

Essays in Empirical Economics

Inaugural-Dissertation
zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von:
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aus Fürth

Kiel, 2024

Gedruckt mit Genehmigung der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

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Tag der Abgabe der Arbeit:	22.11.2024
Tag der mündlichen Prüfung:	06.03.2025

Acknowledgments

On this page I would like to mention those people who have shaped my past six years as a Ph.D. student at Kiel University and as a researcher at the Institute for Employment Research (IAB).

First of all, I would like to thank my supervisor, Prof. Annekatrin Niebuhr. She is the main reason for the start of this thesis and especially for its completion. She always had time for questions, and with her countless comments and remarks, she massively advanced this thesis. I would also like to thank my second supervisor, Prof. Jens Ruhose, for his help, feedback and support during the past years.

I thank Dr. Anja Rossen and Dr. Jan Cornelius Peters, with whom I could co-author the paper of the second chapter. After the last years I am more than happy to call them not only colleagues but also friends. Their experience benefited me greatly, and I learned a lot from their comments and suggestions as co-authors and colleagues. My sincere thanks go to my co-authors for the third chapter, Prof. Rainald Borck and Dr. Robert Gold, for their invaluable contributions and collaboration.

I would like to thank my department head at the IAB, Stefan Fuchs, who has always supported me and helped me with various administrative tasks. Furthermore, I want to mention the colleagues in the IAB Northern Germany who have created a pleasant working atmosphere over the last years.

I would like to thank my family and friends. In particular, my mother, Elisabeth Albrecht-Meister and my siblings, Kai, Anne and Paul who were always there for me and made my several visits at the IAB in Nuremberg the most enjoyable.

Last but not least, the greatest thanks goes to my partner, Friederike Gut. She supported me at all times and she is the first person with whom I could share the successes and failures during the writing of this thesis.

In memory of and with great gratitude to my father, Dr. Günter Meister, who sadly passed away during the writing of this thesis. You will always be a great role model to me.

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Introduction

My dissertation, entitled “*Essays in Applied Economics*”, contains three chapters. Each chapter is an independent paper. Together, they examine important socio-economic phenomena in Germany. The chapters use unique datasets and rigorous econometric methods to provide insights into different but interrelated aspects of applied microeconomics, from labor economics to internal migration and political economy. Together, these essays seek to contribute to our understanding of crucial issues related to labor market responses to global trade shocks, the effectiveness of migration policies, and the socioeconomic determinants of the election results of the far-right. They provide a comprehensive understanding of how economic and social factors interact to shape labor markets and political landscapes in contemporary Germany.

Chapter 1, titled “*Labor Market Impact of Disruptions in Global Value Chains*” investigates the causal impact of global value chain (GVC)-related trade on the German labor market during the COVID-19 crisis. To identify the causal effect of GVC-related trade on the level of short-time work (STW) during the COVID-19 pandemic, I use a continuous treatment difference-in-differences approach combined with entropy balancing and time-varying regional control variables. I use monthly establishment-level data on short-time work from 2019 to 2021 and combine it with information on GVC-related trade.

The results indicate that German establishments register more STW from May 2020 to October 2020 if they are located in economic sectors that rely more on GVC-related trade with China. During that time, an increase in GVC-related trade with China of one standard deviation increases the share of STW by, on average, 5.5 percentage points. However, the significant effects observed for GVC-related trade with China are temporary and already decline during the second half of

2020. For the period when the effects are significantly different from zero, a one standard deviation higher GVC-related trade with China gives rise to an additional spending of approximately €7.3 billion on STW according to the regression results. In contrast to GVC-related trade with China, there is no significant relation between STW and worldwide (excluding China) GVC-related trade for German establishments during the pandemic. The results suggest, in line with findings of other studies, that policies such as “reshoring” large parts of global value chains are probably misguided. Instead, supply chain resilience to shocks is better built by increasing diversification. Efficient strategies could include easier supply and demand switching between trade partners and reducing bottlenecks along the value chains by increasing the number of trade partners (International Monetary Fund, 2022; Lebastard et al., 2023).

