fiscal equalization leads to a welfare gain of 0.33 percent in this model. The data feature a significant dispersion of income between donors and recipients, so we should expect negative aggregate welfare effects from abandoning inter-regional transfers according to this channel. Recall that a transfer of one percent of income from a rich location implies a subsidy of more than one percent in a poorer location. However, we have also observed from Panel (c) of Figure 2.3 that recipient regions are on average more remote as indicated by a higher price index. Transferring money "back" from the periphery to the core

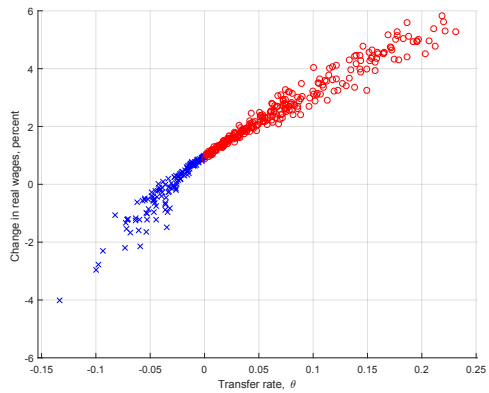
works towards aggregate welfare gains in the model. The estimated positive welfare effect of abandoning the fiscal equalization scheme therefore suggests that geography dominates the effect of income dispersion between donors and recipients.

Figure 2.6: Changes in local public services, real wages and population

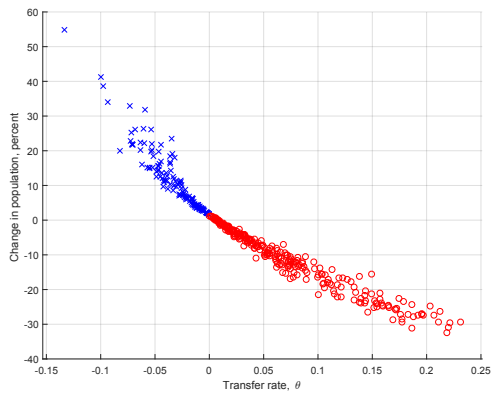
(a) Local public services




(b) Real wages




(c) Population




*Notes:* Panel (a.) shows the association between changes in local public services and the transfer rate $\theta$. Panel (b.) plots the relationship of changes in real wages and the transfer rate $\theta$. Panel (c.) presents the relationship of population changes and the transfer rate $\theta$. Net donors have a negative transfer rate $\theta$ and are marked by x (in blue). Net recipients observe positive transfer rates and are marked by circles (in red).

We explore the components of the welfare function more closely by reformulating (2.2):

$$W(i) = \bar{u}(i)\Omega(i)\frac{w(i)}{P(i)}L(i)^{\beta+\gamma(1-\eta)}. \tag{2'}$$

Abandoning transfers exerts a direct impact via $\Omega(i)$ that is decreasing for recipients and increasing for donors. This effect is illustrated in Panel (a) of Figure 2.6. As welfare has to be equalized in a spatial equilibrium, individuals migrate to previous donor regions. This changes the relative supply of goods and the spatial distribution

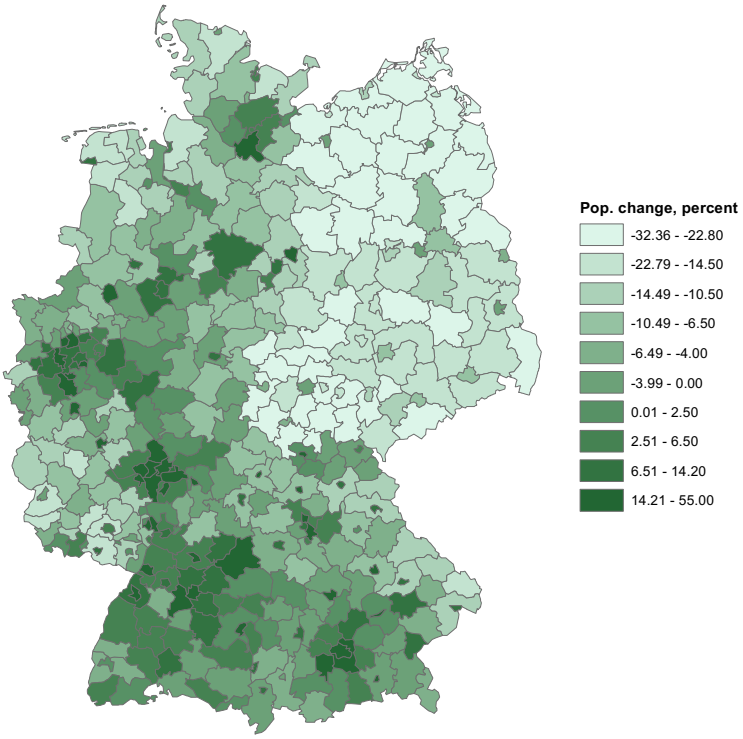
of income in the economy. To ensure goods-market clearing, prices need to fall in regions that experience immigration. This takes place via lower nominal wages and higher labor productivity $A(i)$. As geography matters, however, real wages do not decline in all former donor regions. Those locations with a low negative transfer rate benefit from the overall decline in the price index, so their real wage increases. The real wage increase even compensates the negative effect of abandoning transfers for some former recipient regions with a low positive transfer rate, so those regions even experience immigration. This is evident from Panel (c) of Figure 2.6. The model predicts a very large inflow of individuals in Frankfurt/Main of more than 50 percent in the long run. The city is the largest contributor to the fiscal equalization scheme and also located in the center of Germany. Hence, both a high relative gain in public services and a low price index explain the pronounced increase in attractiveness of this location.

Geographically, migration would take place from East German and less densely populated regions to highly agglomerated regions in the western and southern parts of the country (see Figure 2.7). Locations in East Germany experience the largest decline in population of more than one third. In contrast, wealthy and densely populated areas in the west and south of Germany experience the largest migration inflows. At the aggregate level, abandoning fiscal transfers stimulates migration of 4.6 million individuals or 5.7 percent of the German population.

We have discussed in section 2.2 that shocks lead to new equilibria if dispersion forces are stronger than agglomeration forces. Hence, amenities decline substantially in locations that experience an increase in population. These amenities are difficult to grasp, so the public debate on regional transfers centers around the distribution of income, mostly only in nominal terms. Our counterfactual analysis informs this debate as we can derive changes in average real wages and average (labor) productivity. As is evident from Panel (b) of Figure 2.6, abandoning regional transfers would contribute to a reduction in the dispersion of real wages. Furthermore, the model predicts that real wages increase by about 5.75 percent. The aggregate effect is mainly driven by the relocation of workers from sparsely populated peripheral regions with low productivity to densely populated districts with higher productivity. This reallocation increases average productivity by 9.2 percent.

**Public goods versus per-capita transfers.** So far, we largely ignored the role of $\eta$ in our model. Recall that $\eta$ governs the rivalry of public services in consumption. In the baseline scenario, we assumed public services to be pure local public goods, so $\eta = 0$. In this case, we observe from $(2')$ that local welfare is increasing in pop-

Figure 2.7: Geographical relocation of labor




*Notes:* This figure plots the percentage change in population after abandoning the redistribution scheme.

ulation. Intuitively, a larger market allows higher per-capita consumption of public services when there is no rivalry in consumption. This establishes an additional agglomeration force.

Table 2.4 summarizes aggregate effects of welfare, average real wages, average (labor) productivity and migration in absolute and relative terms. We observe that for $\eta = 1$ aggregate welfare effects become negative (-0.21 percent) when we abolish fiscal equalization payments. Intuitively, welfare has to be smaller in the case of per-capita transfers because resources are re-directed to more populous districts in our application. With $\eta = 0$, this generates an additional advantage compared to the case of $\eta = 1$. Consequently, inter-regional migration flows are less pronounced.

**Weight of public services.** Another important parameter is the Cobb-Douglas parameter $\gamma$ governing the importance of public services in the utility function. Table 2.4 reveals that higher values of $\gamma$ are associated with higher or less negative welfare changes. Intuitively, $\gamma$ affects the strength of agglomeration forces. If individuals value public services more, transferring income leads to more pronounced responses in labor mobility. If population size matters in addition, so $\eta = 0$, then changes in $\gamma$ exert an even stronger effect on aggregate outcome.

Table 2.4: Aggregate Effects: Welfare, real wages, labor productivity and migration

| $\eta$ | $\gamma$ | $\hat{W}$ *(in percent)* | $\widehat{w/P}$ *(in percent)* | $\hat{A}$ *(in percent)* | $\hat{L}$ *(in millions)* | $\hat{L}$ *(in percent)* |
|---|---|---|---|---|---|---|
| 0 | 0.20 | 0.07 | 4.17 | 6.57 | 3.38 | 4.14 |
| 0 | 0.25 | 0.33 | 5.75 | 9.21 | 4.64 | 5.67 |
| 0 | 0.30 | 0.77 | 7.89 | 12.57 | 6.15 | 7.53 |
| 1 | 0.20 | -0.23 | 3.10 | 4.81 | 2.51 | 3.07 |
| 1 | 0.25 | -0.21 | 3.86 | 6.08 | 3.14 | 3.84 |
| 1 | 0.30 | -0.15 | 4.65 | 7.39 | 3.77 | 4.61 |

*Notes:* This table reports changes in welfare, average real wages, labor productivity and migration (in millions and in percent of the total population) for $\sigma = 5$, $\alpha = 0.1$, $\beta = -0.66$ and different parameter values of $\eta$ when income redistribution between locations is abolished.

## 2.4 Conclusions

We have argued in this paper that it is important to account for fiscal transfers between jurisdictions to understand the spatial organization of an economy. We use a general equilibrium model with trade and labor mobility to derive insights about the welfare costs about fiscal equalization. We argue that transfers from rich to poor regions raises welfare as a transfer of one percent of income in donor regions makes up more than one percent in target regions. This effect rises in the dispersion of income. Further, geography matters. If recipients are located in the periphery, one unit of income buys less utility there due to a higher price index.

We quantify the model for Germany with data on population, income and interregional trade and explore aggregate effects by abolishing the fiscal equalization scheme. We find moderate welfare effects of 0.33 percent indicating that geography plays an important role. About 5 percent of the population would change their place of residence and employment to reinstall a spatial equilibrium.

As migration changes the spatial allocation of production as well as local consumption and production amenities, we find that the abolishment of transfers raises average real per-capita income by 5.8 percent in the long run, which is largely driven by an increase in average labor productivity of more than 9 percent. Overall, regional transfers are able to explain up to about 30 percent of the variation in local income.