Chapter 2, titled “*Welcome back! The impact of ‘return initiatives’ on return migration to rural regions*” is joint work with Anja Rossen and Jan Cornelius Peters. We study the effect of return initiatives in rural regions of Germany on interregional return migration. The initiatives aim to increase return migration by, amongst other things, providing information on local employment opportunities and personal support to workers interested in returning to find a job in the former rural region of residence. For our analysis, we merge information on workers labor market biographies with data on regional return initiatives for the years 2000 to 2014. Our identification strategy rests on exploiting the spatio-temporal variation in the establishment of return initiatives and the information on individual return migration decisions. For this, we combine event history analysis and difference-in-differences estimation in a panel event study framework to estimate the likelihood to return after the establishment of a return initiative.

Our results indicate that the return initiatives considered, on average, promote

return migration. However, the estimates also point to heterogeneous effects. First, the increase in return migration seems to occur not immediately in the year in which a return initiative is established, but with a time-lag of two to three years. Second, we find that the results are driven by workers in the middle and at the top of the wage distribution. Here, we observe a statistically and economically significant impact of return initiatives on the likelihood to return. This is not observed for workers at the bottom of the wage distribution. The fact that return initiatives have a greater effect on workers with arguably relatively high abilities could be particularly advantageous for rural regions, which often face a lack of skilled labor. Furthermore, results by Fajgelbaum and Gaubert (2020) suggest that overall welfare might also in principle increase if return initiatives contribute to the redistribution of more skilled workers to rather peripheral areas.

Chapter 3 titled *“The Urban-Rural Divide in Support of the Far-Right”* is joint work with Rainald Borck and Robert Gold. We examine the urban-rural divide in right-fringe voting support from Germany. Although we do not propose a causal explanation for urban-rural voting gaps, our analysis helps us understand spatial patterns in right-fringe voting results. We use a unique election dataset with municipality-level information which is constructed from different data sources for the period 2001-2019. Further we merge this dataset with detailed information on the population as well as labor market characteristics. For the empirical analysis, we use a panel regression approach with region and time fixed effects. In order to observe heterogeneous effects over time and space, we estimate the model for several subsamples.

Our results document an existing urban-rural divide in Germany. On average, right-fringe parties receive a 0.3 percentage points lower vote share in cities with more than 20,000 inhabitants. Since urban and peripheral regions differ in the

composition of their residents, we examine whether – and in how far – the urban-rural voting patterns are driven by the differing composition of their population. Following the literature (see, among others Aggeborn and Persson, 2017; Cavaille and Marshall, 2019; Dustmann et al., 2018; Geys et al., 2022), we analyze the importance of qualification, foreigners, age structure, and wages. We find that our channels individually and jointly can explain the urban-rural populism gap. Hence, sorting of individuals by different characteristics explains the observed urban-rural gaps in the election results of the far-right. We also uncover substantial East-West differences in the relative importance of the different drivers of the urban-rural divide. For West Germany, we find an urban-rural gap in the early period 2001-2010. The effect for the urban-rural gap vanishes when we control for our channels. For East Germany, the urban-rural gap is rather persistent over time.

In conclusion, this dissertation presents three distinct studies that collectively deepen our understanding of how international trade integration, regional policies, and regional characteristics in urban and rural areas shape socioeconomic outcomes in Germany. By addressing unique aspects of labor market resilience, migration, and political dynamics, the chapters provide a nuanced view of the forces that may influence economic outcomes and social cohesion.

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Chapter 1

Labor Market Impact of Disruptions in Global Value Chains*

Moritz Meister

Abstract This paper investigates the causal effect of global value chain (GVC)-related trade on the German labor market during the COVID-19 crisis, using a difference-in-differences approach combined with entropy balancing. The analysis of monthly establishment-level data from January 2019 to December 2021 shows that a one standard deviation increase in GVC-related trade with China leads to an increase in short-time work by, on average, 5.5 percentage points from May to October 2020, where significant positive effects are observed. For this period, the regression results imply that a one standard deviation increase in GVC integration gives rise to an additional expenditure on short-time work of around €7.3 billion. In contrast, GVC-related trade with the whole world as a trading partner does not show a significant impact. Additional survey data support these findings, suggesting that establishments that are more GVC-integrated with China face more difficulties in obtaining inputs or dealing with suppliers in 2020.