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# Appendix

## 2.A Derivation of (2.13)

To derive (2.13), we define

$$\lambda(i) \equiv \frac{(1+\theta(i))\bar{A}(i)^{1-\sigma}w(i)^{\sigma}L(i)^{1-\alpha(\sigma-1)}}{\Omega(i)^{1-\sigma}\bar{u}(i)^{1-\sigma}w(i)^{1-\sigma}L(i)^{(1-\sigma)[\beta+\gamma(1-\eta)]}}.$$

Assuming symmetric trade costs, $\tau(i,n) = \tau(n,i)$, we get from (2.11) and (2.12):

$$\begin{aligned}\frac{\lambda(i)}{1+\theta(i)} &= \frac{\int_N \tau(i,n)^{1-\sigma}\bar{u}(n)^{\sigma-1}\Omega(n)^{\sigma-1}\left(1+\theta(n)\right)w(n)^{\sigma}L(n)^{1+(\sigma-1)(\beta+\gamma(1-\eta))}dn}{\int_N \tau(n,i)^{1-\sigma}\bar{A}(n)^{\sigma-1}w(n)^{1-\sigma}L(n)^{\alpha(\sigma-1)}} \\ &= \frac{\int_N \lambda(n)^{\beta}F(n,i)dn}{\int_N \lambda(n)^{\beta-1}F(n,i)dn},\end{aligned}$$

where $F(n,i) \equiv \tau(n,i)^{1-\sigma}\bar{u}(n)^{(1-\beta)(\sigma-1)}\bar{A}(n)^{\beta(\sigma-1)}\Omega(n)^{(\sigma-1)(1-\beta)}(1+\theta(n))^{1-\beta}$ $w(n)^{\sigma+\beta(1-2\sigma)}L(n)^{1+\beta(\sigma-1)+\beta((\alpha-\beta)(\sigma-1)-1)+(1-\beta)\gamma(\sigma-1)(1-\eta)}$.

Rearranging terms delivers

$$\frac{\lambda(i)^{\beta}}{\lambda(i)^{\beta-1}} = (1+\theta(i))\frac{\int_N F(n,i)\lambda(n)^{\beta}dn}{\int_N F(n,i)\lambda(n)^{\beta-1}dn}.$$

Following the logic in Allen and Arkolakis (2014) and referring to the generalized Jentzsch theorem, $\lambda(i)^{\beta} = (1+\theta(i))\phi\lambda(i)^{\beta-1}$ and thus $\lambda(i)/(1+\theta(i)) = \phi$. Plugging this relationship into the definition of $\lambda(i)$ above yields (2.13).

## 2.B Data

To compile the tax data, we first subtract an amount of 37,895.9 million euros that is primarily used for child allowance. This is the standard procedure in the fiscal equalization scheme and appropriate in our context as this item is a main transfer

for families. As a consequence, overall tax income in 2006 of 526,218.2 million euros shrinks to 488,775.3 million euros. In the following, we describe in detail how we obtain the two key tax variables of interest. First, we need to know how much tax revenue each district has generated in 2010. Second, we compute each district's share of the overall tax budget. These data are not readily available as Germany is characterized by several jurisdictional layers that have both common and individual tax authority. Therefore, tax statistics provide information on tax income for different types of taxes and different jurisdictional entities. As our model abstracts from these layers (and the complexity of different types of taxes), we need to assign tax income to each district.

First, we calculate tax income generated in each district. Using the statistic "Realsteuervergleich" from the German Statistical Office, we obtain information on business and property tax revenues that can be directly linked to each location. Further, we can derive total revenues of VAT and income taxes collected in each district. For this, we take advantage of the fact that municipalities can keep a certain fraction of the total that is fixed at a certain rate for every jurisdiction. As we know the total amount each district can keep, we can infer the total amount collected. VAT and income taxes are the two most important taxes with regard to revenues accounting for about 61 percent of total tax income in Germany. Together with business and property taxes, the share rises to 70 percent that can be unambiguously assigned to each locality. The remaining 30 percent of tax income comprises federal and state taxes that we assign to each district according to the share of tax income that is directly attributable to each location. This follows the idea that districts with higher VAT and income tax revenue are characterized by higher economic activity leading to higher revenues of other taxes as well.

Second, we compute the tax budget of each district. This figure does not necessarily match the previous figure on collected taxes at the local level, as major taxes are shared between different layers of government and, most importantly, there is inter-regional redistribution. From the German Statical Office's "Bruttoeinnahmen der Gemeinden", we know each location's tax budget plus transfers from the state or the federal level. As Germany is characterized by an elaborate federal system where municipalities, states, and the federal level itself are responsible for certain tasks that are fixed by the constitution. Hence, these layers have a claim for a certain share of the overall tax budget. Therefore, tax statistics do only report tax budgets for each layer and we need to distribute the state and federal budgets to each district.

We have shown in the main part of this paper that a substantial amount of resources is transferred between the federal level and the states and between the states. We thus use information about the available tax budget of each state after fiscal equalization. These budgets differ substantially from collected taxes. We then need to make an assumption about how these state budgets are distributed across each state's districts (municipalities). To capture the idea that the state is obliged to install equal living conditions across regions, we distribute these tax budgets according to population shares (rather than tax income shares). What remains is the federal tax budget that we also distribute according to population shares.

Having completed these two tasks delivers two variables: Total tax income of each district before equalization and total tax income of each district after equalization. The difference defines transfers each district pays or receives. Relating these data to local GDP delivers the transfer rate $\theta(i)$.

Table 2.B.1 shows the volume of redistribution at each stage of the process. In sum, this amounts to about 26.5 billion euros or 5 percent of tax revenues.

Table 2.B.1: Volume of redistribution, 2010

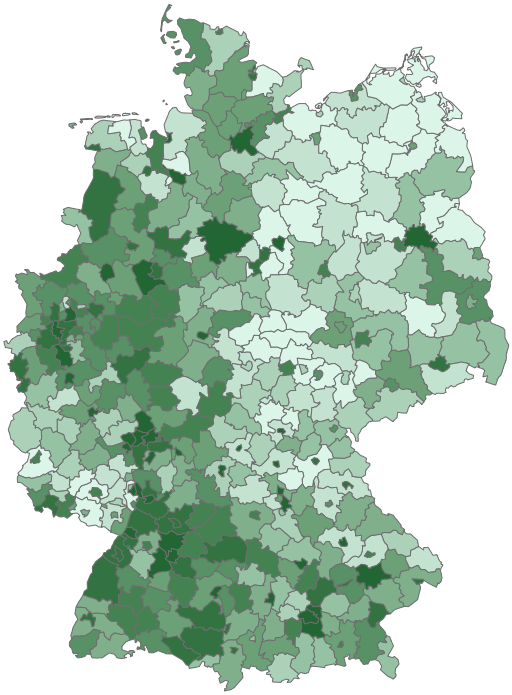
| | VAT redistribution (million euros) | Horizontal equalization (million euros) | General grants (million euros) | Special grants (million euros) | Per capita transfers (euros) |
|---|---|---|---|---|---|
| Bavaria | -1,545 | -3,511 | 0 | 0 | -403 |
| Baden-Württemberg | -1,327 | -1,709 | 0 | 0 | -282 |
| Berlin | 58 | 2,900 | 912 | 1,706 | 1,611 |
| Brandenburg | 864 | 401 | 176 | 1,498 | 1,174 |
| Bremen | -46 | 445 | 146 | 60 | 916 |
| Hamburg | -220 | -66 | 0 | 0 | -160 |
| Hesse | -749 | -1,752 | 0 | 0 | -412 |
| Lower Saxony | 378 | 259 | 127 | 0 | 96 |
| Mecklenburg Western Pomerania | 830 | 399 | 157 | 1,110 | 1,520 |
| North Rhine-Westphalia | -2,204 | 354 | 119 | 0 | -97 |
| Rhineland Palatinate | -393 | 267 | 144 | 46 | 16 |
| Saarland | 125 | 89 | 46 | 63 | 317 |
| Saxony | 2,024 | 854 | 350 | 2,625 | 1,411 |
| Saxony-Anhalt | 1,201 | 497 | 202 | 1,616 | 1,506 |
| Schleswig Holstein | -136 | 101 | 51 | 53 | 24 |
| Thuringia | 1,139 | 472 | 192 | 1,483 | 1,470 |
| Sum | 6,620 | 7,039 | 2,624 | 10,260 | |

*Source*: Federal Ministry of Finance (2015).

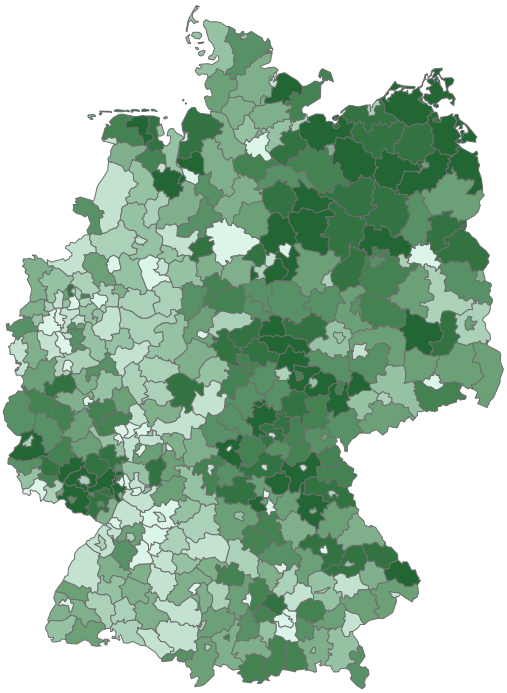
## 2.C Composite productivities and amenities

Figure 2.C.1: Estimated composite productivities and amenities

(a) Composite productivities



(b) Composite amenities

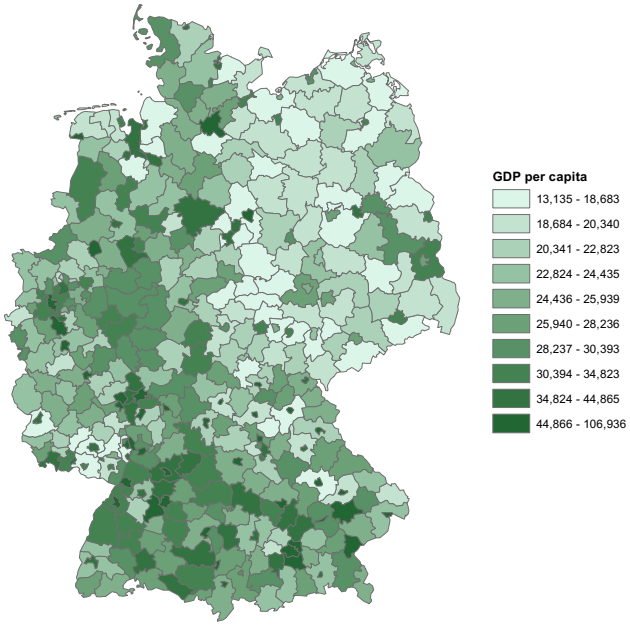


*Notes:* This figure shows composite productivity $A(i)$ and composite amenity $u(i)$ for $\alpha = 0.1$, $\tilde{\beta} = -2/3$, $\gamma = 0.25$ and $\eta = 0$. A darker shading indicates higher values.