*A earlier version of the chapter is available as: Meister, Moritz (2024). *"Labor Market Impact of Disruptions in Global Value Chains"*. IAB-Discussion Paper 10|2024, URL: <https://doku.iab.de/discussionpapers/2024/dp1024.pdf>.

I would like to thank the German Research Foundation (*Deutsche Forschungsgemeinschaft*) as part of the project *"Exploring the impact of COVID-19 on regional resilience and disparities in Germany and China"* (NI 596/7-1) for financial support.

1.1 Introduction

In December 2019, a new coronavirus emerged in Wuhan, China. Not even four months later, the World Health Organization declared the resulting novel viral disease (COVID-19) a pandemic. Not long later, lockdowns and closed borders affected almost every country in the world. Global trade largely came to a standstill. The impact was so great that *The Economist* asked on 14th of May 2020: “*Has COVID-19 killed globalization?*” (The Economist, 2020). In the second quarter of 2020, global trade in goods fell by about 12% compared to the last quarter of 2019. In particular, the volatility of trade in goods that rely heavily on global value chains (GVCs) was high (International Monetary Fund, 2022). In addition, Bonadio et al. (2021) show that countries and economic sectors were more negatively affected if the trading partner in GVC-related trade had stronger and longer lockdowns. These negative consequences, especially at the beginning of the crisis, have renewed the debate on the costs and benefits of globalization in general and on the dependence of GVCs in particular (Arriola et al., 2020). As a result, there is now a debate as to whether increased domestic production, “reshoring”, or greater diversification of GVCs will cushion the negative impact of future shocks (Alvarez et al., 2022; Essletzbichler et al., 2021).

Within this growing canon of literature, the impact on the labor market of a country that is highly integrated in GVCs, such as Germany, has not yet been considered. The integration of Germany in international trade of goods and services is of great importance and has increased in the last two decades. The share of imported and exported goods and services with respect to GDP increased from 32% in 2001 to 47% in 2021. In the same period, the average of all OECD countries increases from 22% in 2001 to 30% in 2021 (OECD, 2023). Further, there is a lack of empirical evidence on whether the disruptions of GVCs during the pandemic

differ between trading partners. This paper aims to fill this gap in the literature and empirical research. In particular, I analyze the specific role of China for the German labor market compared to the general integration in GVCs for the German economy. China is of great interest even after the pandemic, according to a European Central Bank survey. European firms mention China most frequently in terms of perceived risks, either in the company's own supply chain or that of its economic sector. In addition, firms responded that China is the dominant source of critical input (European Central Bank, 2023).

This paper focuses on the economic effects of the disruptions of GVCs during the COVID-19 crisis and the related impact on the German labor market. I investigate whether the level of integration into GVCs has influenced short-time work (STW) of establishments in Germany during the pandemic.² To identify the causal effect of GVC-related trade on the level of STW during the COVID-19 pandemic, I exploit the sectoral variation in GVC-related trade in a difference-in-differences (DiD) setup. The empirical strategy consists of a DiD model with a continuous treatment exposure combined with entropy balancing and time-varying regional control variables. I use monthly information on short-time work from January 2019 to December 2021 and combine it with the OECD Inter-Country Input-Output tables that provide information on GVC-related trade (OECD, 2022). In addition, survey information from the *Institute for Employment Research (IAB) Establishment Panel* and process data from the *IAB Establishment History Panel* are used to control for establishment heterogeneity.

The results indicate that German establishments register more STW from May 2020 to October 2020 if they are located in economic sectors that rely more on GVC-related trade with China. During that time, an increase in GVC-related trade

²Establishment is the unit of observation in the analysis. An establishment might be a branch of a company in a specific location. This also includes parts of a company that are affiliated locally and organizationally. At least one employee must work on behalf of the company (Destatis, 2024).

with China of one standard deviation increases the share of STW by on average 21.5 percentage points. However, the significant effects observed for GVC-related trade with China are temporary and already decline during the second half of 2020. For the period when the effects are significantly different from zero, from May to October 2020, a one standard deviation higher GVC-related trade with China gives rise to an additional spending of approximately €7.3 billion on STW according to the regression results. In contrast to GVC-related trade with China, there is no significant relation between STW and worldwide (excluding China) GVC-related trade for German establishments during the pandemic. The results support the findings of other studies which suggest that policies such as “reshoring” large parts of global value chains are probably misguided. Instead, supply chain resilience to shocks is better built by increasing diversification. Efficient strategies could include easier supply and demand switching between trade partners and reducing bottlenecks along the value chains by increasing the number of trade partners (International Monetary Fund, 2022; Lebastard et al., 2023).