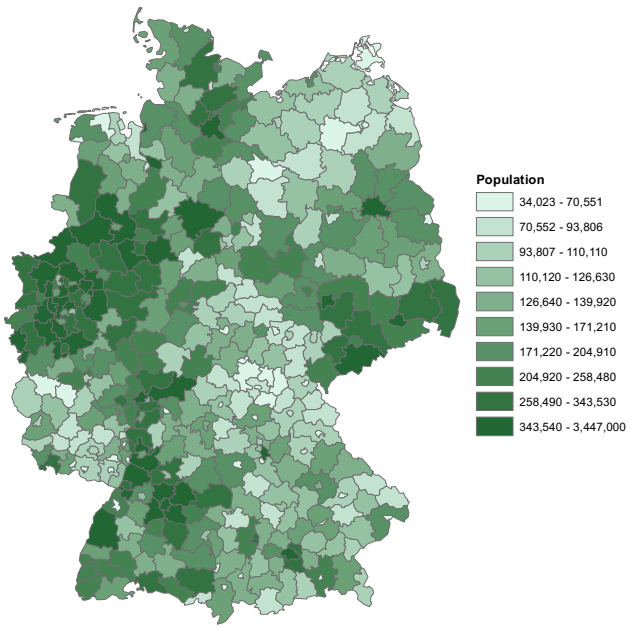
## 2.D GDP per capita and population density

Figure 2.D.1: Distribution of GDP per capita and population density in 2010

(a) GDP per capita




(b) Population




*Notes:* This figure plots the quantiles of the GDP per capita distribution in Panel (a) and of the population distribution in Panel (b) for the year 2010. A darker shading indicates higher values.

# Chapter 3

# Decomposing the role of urbanization in wage inequality in Germany: Unequal pay in cities?

*I identify the role of urbanization in the development of wage inequality in Germany between 1985 and 2009. Urbanization contributes about 30 percent to the growth of overall wage inequality. To understand the underlying channels of this location-inequality premium, I construct counterfactuals that simulate the evolution of wage distributions with (i) a constant (as of 1985) spatial distribution of skills or (ii) an equal change in the relative remuneration for skills across locations of different population densities. The largest part of the location-inequality premium is due to an increasingly unequal pay of workers with an initially high within-group inequality in larger cities compared to smaller cities. An increased sorting of employees on the basis of their observable skills did not contribute to the increase in wage inequality. Up to half of the location-inequality premium is due to the occupational structure or job task content, about 30 percent is due to firm size, and about 25 percent is due to the industrial structure.*

## 3.1 Introduction

Seek the welfare of the city and you will prosper. More than 50 percent of the worldwide population follows this rule and lives in cities. This figure will increase

to 66 percent by 2050, according to the United Nations (2014). The economic literature suggests that this trend is promising, as cities make people and firms more productive (see, for example, Rosenthal and Strange, 2004, and Puga, 2010 for reviews). One interesting implication of urbanization that we know little about is its relationship with wage inequality. Does increasing urbanization broaden or widen the wage disparity among workers? Recent work by Baum-Snow and Pavan (2013) documents that urbanization increases the wage gap between workers. The surge of wage inequality in larger cities explains at least a quarter of the increase in wage inequality in the United States (US) between 1979 and 2007. It is unclear, however, whether a similar link between location size and inequality exists even under different conditions. If yes, which channels affect this relationship?

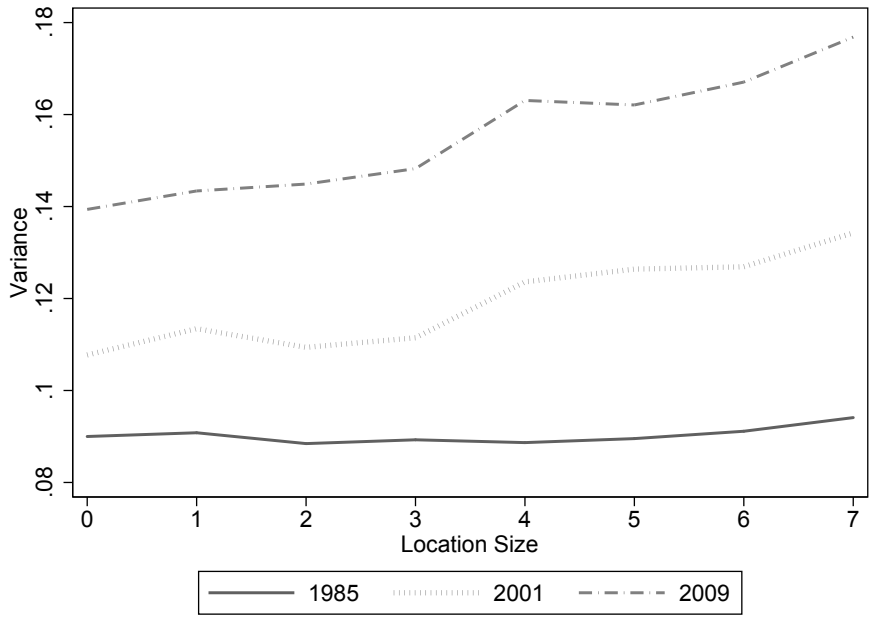
This paper has two goals. First, I explore the link between urbanization and wage inequality by using administrative data from (West) Germany. This is interesting as Germany differs from the US in important ways. For example, workers in Germany are far less mobile across regions and a fiscal redistribution scheme mitigates spatial inequality. Locations not only differ in their workers' productivity levels in producing goods and services but also vary in their industrial, functional, and skill composition. Second, I study the relative importance of worker- and firm-specific dimensions—like the distribution of firm size, occupational structure, and job tasks—that describe the composition of cities more precisely.

Figure 3.1 documents the increased importance of location size for wage inequality in (West) Germany between 1985 and 2009. In 1985, the variance in wages was smaller, and the relationship between location size and wage inequality lower than in 2009. But the variance increased over time with a higher growth in larger urban, densely populated locations ($T = 1, ..., 7$) than in rural, less densely populated areas ($T = 0$).

Behrens and Robert-Nicoud (2015) provide a discussion on the different ways location size influences wage inequality. In short, the effect of location size is the joint outcome of differences in the composition of cities and relative remuneration of skills across locations. For example, workers who are generally paid unequally—that is, workers with a higher within-group inequality—sort into larger cities whereas homogeneous groups reside in small, rural locations. Besides sorting, one can imagine that the skill heterogeneity increased in large cities. So, a change in the relative remuneration of skills translates to higher inequality there.[1]

[1]See, for example, Behrens and Robert-Nicoud (2014), and Eeckhout, Pinheiro, and Schmidheiny (2014).

Figure 3.1: Wage Inequality by Location Size, 1985–2009




*Source:* SIAB sample for full-time workers between 21 and 60 years of age.
*Notes:* The figure plots the variance in log (real) wages in (West) Germany against an increasing index of location size for each time period—1985, 2001, and 2009.

To identify the existence of a *location-inequality premium* and to quantify the importance of the underlying channels, I construct counterfactual distributions that retain the composition of observable skills as well as relative remuneration at a reference level. This allows me to decompose the change in wage inequality into two parts: (i) a *composition effect*, which represents the distribution and sorting of workers across locations, and (ii) a *price effect*, which describes divergent changes in remuneration across space.[2]

A comparison of the actual change in wage inequality with the counterfactual change identifies a *location-inequality premium*. I find that location size has contributed to the rise in wage inequality by about 25–31 percent, depending on the specification. This effect varies across the wage distribution with large positive effects for high-wage workers. Workers at the upper part of the distribution are increasingly paid unequally in larger, more densely populated locations compared to smaller, less densely populated locations.

The results show that differences in skill composition and the subsequent sorting of workers across locations are not important for the increase in wage inequality since the mid-1980s. Instead, variations in the remuneration for skill explain the largest

[2]See Fortin, Lemieux, and Firpo (2011) for a review of decomposition methods in economics.

part of the *location-inequality premium*. But it is unclear which channels affect this relationship. To get a better understanding of this link, I determine how much of the higher increase of within-group inequality in larger locations results from a finer depiction of the composition of cities and consider additional observable worker and firm characteristics. In particular, in addition to industry structure, I examine the distribution of firm size, occupational structure, and job tasks. I include these additional direct measures of skill, as the returns to skill vary across occupations or the task content of jobs.[3] The distribution in firm size accounts for the fact that larger and more productive firms pay higher wages on average.

The decomposition shows that worker characteristics are more important than firm characteristics for the *location-inequality premium*. Up to one-half of the effect occurs because occupations or job tasks with a greater increase in wage inequality are more concentrated in larger locations. Firm size explains around one-third, while differences in the industry composition only account for around one-fourth of the *location-inequality premium*. Sorting of workers within those groups across locations only explains a small part. In sum, groups of workers with an initial unequal pay in the mid-1980s today face even higher inequality in larger cities compared to smaller cities. Thus, urbanization boosts higher within-group inequality and contributes to greater inequality especially among high-skilled workers in Germany. This is important as it shows that location size affects the distribution of wages differently for similar workers. Cities pay their workers unequally.

The paper is related to recent findings in urban economics on wage inequality. The regional and urban economics literature—including the work of Glaeser, Resseger, and Tobio (2009), Behrens and Robert-Nicoud (2014), la Roca and Puga (2015), Davis and Dingel (2012), Lindley and Machin (2014), and Eeckhout et al. (2014)—examines agglomeration economies, tougher selection of entrepreneurs and firms, and skill composition across locations to explain the higher productivity in cities. A greater skill bias of agglomeration economies and change in the relative supply of skilled versus unskilled labor induces higher inequality in cities. Within this line of research, Baum-Snow and Pavan (2013) develop a decomposition method to determine the fraction of the increase in wage inequality that is due to differences in the composition of cities and relative remuneration for skills across locations. Baum-Snow and Pavan (2013) account for different industrial structures across cities. This makes sense as larger cities employ more high-skilled workers in high-wage indus-

[3]See, for example, Gibbons, Katz, Lemieux, and Parent (2005), who show that the returns to skill are higher in occupations that employ workers with higher skill levels.

tries.[4] But the composition of locations and its relationship with location size differ not only in terms of their industrial structure. The literature documents that workers performing non-routine and cognitive routine tasks earn more than their colleagues with manual routine and manual non-routine tasks. Bacolod, Blum, and Strange (2009), for example, find for the US that the composition of cognitive and non-cognitive skills is similar across locations of various sizes, but that the returns for soft skills and some more technical skills are larger in bigger cities. To account for this, I consider a more precise depiction of the composition of cities and explore the importance of other aspects, like changes in the occupational structure or the task content of jobs.

Finally, this study is also related to the empirical labor economics literature that has examined the relative importance of worker and firm characteristics for overall wage inequality. In their empirical study for Germany, Card, Heining, and Kline (2013) report an increased importance of worker heterogeneity at the firm level. Assortative matching between workers and firms leads to firm-specific wage premiums. High-skilled individuals work more often in high-skilled occupations and high-wage firms than less-skilled workers. The increased concentration of high-skilled workers contributes to skill and consequently to wage inequality across firms. However, Card et al. (2013) do not specify which firm characteristics are important to explain the change in wage inequality, and do not relate it to urbanization and the characteristics of the location of work. Recent theories of firm heterogeneity explain residual inequality through the wage differentials between firms—including the theories of Combes, Duranton, Gobillon, Puga, and Roux (2012) and Behrens, Duranton, and Robert-Nicoud (2014).[5] Tougher firm selection and sorting of more productive firms into larger, high-density markets emanate in a wider distribution of firm productivities. This helps to explain bigger residual wage inequality, as the more productive firms pay higher wages on average. In a more recent study Dauth, Findeisen, Moretti, and Suedekum (2016) show that worker-firm matching in denser local labour markets is indeed a key driver of higher wages in cities. To highlight the importance of this dimension, I account for the heterogeneous firm size distribution and compare workers across different firm size groups. Ehrl (2016) also finds that occupational attributes turn out to be the most important wage determinant. Ehrl (2016) follows a regression-based decomposition method to decompose wage inequality in Germany into region-, worker-, firm-, and sector-

[4]See, for example, Davis and Dingel (2014).

[5]See Akerman, Helpman, Itskhoki, Muendler, and Redding (2013) for a short summary of the literature on firm heterogeneity and wage inequality.

specific components. In this paper, however, I have a narrower focus by attempting to isolate the role of location size or density and the underlying channels for the *location-inequality premium*.

The structure of the paper is as follows. Section 3.2 provides an introduction to the development of wage inequality in Germany. Section 3.3 discusses the underlying method to analyze changes in the (West) German wage structure between 1985 and 2009. In Section 3.4, I introduce the data. Section 3.5 presents the results and alternative specifications, including the role of firm size, occupations, and industry structure, before I conclude in Section 3.6.

## 3.2 Wage inequality in Germany

Wage inequality increased from 1985 to 2009 in (West) Germany. This trend is already well documented in previous empirical findings on the German labor market. For descriptions of the recent developments, see, for example, Dustmann et al. (2009), Dustmann, Fitzenberger, Schoenberg, and Spitz-Oener (2014), and Card et al. (2013).

Table 3.1 presents different inequality statistics for full-time employed German males between 21 to 60 years of age. I report inequality statistics for the time periods from 1985 to 2001 and 1985 to 2009.[6] Panel (a) displays the numbers for each year. Panel (b) presents the corresponding changes over time. These changes will provide the benchmark against which I will compare counterfactual changes in wage inequality later in the analysis (explained below).

First, I compute the mean wages for groups of workers with the same observable characteristics and the corresponding individual deviation from the mean. To differentiate between groups of workers, I control for worker- and region-specific factors. Specifically, I condition on age, education, and the population density of the workplace district. Then I compare several inequality statistics between and within those groups of workers.

Between 1985 and 2009, the variance in total wages increased by 0.067 log points—that is, 70 percent (Column 1). These changes will provide the benchmark against which I will compare counterfactual changes in wage inequality later in the analysis (explained below). Both between and within groups of workers, inequality increased over time (see Columns 4 and 5). The increase in wage inequality, how-

[6] I abstract from the time period between 1985 and 1993, as only minor changes took place.

ever, differs across the wage distribution. To highlight the difference between the lower and upper parts of the wage distribution, I also present the 85–50 percentile gap and the 50–15 percentile gap. The underlying data set requires computing the gap between the 85th and 50th percentiles, and the gap between the 50th and 15th percentiles, because wages are censored at the top of the distribution.

Within groups of workers with similar observable characteristics, the (residual) variance in wages experienced a higher increase than between groups of workers. The variance in residual wages increased by 0.048 log points—that is 71 percent (column 5). One interesting development stands out: The increase in residual inequality was more pronounced in the lower part of the distribution. The 50–15 percentile gap in residual wages increased more than the 85–50 percentile gap. The 85–50 percentile gap rose by 0.111 log points, or 28 percent (Column 2), and the 50–15 percentile gap by 0.133 log points, or 50 percent (Column 3) between 1985 and 2009. This is interesting, as the opposite was found for the US by Autor, Katz, and Kearney (2008). Hence, in the US, high-wage workers at the top of the distribution experienced relatively higher real wage increases compared to workers in the middle and the lower parts of the distribution. But in (West) Germany, wage inequality increased especially in the lower part of the wage distribution.

Some specialties about the development of the German labor market might help to differentiate between the US and Germany. In the first half of the 1990s, the economic situation of Germany deteriorated and the unemployment rate increased to around 10 percent. In subsequent years, the wage-bargaining system started to decentralize. Wage bargaining shifted from the industry level to the level of the single firm or worker. This process initiated a decline in wages, especially at the bottom of the wage distribution. In the late 1990s and early 2000s, the unemployment rate, however, was still at around 10 percent. As a consequence, the "Hartz" reforms were initiated between 2002 and 2005. These reforms led to institutional changes and to a liberalization of the labor market. These developments were especially important for the development at the bottom of the wage distribution. Higher demand for high-skilled workers, due to technological change, international trade, and an increased importance of specific knowledge raised wage inequality between (skill) groups, especially at the top of the distribution.

The specific role of urbanization in wage inequality in Germany, however, has not been empirically analyzed so far. In the following, I try to fill this gap.

Table 3.1: Trends in log-wage inequality

| | Total | | | Between | Residual | | | |
|---|---|---|---|---|---|---|---|---|
| Year | Variance | 85–50 Gap | 50–15 Gap | Variance | Variance | 85–50 Gap | 50–15 Gap | N |
| | | | | Panel (a) | | | | |
| 1985 | 0.096 | 0.394 | 0.266 | 0.028 | 0.068 | 0.248 | 0.237 | 566,130 |
| 2001 | 0.125 | 0.440 | 0.321 | 0.033 | 0.092 | 0.275 | 0.286 | 571,051 |
| 2009 | 0.163 | 0.504 | 0.399 | 0.047 | 0.116 | 0.307 | 0.346 | 533,767 |
| | | | | Panel (b) | | | | |
| 1985 to 2001 | 0.029 | 0.047 | 0.055 | 0.005 | 0.024 | 0.028 | 0.049 | 566,130 |
| 1985 to 2009 | 0.067 | 0.111 | 0.133 | 0.019 | 0.048 | 0.059 | 0.108 | 533,767 |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* Panel (a) reports the variance and percentile gaps of the overall, between, and residual log real wage distributions for each time period. The residuals are obtained as individual deviations from the group means (conditional on age, education, and location size). Changes over time in Panel (b) represent benchmarks against which counterfactual changes absent in location size effects will be compared.

## 3.3 Methodology

To analyze the effect of location size on the development of wage inequality, I apply the procedure proposed by Baum-Snow and Pavan (2013). First, I assess the role of the composition of observable skills and relative remuneration across locations. For that, I apply the "cell-by-cell" nonparametric re-weighting method of DiNardo, Fortin, and Lemieux (1996), and Lemieux (2006). Then I combine the re-weighting procedure with the change-in-changes (CIC) method of Athey and Imbens (2006) to analyze growth in residual inequality. Finally, I extend the analysis of Baum-Snow and Pavan (2013), and employ a wide range of additional regression-based decompositions. The aim is to disentangle various worker- and firm-specific factors that contribute to the *location-inequality premium.* The following subsections discuss the fundamental idea behind the method, the empirical problems, and the identifying assumptions.

### 3.3.1 Set-up

A vector of observable characteristics $G = x$ interacts with a vector of location size $T$ to form a *mutually exclusive group* for each worker $i$. I use a combination of three education and eight age groups to form 24 skill groups, $x$. $T$ is an increasing index of the location size of the workplace district. Each worker $i$ with observable characteristics $G$ in location group $T$ earns a (log) wage $y_{it}(G, T)$ at time $t$:

$$y_{it}(G, T) = m_t(G, T) + \epsilon_{it}(G, T). \tag{3.1}$$

The wage structure is linear and additively separable. This allows me to separate contributions of observables $(G, T)$ from that of unobservables $\epsilon$. The wage is a function of the mean wage $m_t(G, T)$ and the individual deviation from the mean $\epsilon_{it}(G, T)$. I construct the residuals $\epsilon$ to have a zero mean conditional on the observables $(G, T)$. The *zero conditional mean* assumption ensures that only observable components influence mean wages. Furthermore, I assume *strict monotonicity* in $\epsilon$. This ensures a mapping of individual unobserved characteristics to the outcome $y$. I integrate all individual information over skill and location size groups. This gives me the corresponding distribution function for residual or total log wages:

$$F_t(y) = \int F_t(y|G, T)F_t(G, T)dGdT. \tag{3.2}$$

$F_t(y|G, T)$ represents the conditional distribution of wages observed across space $T$. The joint cumulative distribution function (CDF) of observable characteristics $F_t(G, T)$ represents the skill composition of the workforce. It consists of two parts:

$$F_t(G, T) = F_{at}(T|G)F_{bt}(G) \tag{3.3}$$

The first function—the CDF conditional on skill groups $F_{at}(T|G)$—accounts for the sorting of workers across locations $T$ on their observable characteristics $G$. In technical terms, it represents the probability of an individual with observable skills $G$ to work in a location of size $T$. To deal with the sorting of workers across locations on the basis of their observable skills, I assume that the probability of being located in $T$ does not vary for workers within the same skill group $G$. The second function—the marginal or unconditional probability density function (pdf) $F_{bt}(G)$—accounts for the overall development of observable skills across time. First, it describes the change in the demographic composition of the workforce over time. This is important, as the share of old workers increased, whereas the share of the youngest cohort declined drastically over the last decades. Second, it depicts the increase in the overall education level of the workforce over time, that is the general increase in high-skilled workers relative to low-skilled workers.