The remainder of this paper proceeds as follows. Section 1.2 provides a brief overview of the evidence on the economic effects of GVC disruptions caused by the pandemic and discusses how the paper adds to the literature. In Section 1.3, I describe the data sources and how I link them, while I explain the indicators applied to measure the integration of GVC in Section 1.4. In Section 1.5, I describe the empirical model and the identification strategy. Section 1.6 presents and discusses the results of the regression analysis. Section 1.7 provides further insight into the mechanism behind the results. In addition, some robustness are presented in this section. Section 1.8 concludes.

1.2 Literature review

This paper contributes to the literature on the economic impact of the COVID-19 pandemic due to the breakdown of international trade via disruptions of global value chains (see, among many others, Bonadio et al., 2021; Eppinger et al., 2021; Lebastard et al., 2023; Meier and Pinto, 2020; Meinen et al., 2021). A value chain can be defined as the series of stages in the production of a good or service for end use. Each stage adds value to the good or service. If at least two stages take place in different countries, the value chain can be designated as a global value chain (GVC) (World Bank, 2020). Participating in GVCs can have several advantages for countries and companies. The literature mentions, among others, lower input costs (Antràs and Chor, 2013; Gereffi et al., 2005), a higher degree of specialization (Koopman et al., 2014), access to new markets (Baldwin and Venables, 2013) and better knowledge and technology transfer (Ernst and Kim, 2002). For Germany, with its export-oriented growth model, these advantages of GVCs have been a key factor in the country's economic success over the last decades.

The COVID-19 pandemic had significant consequences for GVCs. Lockdowns, firm closures and closed borders led to an almost complete standstill in global trade. Companies for which international trade plays a major role in their value chains should have been particularly negatively affected by these circumstances. They had problems exporting intermediate goods and suffered from a lack of intermediate goods for their own production (Lebastard et al., 2023).

Several studies give empirical evidence that higher participation in GVCs amplified economic contagion during the crisis. Espitia et al. (2022) used trade data for 28 exporting countries at the sector level between February and June 2020.

They use a gravity model with a comprehensive set of fixed effects to investigate the role of sector characteristics that likely influence the size of the COVID-19 shock. Among others, they find that while participation in GVC increased an exporter's vulnerability to foreign shocks, it reduced vulnerability to domestic shocks in the short run. Kejžar et al. (2022) also use a gravity model and find results that go in the same direction. They show that forward GVC linkages act as a channel for the transmission of shocks in GVC trade. An increase in the incidence of COVID-19 cases in the destination country leads to a larger decrease in domestic exports of intermediate goods in those countries with which a country has stronger forward linkage in GVCs. Lebastard et al. (2023) use monthly transaction-level data for the universe of French export firms. They apply a difference-in-differences methodology, as well as a logit model, to identify the causal effects of supply chain linkages on exporter performance and the probability of survival in the export market during the crisis. They show that participation in GVCs increased the firms' vulnerability to the COVID-19 shock in both export performance and survival probability. Meinen et al. (2021) analyze regional labor market outcomes in France, Germany, Italy, and Spain. They use monthly data on regional short-time work for the first phase of the pandemic. They find that the stringency of government containment measures does not fully explain the impact of the pandemic on regional labor markets. They show that the regional economic structure and trade linkages help to explain the regional within-country heterogeneity of the labor market impact. Regions that are highly integrated in supply chains with foreign regions hit hard by the pandemic showed the worst labor market outcomes.