**Identification.** Two main problems complicate the identification of a causal relationship between location size and wage inequality. The first problem is a missing random source in the variation of location size. The second problem arises due to selective sorting of workers on unobservable characteristics $\epsilon$ (for example, unobserved ability, effort, or skills) into location size groups $T$. In technical terms, unobservables may differ across location size groups $T$ with the same observables

$G$, and some part of those unobservables that influence the outcome $y$ may be correlated with $T$.[7] For example, the positive sorting of high-ability and low-ability workers into larger locations may lead to an upward bias of the *location-inequality premium.*

The challenges of no exogenous source of variation in $T$ and potential selection bias indicate the need to impose two identifying assumptions. First, the assumption of *common support* demands for each $[G', \epsilon']'$ in the total set of observables and unobservables $G \times \epsilon$ a nonnegative probability of this combination across space, $0 < \Pr[T = s|G = x, \epsilon = e] < 1$. This ensures that all values of $G$ and $\epsilon$ can be compared across all location size groups $T$. Second, the assumption of unconfoundedness rules out the problem of selective sorting or any other potential endogeneity of covariates. Here, I implicitly assume that the distribution of unobservables is the same across groups $T$, conditional on observables $T \perp \epsilon | G$. This amounts to the assumption that, conditional on $G$, the relationship between $T$ and $\epsilon$ is identical for each worker. At this stage, it is important to note that the primary goal of the study is not to identify a causal effect. I construct counterfactuals to single out the potential direction of the *location-inequality premium.* The results should then serve as a benchmark for further investigations.

### 3.3.2 Counterfactuals

The assumptions of *common support* and *unconfoundedness* allow me to re-weight the full composition of observable characteristics and to identify counterfactuals. Counterfactuals represent situations without a shift in relative remuneration across locations and/or the composition of observable skills between time $t$ and a reference period—here $t = 1985$. To construct counterfactual CDFs $F_t^c(\cdot)$—so-called *'what if' scenarios*—I manipulate either the conditional distribution of wages $F_t(\cdot|G, T)$, and/or the CDF of observable characteristics $F_t(G, T)$.

**Quantity re-weighting.** With the first counterfactual scenario, I intend to draw implications on the role of changes in the skill composition across locations. It represents the selective sorting on observables (for example, skill groups) across space. I hold the distribution of observable characteristics across locations $F_{at}(T|G)$ fixed to a reference period—here 1985. However, I allow the overall distribution of

[7] See, for example, Combes, Duranton, and Gobillon (2008).

observables $F_{bt}(G)$ to change as it actually did.

$$F_t^c(G,T) = \int F_{a1985}(T|G)F_{bt}(G)dGdT \tag{3.4}$$

**Price re-weighting.** Next, I abstract from spatial differential changes of observed and/or unobserved skill prices over time. First, I adjust the conditional means that serve as observed (skill) prices $m_t(G,T)$ to represent the relationship with location size in the reference period—here 1985.

$$m_t^c(G,T) = m_t(G) + (m_{1985}(G,T) - m_{t,1985}(G)), \tag{3.5}$$

with $m_t(G) = \int m_t(G,T)F_{a1985}(T|G)dT$. The difference between group means and location-specific group means remains constant at the 1985 values—that is, $m_{1985}(G,T) - m_{t,1985}(G)$. This means the urban wage premium remains constant across the time conditional on observable characteristics. For the calculation of conditional means $m_t(G)$, however, I account for changes in the mass of workers—that is, $m_t(G) = \int m_t(G,T)F_{a1985}(T|G)dT$. Second, I construct counterfactual distributions of within-group inequality $F_t^c(\epsilon|G,T=s)$. To analyze the extent to which residual inequality changed across different locations, I apply the CIC procedure of Athey and Imbens (2006), which represents an extension of the *difference-in-differences* method. I assign each residual value of the actual distribution to the corresponding change of a reference location—here the rural district $T=0$—to construct the counterfactual distribution. First, I determine for each residual value its corresponding percentile in the reference group. Then I impose for each percentile in the actual distribution the change in the reference group over time

$$F_t^c(\epsilon|G,T=s) = F_t(\epsilon|G,T=0)\left(F_{1985}^{-1}(\epsilon|G,T=0)(F_{1985}(\epsilon|G,T=s))\right). \tag{3.6}$$

The application of the CIC method allows me to construct two counterfactual scenarios. The first counterfactual scenario is without any adjustment of the conditional mean. I only adjust the residuals. The second counterfactual scenario additionally adjusts the urban wage premium for each group of workers to 1985 values. Finally, I follow the same procedure as before but construct a counterfactual scenario that excludes the composition of observed characteristics.

### 3.3.3 Decomposition

For each time period, I calculate the change in a distributional statistic $\nu_{t,1985}$, since $t = 1985$. Then I compare the difference between changes in actual inequality $\nu\left(F_{t,1985}(y)\right)$ and counterfactual inequality $\nu\left(F^c_{t,1985}(y)\right)$ to isolate the effect of *location size*. One shortcoming of this approach is that it rules out general equilibrium effects by assumption. It relies on the assumption of *invariant conditional distributions* that requires changes in marginal distributions $F_t(G,T)$ and conditional wage distributions $F_t(\cdot|G,T)$ to be independent. Changes in the remuneration do not affect the number of workers and vice versa. One advantage of this approach of double differencing is, however, that it removes any common distributional elements like the importance of locational fundamentals. All assumptions together allow me to decompose the *difference-in-differences* $\Delta^\nu_o$ into a *composition effect* and a *price effect*:

$$\begin{aligned}\Delta^\nu_o &= \nu_{t,1985}\left(F_t(y)\right) - \nu_{t,1985}\left(F^c_t(y)\right) \qquad (3.7)\\ &= \underbrace{\nu_{t,1985}(F_t(G,T)) - \nu_{t,1985}(F^c_t(G,T))}_{\Delta^\nu_G} + \underbrace{\nu_{t,1985}(F_t(y|G,T)) - \nu_{t,1985}(F^c_t(y|G,T))}_{\Delta^\nu_p}\end{aligned}$$

The *composition effect* $\Delta^\nu_G$ represents differences in the composition of observable skills $F_{at}(T|G)$, across locations. The *price effect* $\Delta^\nu_p$ represents differences in the relative remuneration of workers across locations, the conditional CDFs $F_t(\cdot|G,T)$. It consists of two parts: Conditional means $m_t(G,T)$ serve as observed skill prices in different locations. Changes in $F_t(\epsilon|G,T)$ solely reflect an unobserved price effect.

To interpret changes in $F_t(\epsilon|G,T)$, as changes in unobserved prices I assume a *time-invariant* conditional distribution of unobserved skill quantities. I follow Juhn, Murphy, and Pierce (1993) to interpret each residual $\epsilon_{it}(G,T)$ as a product of two unobservables $\epsilon_{it}(G,T) = \rho_t(G,T)u_{it}(G,T)$, where $u_{it}(G,T)$ represents the quantity and $\rho_t(G,T)$ the return to unobserved skills. I assume the mean and variance of the distribution of unobserved characteristics $u(G,T)$ to be independent of time for groups of workers with the same observable characteristics. This allows me to interpret changes in $F_t(\epsilon|G,T)$ solely as changes in the prices of unobserved skills. Any change in the composition of unobservables within groups over time drops out due to the differencing across time. Please note, however, that unobservable individual characteristics—for example, analytical, social skills, or match-specific ability—are still allowed to change over time. Hence, this assumption does not deviate from the literature on within-group wage inequality, where theoretical explanations focus on the effect of technological progress and organizational change on unobservable

individual characteristics. The only assumption here is that the *distribution* of unobserved characteristics within groups of workers with similar observables does not change over time.

All assumptions together allow me to draw implications on the effect of sorting, the effect of spatial differential changes in observed skill prices $F_t(y - m_t(G,T)|G,T)$, and/or spatial differential changes in unobserved skill prices $F_t(\epsilon|G,T)$ for the development of wage inequality.

### 3.3.4 Regression-based decompositions

The previous procedure matches workers directly on their observable characteristics, $G$, and work place location, $T$. This allows a complete nonparametric specification of mean and residual wages. One shortcoming of this approach is that the common support assumption might not be fulfilled for small sample sizes if one wants to include a more detailed set of observable characteristics. Hence, to introduce additional worker- and firm-specific controls, I will follow the approach inspired by Juhn, Murphy, and Pierce (1993). This requires applying a more parametric approach, where group means and residuals are predicted after a simple linear regression.

I regress the (log) wage $y_{igjst}$ of each worker $i$ in location $s$ at time $t$ on skill groups $g$ plus one additional indicator variable $j$ that represents worker- or firm-specific characteristics and varies with the specification. I estimate the regression separately for each year to allow time-varying returns to observable characteristics. Additionally, I interact the independent variables with an indicator of location size to account for location-specific effects, and to be able to adjust the distribution of observables. This gives the following specification to estimate the contribution of observable skills $g$ and additional observable characteristics $j$ for the (log) wage $y_{igjst}$ of each worker $i$ in location $s$ at time $t$:

$$\ln y_{igjst} = \alpha_{gst} + \beta_{gjt} + \delta_{jst} + \epsilon_{igjst}. \tag{3.8}$$

In a first step, I predict conditional means $m_{gjst}$. In a second step, I predict within-group variance terms after a regression of $\epsilon^2$ from the first step on the same set of indicators, as there is not enough information within each cell due to the small sample size. To analyze the different contributions of observable characteristics for the development of wage inequality over time, I decompose the overall variance in

log wages $Var(\ln y_{igjst})$ into "between" and "residual" parts:

$$Var(\ln y_{igjst}) = \sum_{g,j,s} \theta_{gjst} Var(\alpha_{gst} + \beta_{gjt} + \delta_{jst}) + \sum_{g,j,s} \theta_{gjst} Var(\epsilon_{gjst}), \tag{3.9}$$

where $\theta_{gjst}$ is the share of group $gjs$ at time $t$. The first term represents the between part and the second term the within part of the overall variance in log wages. I construct counterfactuals similar to the previous analysis. First, I re-weight quantities with $\theta_{gjs1985}$. Second, I adjust residual variances according to

$$Var^c(\epsilon_{gjst}) = Var(\epsilon_{gj0t}) + Var(\epsilon_{gjs1985}) - Var(\epsilon_{gj01985}). \tag{3.10}$$

## 3.4 Data

Decomposing the role of urbanization in wage inequality requires individual-specific information about wages, education, age, occupation, job tasks, firm-specific data about industry and firm size, as well as location-specific data about the population density of the workplace district.

### 3.4.1 Employment data

This study uses the Sample of Integrated Labour Market Biographies (SIAB 1975–2010), a two percent random sample from the full population of the Integrated Employment Biographies provided by the Institute of Employment Research at the Federal Employment Agency.[8]

I select the sample in a way that limits the possibility that any kind of discrimination (that is, gender or ethnicity) or structural differences between groups of workers (that is, employment status) influence the results. I restrict the sample to German men aged between 21 and 60 years who are employed full-time. I account for multiple job holdings per year and include only observations with one full-time job per year. Hence, workers work at least 27 weeks (185 days) in their job per year. This ensures that I also exclude part-time jobs and jobs in which individuals work less than 50 days per calendar year—the so-called "mini-jobs" (only included after 1999) or jobs in which individuals are undergoing training. Note that workers with

[8]See Dorner, Heining, Jacobebbinghaus, and Seth (2010); vom Berge, Koenig, and Seth (2013). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

a mini-job do not earn more than a legally restricted threshold (for example, EUR 400 in the year 2009). Including them would bias the results. To restrict to full-time workers, I exclude any observation with a daily wage below the marginal part-time income threshold. For example, I exclude any observation with a daily wage less than EUR 13.15 in year 2009.

I select the time period between 1985 and 2009 because wage inequality started to increase in Germany during the mid-1980s. The data also suffers from a structural break in 1984. Bonus payments as well as other one-time payments come on top from 1984 onward. Then I pool years together to improve the precision of the results. For example, I pool the years 1985 to 1987 for the base period, and the years 2008 to 2010 for the end period. This ensures that enough information is included for the analysis. I only concentrate on West Germany, due to structural differences (wage structure, demographic composition, and unemployment rates) between East and West Germany for the years 1985 to 2009.

Earnings information in the SIAB data is right-censored at the social security maximum. According to Card et al. (2013), around 11 percent of male wages are censored each year. Top percentiles, however, play a large role in the development of wage inequality. I follow the imputation procedure of Dustmann, Ludsteck, and Schoenberg (2009) to fully address the problem of censoring. For this, I estimate separate interval regressions for each year. Interval regressions are a generalization of the tobit regression and account for any kind of truncation or censoring. I include three-way interactions between three education-group dummies, six age-group dummies, and eight location-group dummies as controls. I impute the right-censored values as the sum of predicted wages and an error term drawn from a normal distribution. The imputed daily wages then allow me to compute a richer set of wage residuals. In sum, the selected sample, together with the data limitations, provides a lower bound of overall wage inequality in Germany.

To measure work experience, I classify eight age groups (21–28, 29–33, 34–39, 40–45, 45–51, and 52–60 years). The demographic composition of the workforce changed over time. The share of old workers increased, whereas the share of the youngest cohort declined drastically. The share of full-time working men aged 21 to 28, for example, declined from 21 percent in 1985 to 12 percent in 2009. On the other side, the share of full-time working men aged 40 to 45 increased from 15 percent in 1985 to 22 percent in 2009.

To control for skill, I define three different education categories: low (without completed vocational training and post-secondary education that is no Abitur),

medium (completed vocational training/apprenticeship and/or a high school degree that is Abitur), and high (graduated from a university or university of applied sciences). Between 1985 and 2009, on average, 16 percent of the selected sample comprises low-educated, 73 percent medium-educated, and 11 percent highly educated workers. The overall education level of the workforce increased over time. From 1985 to 2009, the share of highly educated workers increased steadily (from eight percent in 1985 to 15 percent in 2009). Correspondingly, the share of low-educated workers declined (from 20 percent in 1985 to 14 percent in 2009).

Later in the analysis, I rely on additional measures of skill. I use a classification of occupations into 12 different categories introduced by Blossfeld (1985): agricultural occupations, simple manual occupations, qualified manual professions, technicians, engineers, simple services, qualified services, semi professions, professions, simple commercial and administrative professions, qualified commercial and administrative professions, and managers.

Moreover, I control for different main job tasks performed at each occupation. For this, I merge information based on the expert database BERUFENET of the German Federal Employment Agency provided by Dengler, Matthes, and Paulus (2014). The data differentiates between five main job tasks: analytical non-routine tasks, interactive non-routine tasks, cognitive routine tasks, manual routine tasks, and manual non-routine tasks.

I merge establishment characteristics, like the place of work, the size of the firm (that is, the total number of employees), and the branch of economic activity from the Establishment History Panel (BHP) to the individual characteristics of the SIAB file. To control for firm size, I generate five groups based on the information on the number of full-time workers per establishment. The size of the firms ranges between 0–9, 10–49, 50–199, 200–499, and above 500 workers. As a measure for the different industry structures, I construct 10 groups based on time-consistent one-digit industry codes of the classification of economic activities (w93).

### 3.4.2 Population data and consumer price index

Information on population density and the consumer price index (CPI) comes from the German Statistical Office (Destatis). I deflate wages with the national CPI and choose 1995 as the base year. To define rural and urban areas, I combine information about population density with a classification scheme from the Institute for Research

on Building, Urban Affairs and Spatial Development (BBSR). $T = 0$ represents rural and $T = 1, ..., 7$ urban districts.

Then I allocate urban districts to eight different size classes according to the percentiles of the urban population density distribution in 2009. Hence, $T = 7$ represents the largest, most densely populated urban locations.

## 3.5 Results

To identify the role of urbanization in wage inequality, I compare the change in actual inequality with counterfactual changes in inequality. I use the actual trends in wage inequality (variance and percentile gaps) from Table 3.1 as the benchmark for the subsequent analysis. Specifically, I study the contribution of (i) increased sorting of workers across locations and (ii) changes in relative remuneration for skills across locations of different sizes. With the first counterfactual scenario (CF1), I examine the contribution of sorting and fix the distribution of workers at the 1985 values. With the second counterfactual scenario (CF2a), I presume the same change in residual wages across all locations conditional on skill. Then I examine the importance of distinct changes in the wages of several skill groups across locations that differ in size. But, in addition, I hold the impact of location size within skill groups constant over time (CF2b). This gives me the full effect of location size for wage inequality. Finally, I abstract from skill groups (CF3) to highlight the importance of the observed skill composition for the *location-inequality premium.*

### 3.5.1 Decomposing the role of urbanization for wage inequality

**Sorting.** Table 3.2 presents percentage reductions in the change in counterfactual statistics relative to actual inequality statistics.[9] Column 1 shows that sorting across locations was not important for the change in wage inequality during any of the sample periods. Shifts in the skill composition across locations had almost no effect on any measure of wage inequality.

**Residual Prices.** I reweight quantity, as in Column 1, and residual components together. To construct counterfactual residual distributions, I apply the CIC procedure with rural locations as the reference group and urban locations as different

[9]For similar results of residual wage inequality, see Table 3..4 in the Appendix **??**.

"treatment groups." This method presumes for urban workers within a specific skill group the same change in unobserved skill prices (that is, residual wages) as in rural areas. Mean log wages within the skill group, $m_t(G)$, however, vary freely over time. Column 2, Panel (a) documents a relatively higher growth of actual compared to counterfactual inequality. It documents a reduction in the growth of the variance in wages by 28 percent between 1985 and 2009. If observed quantities and unobserved skill prices had not changed across locations as they did, the variance of log (real) wages would have grown 28 percent less than it actually did. The main contribution to the increase in wage inequality comes from a greater dispersion of unobserved skill prices across locations over time. The relevance of unobserved skill prices for the location size effect, however, is unbalanced between the upper and lower parts of the distribution. For the 85–50 percentile gap, Panel (b) documents a reduction in inequality by 77 percent between 1985 and 2009. For the 50–15 percentile gap, Panel (c) reports a rise of 17 percent.

**Total Prices.** Column 3 presents the full effect of location size for wage inequality. The results indicate that a greater dispersion of unobserved and observed skill prices in larger locations have contributed to the *location-inequality premium.* Panels (b) and (c) show a positive effect of location size for the 85–50 percentile gap and a negative effect for the 50–15 percentile gap. Column 3, Panel (a) documents the full effect of location size. It accounts for around 28 percent of the increase in the variance, independent of observable skill. Comparisons of Columns 2 and 3 reveal that differences in unobserved skill prices mainly drive the *location-inequality premium.*

**Skill Composition.** A comparison of the results in Column 4 with the results in Column 3 allows me to draw implications about the importance of the observed skill composition for the *location-inequality premium.* The results show that the effect of location size depends on the observed skill composition. Not accounting for the observed skill composition reduces the *location-inequality premium* by 19 percent, from 28 percent to 23 percent. For the 85–50 percentile gaps, the observed skill composition is highly important. Comparisons of Column 4 with Column 3 show a reduction in the *location-inequality premium* by 99 percent—from 77 percent to one percent. For the 50–15 percentile gaps, however, not accounting for the observed skill composition leads to a reversion of sign, from -17 percent to 12 percent.