Within this literature, some studies emphasize China's special role as a trading partner in value chains during the pandemic (see among others, Eppinger et al., 2021; Kejžar et al., 2022; Meinen et al., 2021). Following the argumentation of Bonadio et al. (2021), relying on China in GVCs should have negative effects on

the trade partner, since China was hit hard by the pandemic, particularly in the early phase. Kejžar et al. (2022) call it the “China effect”. They provide evidence that shock transmission is amplified if the exporting country shows a high share of supply chain trade with China. Eppinger et al. (2021) and Gerschel et al. (2020) study the propagation of the production slowdown in the Chinese province of Hubei to the global economy through global trade and GVCs. Lafrogne-Joussier et al. (2023) use transaction-level import and export data from French firms and use the early lockdown in China as an exogenous shock to quantify the causal effect of GVC disruptions on exports and domestic sales. Firms sourcing their input from China experienced a drop in exports compared to GVC firms importing inputs from other countries in April 2020. The reasons for the drop are a reduction in the number of products shipped or a temporary exit from specific destination markets.

Following Lafrogne-Joussier et al. (2023), this paper also considers China as the main analyzed trade partner compared to general worldwide trade. This study makes several contributions to the literature. First, this paper analyzes the effects of GVC disruptions during the pandemic for German companies. So far, evidence on Germany, an important agent in GVCs, is scarce. The role of China in German GVCs is particularly important. In recent years, China has become Germany’s most important trading partner in international trade in goods. According to a survey by the *ifo Institute*, 46% of all German manufacturing companies are currently relying on important input from China (Baur and Flach, 2022). Second, this paper focuses on the labor market effects for German firms, while the previous literature has mainly focused on changes in international trade. It attempts to provide an answer to the question of whether GVC integration led to negative labor market outcomes during the COVID-19 pandemic. Third, this paper covers the full years 2020 and 2021 while most earlier studies investigate the impact of the initial

shock in spring 2020. With a longer observation period, it is possible to examine the duration of the effects not only in the short run, but also in the medium-time phase.

1.3 Data

This section describes the different datasets that are used and explains how they are merged for the analysis. The dataset for the main analysis contains information on short-time work (STW) for establishments on a monthly level. In addition, the dataset includes time-varying information on labor market regions during the COVID-19 pandemic. Due to a standardized establishment identifier, it is possible to link survey information from the IAB Establishment Panel (BP) and process data from the IAB Establishment History Panel (BHP) to the STW dataset. Furthermore, the industry classification (ISIC Rev.4) of the establishments is used to merge global value chain indicators generated by the OECD's Inter-Country Input-Output (ICIO) database.³

1.3.1 Monthly panel data

Short-time work is one of the most important labor market policy instruments to avoid mass layoffs during major economic crises. One reason why the unemployment rate showed a relatively moderate increase during the COVID-19 pandemic in Germany was the extensive use of STW. The main mechanism of STW is that governments temporarily subsidize a portion of the employer's payrolls when labor demand declines during the crisis. In Germany, establishments that have to reduce the working hours of their employees can apply for subsidies from the Federal Employment Agency (FEA) (Naujoks et al., 2022). The data is based on

³A detailed overview of the sample restrictions for the datasets is presented in Section 1.A and for summary statistics, Section 1.C in the appendix.

payroll lists and is collected on the basis of claims. I use only realized STW claims. This means that only claims that actually resulted in a wage subsidy are taken into account. In the data, it is also possible to distinguish between STW claims for structural economic reasons, such as seasonal STW in the construction sector, and STW for non-structural economic reasons, the so-called cyclical STW (Federal Employment Agency, Statistics/Labour Market Reporting, 2021). The cyclical part of the STW reports is therefore suitable as a performance indicator at the establishment level and is used as the main outcome variable in the analysis.

For the analysis, a balanced panel is constructed for the period from January 2019 until December 2021. The main variable is the share of workers in STW in a given month divided by the number of all workers in June 2019.⁴ An advantage of the dataset is that it contains a unique establishment identifier, which can be used to merge establishment information from datasets such as the IAB Establishment Panel (BP) and the IAB Establishment History Panel (BHP).