In sum, the results so far show that workers are increasingly paid unequally in West German cities. The decomposition suggests that wage inequality would have

Table 3.2: The role of urbanization in the development of total log wage inequality

| Re-weighting: | CF1 Quantities | CF2a Residuals and Quantities | CF2b Total Prices and Quantities | CF3 Total Prices and Quantities |
|---|---|---|---|---|
| | | (a) Variance | | |
| 1985 to 2001 | -2% | 47% | 47% | 35% |
| 1985 to 2009 | -2% | 28% | 28% | 23% |
| | | (b) 85–50 Percentile Gap | | |
| 1985 to 2001 | 5% | 93% | 81% | -18% |
| 1985 to 2009 | 2% | 70% | 77% | 1% |
| | | (c) 50–15 Percentile Gap | | |
| 1985 to 2001 | -6% | -16% | -17% | 18% |
| 1985 to 2009 | -5% | -17% | -17% | 12% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,765$. The numbers indicate the reduction in the growth of total log wage inequality. For each counterfactual scenario (listed in the column headers), the development of inequality measures are compared to the actual change (see Table 3.1, Panel (b), Columns 5–7).
*Interpretation:* Column 2, Panel (a) documents a reduction in the growth of the variance in wages by 28 percent between 1985 and 2009. Without changes in observed quantities and unobserved skill prices across locations, the variance in log (real) wages would have grown 28 percent less than it actually did.

grown 28 percent less than it actually did, when I shut down location size-specific wage developments. This general result is in line with the recent findings of Baum-Snow and Pavan (2013) for the US, where a more rapid growth in larger locations explains around 23 percent of the overall increase in the variance in wages between 1979 and 2007. A conservative comparison of the results with the findings of Baum-Snow and Pavan (2013) confirms the importance of more rapid growth in within-group inequality in larger locations compared to smaller locations. However, changes in observed skill prices were less important for the development of wage inequality in West Germany. Baum-Snow and Pavan (2013) also find evidence of a larger dispersion in the prices of observed skills. Hence, they even play the opposite role in West Germany than in the US, pushing the *location-inequality premium* down rather than up. Moreover, the decomposition reports a different importance of location size for the upper and lower parts of the wage distribution in West Germany. Specifically, Baum-Snow and Pavan (2013) find for the US that location size effects were large and positive at the upper part of the wage distribution and small (but still positive)

at the lower part of the distribution. In West Germany, however, the effects are massive and positive at the upper part of the wage distribution but negative (and sizable) at the lower part of the distribution. This asymmetric effect of location on the upper and lower tails of the wage distribution has also been recently described by Ma and Tang (2016) for the US.

### 3.5.2 Unequal pay in cities: The role of worker and firm characteristics

To better understand the underlying channels and differences between the US and Germany, I proceed to analyze how differences between worker and firm characteristics affect the *location-inequality premium*. I consider a richer set of observable characteristics to investigate the role of location size in determining the change in wage inequality independently of additional direct measures of skill. I control for the distribution of industry (10 categories), occupation (12 categories), and main job task (five categories) across localities. I include occupations or main job tasks (analytical non-routine, interactive non-routine, cognitive-routine, manual-routine, and manual non-routine) as additional indicators to control for the spatial dimension of the technological change and to examine the spatial dimension of relative changes in job tasks across time. Furthermore, I add an indicator for firm size (five categories) as a proxy for the heterogeneity of firm productivities across locations.

From now on, I follow the regression-based approach introduced above. I have to switch the methodology because the SIAB data set does not provide enough information to define for each specific group residuals and mean wages in a nonparametric way as was done before. Recall that the common support condition requires every value of each covariate to appear in combination with every value of skill groups across locations. To fulfill the assumption of common support, I follow the standard solution proposed in the literature and redefine the groups of observable characteristics. I define four age groups and combine them with three education groups. This gives me 12 demographic groups that I use as controls for skill. To construct counterfactuals, I proceed as before.

**Occupational structure or job tasks.** The classification of occupations highly correlates with the job tasks structure in such a way that the decomposition provides similar results for both of them. Table 3.3 shows the results with 12 occupation groups and Table 3..7 in the Appendix reports the results with five main job tasks. Columns 4 to 6 report the effects of changing quantities and prices together. Column

4 shows that accounting for occupation or job tasks, location size has more or less no impact on the growth of the between-variance component over the full sample period. Columns 5 and 6 report a *location-inequality premium* of 25 percent for the residual variance and 18 percent for the total variance over the full sample period. Comparisons of Panel (a) and (b) show that up to one-half of the *location-inequality premium* is due to the different occupational or job task structures across locations. This effect is mainly driven by changes in residual prices. The sorting of workers across locations within occupations or the main job task explains only a small part of the increase in wage inequality over time. Hence, occupations or main job tasks with a greater increase in wage inequality have already been concentrated in larger locations in 1985.

**Firm size distribution or industrial structure.** Next, to analyze the importance of differences between firms, I account for the spatial pattern of industries and the firm size distribution. Tables 3..5 and 3..6 in the Appendix report the results of the decomposition with five firm-size groups or 10 industry groups as additional controls. Both specifications are comparable to the previous results. They report 31 percent to 26 percent for the residual variance and 16 percent to 18 percent of the total variance. Most of the *location-inequality premium* is due to increases in residual inequality. A comparison of Panels (a) and (b), however, shows that the firm size distribution explains only one-third of the *location-inequality premium.* A different remuneration within the same firm-size group across locations contributes slightly to the *location-inequality premium.* For example, high-wage workers in large firms face higher inequality in larger locations compared to smaller locations. Up to one-fourth is due to the industrial composition.

In sum, the results suggest that a more heterogeneous compensation of workers with the same occupation or the same main job task explains around one-half of the *location-inequality premium.* In contrast, firm size explains only one-third of the location-inequality premium, while industry structure across locations explains only one-fourth. The largest part of the location-inequality premium is due to a more rapid growth in inequality between workers with an initially high within-group inequality in larger cities. I conclude that changes in the compensation of worker characteristics explain most of the location premium. Workers in high-wage occupations—for example, engineers or managers—now face higher inequality in larger locations compared to smaller locations.

### 3.5.3 A breakdown of the location-inequality premium

The previous results have shown that the specifications with occupations or main job tasks as additional controls explain the largest part of the *location-inequality premium*. Now, I calculate how much the skill sorting across locations and the composition of locations explain the size of the effect. For each specification, I compare again the actual with the counterfactual change in the variance in log wages. But I calculate the counterfactual with only location size as a covariate in the regression (that is, I exclude skill groups). This gives me a *location-inequality premium* that varies according to the sample size of each specification, and allows me to isolate the role of worker and firm characteristics in relation to the *location-inequality premium*.

Table 3.3: Changes in the variance of log wages: The role of occupations

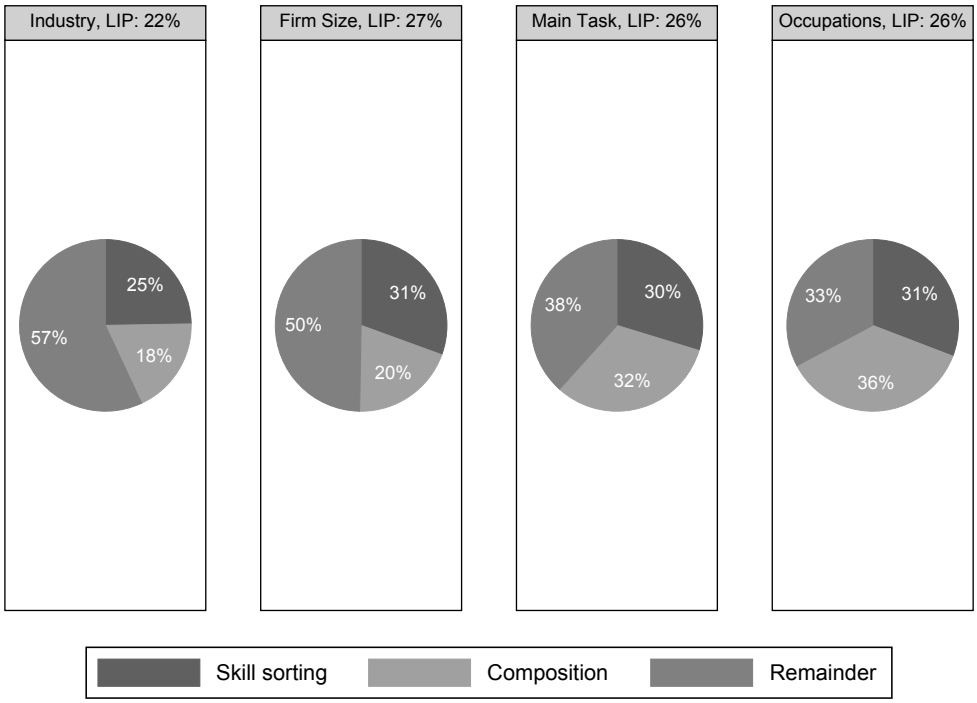
| Re-weighting: | Quantities | | | Prices and Quantities | | |
|---|---|---|---|---|---|---|
| | Between | Residual | Total | Between | Residual | Total |
| | | | (a) Skill, Occupation, and Location Size | | | |
| 1985 to 2001 | -1% | -2% | -2% | -6% | 24% | 14% |
| 1985 to 2009 | -1% | -2% | -1% | -1% | 16% | 9% |
| | | | (b) Skill and Location Size | | | |
| 1985 to 2001 | -5% | -1% | -2% | 23% | 39% | 33% |
| 1985 to 2009 | -3% | -1% | -2% | 9% | 25% | 18% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 527,061$. Analogously to Tables 3..4 and 3.2, the numbers indicate a reduction in growth between the actual and counterfactual development of variance in wages. Counterfactual adjustments of prices and/or quantities are calculated as before. But group means and residuals are predicted after running a regression model that also includes occupation indicators interacted with age or education and separately with location size categories.

Figure 3.2 summarizes the breakdown of the *location-inequality premium* from 1985 to 2009.[10] The header presents the proportion of growth of the variance that is due to location size. Then, based on the previous results, each pie chart represents how much the following parts help to explain the *location-inequality premium*: (i) skill sorting across locations, (ii) the composition of locations based on the worker (occupational or main job task composition) or firm characteristics (industry or

[10]See Tables 3..8 to 3..10 in the Appendix for the individual results of the decomposition.

Figure 3.2: A breakdown of the location-inequality premium




*Notes:* The figure plots the breakdown of the location-inequality premium (LIP) for each specification, including worker or firm characteristics in addition to skill. The following parts explain the location-inequality premium: (i) skill sorting across locations, (ii) the composition of locations based on the observable worker (occupational or main job task composition) or firm characteristics (industry or firm size structure), and (iii) a remainder.

firm size structure), and (iii) a remainder that is difficult to interpret. Baum-Snow and Pavan (2013) relate the unexplained part to additional productivity generated through agglomeration economies. All specifications report a *location-inequality premium* between 22 and 27 percent, and a remainder between 33 and 57 percent. The results confirm that worker characteristics—like occupational structure and main job tasks—are more important than firm characteristics for the *location-inequality premium.*

The specification with indicators for industry or firm size as additional covariates in the regression report a *location-inequality premium* between 22 percent and 26 percent. Skill sorting across locations explains 25 percent to 31 percent of the *location-inequality premium.* Industry composition accounts for 18 percent and firm-size distribution across locations accounts for 20 percent of the *location-inequality premium* between 1985 and 2009. Both specifications explain only up to one-half of the *location-inequality premium* with a remainder of 50–57 percent. Analogously, in the specification with occupations as additional covariates, the *location-inequality*

*premium* is 26 percent. It consists of 31 percent that is due to sorting across locations, 36 percent that is due to occupational structure, and a remainder of 33 percent. For the specification with main job tasks, I obtain a *location-inequality premium* of 26 percent. Sorting across locations explains 30 percent, the main job task performed by workers explains 32 percent, and 38 percent remains unexplained.

## 3.6 Conclusions

Urbanization plays a positive role in the rise of German wage inequality between 1985 and 2009. Today, groups of workers who already had unequal pay in 1985 face higher wage dispersion in larger, more densely populated locations compared to smaller, less densely populated locations. To identify this *location-inequality premium*, I construct counterfactual distributions that keep the composition of observable skills and relative remuneration at 1985 values. Comparisons of actual with counterfactual changes in inequality reveal that around one-third of the increase in the variance of wages is due to population density independent of the observed skill heterogeneity of workers across locations. To account for the most important explanations, I decompose the change in wage inequality into a composition effect, which represents the distribution and sorting of workers across locations, and a price effect, which describes divergent changes in remuneration across space. A higher increase in within-group inequality in larger, more densely populated locations drives the *location-inequality premium*. Hence, a larger increase in residual inequality, especially in larger locations, is important to explain the change in German wage inequality.

To get a better understanding of the underlying channels of the *location-inequality premium*, I study additional worker- and firm-specific dimensions, like the distribution of firm size, occupational structure, and job tasks. This gives me a finer depiction of the composition of cities. I calculate how much the skill sorting across locations and the composition of locations, according to the additional observable characteristic, explain the size of the effect. Up to one-half of the effect is due to occupation or main job task, one-third due to firm size, and up to one-fourth is due to the industrial structure. The largest part of the *location-inequality premium* is due to a greater wage inequality within groups of workers that are generally more concentrated in larger locations. An increased sorting of employees on the basis of their observable skills did not contribute to the increase in wage inequality since the mid-1980s. A breakdown of the *location-inequality premium*, however, reveals that

the skill sorting of workers within worker- and firm-specific groups explains up to one-third.

In sum, cities pay their workers in an increasingly unequal manner. The increased unequal pay of similar workers especially in larger cities is also documented by Baum-Snow and Pavan (2013) for the US. Some interesting results about the (West) German experience, however, stand out. First, location size has positive effects at the upper part and a negative influence at the lower part. Second, the results suggest that the dispersion of wages between skill groups plays the opposite role in West Germany compared to the US. I contribute to the literature and show that especially high-inequality occupations or job tasks drive the *location-inequality premium*.

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# Appendix

Table 3..4: The role of urbanization in the development of residual log wage inequality

| Re-weighting: | CF1 Quantities | CF2 Residuals and Quantities | CF3 Residuals and Quantities |
|---|---|---|---|
| | | (a) Variance | |
| 1985 to 2001 | -1% | 59% | 25% |
| 1985 to 2009 | -1% | 40% | 1% |
| | | (b) 85-50 Percentile Gap | |
| 1985 to 2001 | -3% | 44% | -21% |
| 1985 to 2009 | -3% | 54% | -22% |
| | | (c) 50-15 Percentile Gap | |
| 1985 to 2001 | -4% | 26% | 31% |
| 1985 to 2009 | -3% | 16% | 15% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,765$. The numbers indicate the reduction in growth of total log wage inequality. For each counterfactual scenario (listed in the column headers), the development of inequality measures is compared to the actual change (see Table 3.1, Panel (b), Columns 5–7).
*Interpretation:* Column 2, Panel (a) documents a reduction in growth of the variance in wages by 28 percent between 1985 and 2009. Without changes in the observed quantities and unobserved skill prices across locations, the variance in log (real) wages would have grown 28 percent less than it actually did.

Table 3..5: Changes in the variance in log wages: The role of industry

| Re-weighting: | Quantities | | | Prices and Quantities | | |
|---|---|---|---|---|---|---|
| | Between | Residual | Total | Between | Residual | Total |
| | | | (a) Skill, Industry, and Location Size | | | |
| 1985 to 2001 | -8% | 2% | -1% | -4% | 25% | 18% |
| 1985 to 2009 | -5% | 1% | -1% | 1% | 19% | 12% |
| | | | (b) Skill and Location Size | | | |
| 1985 to 2001 | -5% | -1% | -2% | 0% | 36% | 27% |
| 1985 to 2009 | -3% | 0% | -1% | -1% | 26% | 16% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,765$. Analogously to Tables 3..4 and 3.2, the numbers indicate a reduction in growth between the actual and counterfactual development of the variance in wages. Counterfactual adjustments of prices and/or quantities are calculated as before. But group means and residuals are predicted after running a regression model that also includes one-digit industry indicators interacted with age or education and separately with location size categories.

Table 3..6: Changes in the variance in log wages: The role of firm size

| Re-weighting: | Quantities | | | Prices and Quantities | | |
|---|---|---|---|---|---|---|
| | Between | Residual | Total | Between | Residual | Total |
| | | | (a) Skill, Firm Size, and Location Size | | | |
| 1985 to 2001 | -4% | 0% | -1% | -7% | 35% | 22% |
| 1985 to 2009 | -2% | 0% | -1% | -3% | 25% | 13% |
| | | | (b) Skill and Location Size | | | |
| 1985 to 2001 | -3% | -2% | -2% | 9% | 45% | 33% |
| 1985 to 2009 | -2% | -1% | -2% | 1% | 31% | 18% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,767$. Analogously to Tables 3..4 and 3.2, the numbers indicate a reduction in growth between the actual and counterfactual development of the variance in wages. Counterfactual adjustments of prices and/or quantities are calculated as before. But group means and residuals are predicted after running a regression model that also includes firm size indicators interacted with age or education and separately with location size categories.

Table 3..7: Changes in the variance in log wages: The role of main job task

| Re-weighting: | Quantities | | | Prices and Quantities | | |
|---|---|---|---|---|---|---|
| | Between | Residual | Total | Between | Residual | Total |
| | | | (a) Skill, Main Job Task, and Location Size | | | |
| 1985 to 2001 | -3% | -1% | -2% | -5% | 36% | 21% |
| 1985 to 2009 | -2% | 0% | -1% | -2% | 20% | 10% |
| | | | (b) Skill and Location Size | | | |
| 1985 to 2001 | -4% | -1% | -2% | 22% | 41% | 34% |
| 1985 to 2009 | -3% | -1% | -2% | 11% | 25% | 18% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 516,976$. Analogously to Tables 3..4 and 3.2, the numbers indicate a reduction in growth between the actual and counterfactual development of the variance in wages. Counterfactual adjustments of prices and/or quantities are calculated as before. But group means and residuals are predicted after running a regression model that also includes main job task indicators interacted with age or education and separately with location size categories.

Table 3..8: A breakdown of the location-inequality premium: Industry

| | Between | Residual | Total |
|---|---|---|---|
| | | (a) 1985 to 2001 | |
| Total location size-specific | 25% | 30% | 29% |
| Skill sorting across locations | 101% | -19% | 6% |
| Group sorting across locations | 13% | 37% | 32% |
| Remainder | -14% | 83% | 62% |
| | | (b) 1985 to 2009 | |
| Total location size-specific | 27% | 18% | 22% |
| Skill sorting across locations | 104% | -41% | 25% |
| Group sorting across locations | -7% | 40% | 18% |
| Remainder | 4% | 102% | 57% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,765$.

Table 3..9: A breakdown of the location-inequality premium: Firm size

| | Between | Residual | Total |
|---|---|---|---|
| | | (a) 1985 to 2001 | |
| Total location size-specific | 33% | 43% | 40% |
| Skill sorting across locations | 74% | -4% | 17% |
| Group sorting across locations | 47% | 21% | 28% |
| Remainder | -21% | 83% | 55% |
| | | (b) 1985 to 2009 | |
| Total location size-specific | 27% | 26% | 26% |
| Skill sorting across locations | 95% | -18% | 31% |
| Group sorting across locations | 16% | 23% | 20% |
| Remainder | -11% | 96% | 50% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 533,767$.

Table 3..10: A breakdown of the location-inequality premium: Main job task

| | Between | Residual | Total |
|---|---|---|---|
| | | (a) 1985 to 2001 | |
| Total location size-specific | 40% | 42% | 41% |
| Skill sorting across locations | 45% | 2% | 17% |
| Within-group sorting across locations | 68% | 12% | 31% |
| Remainder | -13% | 86% | 52% |
| | | (b) 1985 to 2009 | |
| Total location size-specific | 33% | 21% | 26% |
| Skill sorting across locations | 67% | -20% | 30% |
| Within-group sorting across locations | 39% | 22% | 32% |
| Remainder | -6% | 98% | 38% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 516,976$.

Table 3..11: A breakdown of the location-inequality premium: Occupation

| | Between | Residual | Total |
|---|---|---|---|
| | | (a) 1985 to 2001 | |
| Total location size-specific | 49% | 36% | 40% |
| Skill sorting across locations | 53% | -7% | 17% |
| Group sorting across locations | 59% | 40% | 47% |
| Remainder | -12% | 67% | 36% |
| | | (b) 1985 to 2009 | |
| Total location size-specific | 36% | 19% | 26% |
| Skill sorting across locations | 74% | -32% | 31% |
| Group sorting across locations | 30% | 45% | 36% |
| Remainder | -4% | 87% | 33% |

*Source:* SIAB sample for full-time working men between 21 and 60 years of age.
*Notes:* $N = 527,061$.

# Conclusion

In this dissertation I have analyzed the causes and consequences of spatial inequality.

Theoretically, I have applied a quantitative spatial model to study the implications of European integration and to show that regional income transfers are quantitatively important for understanding the spatial allocation of economic activity. First, the dismantling of trade barriers in Europe has led to a more homogeneous spatial distribution of economic activity. Second, the abolishment of fiscal equalization in Germany would lead to a moderate welfare gain of about 0.33 percent implying migration of about 5 percent of the population in the long run.

Empirically, I have shown that in the particular context of (West) Germany, location size itself is an important driver of economic inequality within regions. Especially, cities pay their workers in an increasingly unequal manner. Urbanization contributed about one-third to the growth of overall wage inequality between 1985 and 2009.

A fruitful direction for future research would be, for example, to develop a dynamic model and examine how bilateral capital flows affect the spatial distribution of economic activity. In particular, how investment decisions—in an incomplete financial markets environment—affect the growth and decline of regions.