During the COVID-19 pandemic, establishments faced different restrictions depending on the region of Germany where they were located. To account for that, I add three additional time-varying variables at the labor market region level for each month. I consider a measure of the regional strictness of measures imposed to contain the spread of the pandemic, i.e., the stringency index available in the *Corona Datenplattform*⁵. It is calculated taking the mean value of 23 different policy responses and ranges from 0 to 100 where higher values indicate higher levels of strictness. From the same data source, I also use the number of monthly reported COVID-19 infections. In addition, I use daily mobility flows, which are derived from mobile phone data by the mobile phone provider *Telefónica* and prepared by the *Teralytics GmbH* (for more information, see Brockmann and Robert

⁴See Section 1.A for sample restrictions and numbers of observations.

⁵For more information on the data, see <https://www.healthcare-datenplattform.de/>.

Koch Institute, 2022). The data enables me to include changes in mobility with reference to the average daily mobility in the corresponding month in 2019. To receive monthly data, I calculate the mean on all days of the relevant month.

1.3.2 Yearly establishment data

In addition to the monthly panel dataset, I set up an establishment dataset for 2019. This serves primarily as the basis for the entropy balancing explained in Chapter 1.5.2. All establishment characteristics in the dataset are measured in the year 2019. This is the year directly before the crisis and therefore measures the characteristics of the establishment that have not yet been affected by the COVID-19 pandemic.

First, I use the IAB Establishment Panel (BP) which is an annual survey on the establishment level for Germany. It covers a representative share of all establishments in Germany and is also representative for all sectors and establishment sizes (Ellguth et al., 2014; Fischer et al., 2009).⁶ For the analysis, the survey wave 2020 is used. It contains, among other things, information on the proportion of business volume achieved outside of Germany and the share of sales that is attributed to intermediate inputs and external costs from the previous financial year, that is, 2019.⁷

The second dataset is the IAB Establishment History Panel (BHP) which covers all establishments throughout Germany with at least one employee subject to social security as of 30 June of a given year. The data source for the BHP is the employee history dataset of the IAB. The individual employee information contained in the employee history datasets is aggregated yearly to the establishment level (Ganzer

⁶For technical information on the dataset see Gensicke et al. (2022).

⁷These two variables are particularly important but they suffer problems with missing values. To keep the representativity of the sample, I replace the missing observations with the mean of all non-missing observations. For further information, see Section 1.B in the appendix.

et al., 2022). Overall, 6,736 establishments can be merged with the BP using the unique establishment identifier.

The BHP covers detailed information on the employee composition and on wages. Here, I use the share of managers, high- and medium-skilled workers, employees in highly complex tasks, workers in (science, technology, engineering or math) STEM occupations and workers with university degree. In addition, I use the 25th, 50th and 75th percentiles of the establishment wage distributions.

To account for other channels which could influence the establishment performance during the COVID-19 pandemic further variables are added. I use the distance to an early hot spot of the COVID-19 pandemic, Bergamo, for each German municipality to capture the regional variation in the spread of the pandemic over space (Felbermayr et al., 2021). I assign the distance according to where the establishments are located. The loss of value added is taken from Bauer and Weber (2021). It indicates the change in the gross value added of every industry caused by the hypothetical closures via their linkages in an input-output table to all other industries in Germany. This describes the affectedness of an industry when other industries close on a national level and could be regarded as domestic spillover effects. Furthermore, I include the working from home capacity (WfH) from Alipour et al. (2023). The index assigns a level of capacity of how much could be worked from home to each ISIC industry and I match them via the industry information to each establishment. Finally, I add an establishment effect that controls for the establishment-specific wage premia by using firm information from 2010-2017 (Abowd et al., 1999; Bellmann et al., 2020; Card et al., 2013).

1.3.3 OECD's Inter-Country Input-Output (ICIO) database

To measure in which way different economic sectors in Germany are integrated into global value chains (GVCs), I use the 2022 edition of the OECD Inter-Country

Input-Output (ICIO) tables which provide information for 76 single countries and a category which summarizes the rest of the world. For the year 2019, the dataset covers 93% of the worldwide GDP, 92% of all exports and 90% of all imports. The time span of the dataset ranges from 1995 until the year 2020 (OECD, 2022).⁸ The input-output tables show the monetary amount of input to produce the final amount of output of a specific industry. Further, they decompose output into final consumption and intermediate goods and combine national input-output tables to describe the sale-purchase relationships between and within industries and countries (Belotti et al., 2020). The dataset provides the basis for calculating the indices to measure GVC integration that are described in Section 1.4. The OECD ICIO contains 45 economic sectors according to the ISIC Rev.4 classification, which also serves as the identifier to match the indices to the establishments.

1.4 Measuring GVC-related trade

In this section, I describe how I measure the participation of industries in global value chains (GVCs). GVCs are measured as part of international trade flows and the definition of what should be considered a trade flow related to GVC activities originates from Hummels et al. (2001). The idea is that goods and services must cross an international border more than once during the production process to be regarded as GVC-related activities.

In this analysis, I use the indices proposed by Borin and Mancini (2015, 2019) and Borin et al. (2021). The authors use the concept of GVC-related trade via the exporting sector to identify the level of GVC integration of a specific industry. As a starting point, they use the gross exports ($GEXP^e$) of the exporter country e to a trading partner v . In the setup used in this analysis, e is always equal to Germany and therefore neglected in the following. The trading partner can have different

⁸For more information on the latest OECD ICIO database, see <http://oe.cd/icio>.

levels of aggregation. It could be either a specific country, a group of countries like the OECD or the entire world.

In a second step, they derive the domestic value-added absorbed directly by the importer ($DAGEXP^v$) as a part of the gross exports. Following the authors, this part of gross export is *not* part of GVC-related trade and therefore $DAGEXP^v$ includes:

- Exports that are produced in Germany and consumed abroad.
- Intermediate goods that are produced in Germany and used by the importing country to produce final goods for its domestic market (Borin and Mancini, 2019).

Conversely, the remaining part of the gross exports ($GVCGEXP^v$) is related to GVC, that is, it crosses more than one border:

$$GVCGEXP^v = GEXP^v - DAGEXP^v \quad (1.1)$$

Regarding bilateral trade flows e.g. from Germany to China that are related to GVC activities $GVCGEXP^v$ involves accounting for double-counting as value-added produced and exported by a country might be re-imported and further processed by this country in later stages of the GVC. Suppose, for example, that along the production process, a certain intermediate input is shipped from country A first to country B where it is processed and then shipped back to country A. Afterwards, the good is finalized and then shipped to country C. In this case, when a portion of the good crosses the border of the same country more than once, it has to be assigned to the flow of one country, whereas it is corrected as “*double counted*” in the other countries. To control for this, Borin and Mancini (2019) use

the so-called source-based approach by Nagengast and Stehrer (2016) to calculate their GVC indices. The rationale behind the source-based approach is that the generated value-added is recorded as closely as possible to the moment when it is produced.

To measure the relative importance of GVCs in all exports, GVC-related trade can be expressed as a fraction of gross exports.⁹ This has the favorable feature that the index expresses a relative measure and is bounded between zero and one. The share of GVC-related trade (GVC^v) in gross exports is given by:

$$GVC^v = \frac{GVC GEXP^v}{GEXP^v} \quad (1.2)$$

Further, the index allows a flexible decomposition from the global measure to country-, sector- and country-sector-specific measures.¹⁰ This allows me to consider GVC connections between pairs of countries such as China and Germany as well as for specific industries.

1.5 Empirical strategy

To identify the causal effect of GVC-related trade on the level of short-time work (STW) during the COVID-19 pandemic, I exploit the sectoral variation in GVC-related trade in a difference-in-differences (DiD) setup. The empirical strategy consists of a DiD model with a continuous treatment exposure combined with entropy balancing for continuous treatments (EBCT) and time-varying regional control variables. The entropy balancing weights and controls are included in a two-way fixed effects (TWFE) model in a standard event-study specification. The

⁹In the paper, GVC-related exports and GVC-related trade are used interchangeably.

¹⁰I would like to thank Federico Belotti, Alessandro Borin and Michele Mancini for providing the ICIO package, which allows me to calculate all relevant indices.

strategy allows the identification of effects by making establishments comparable in their pre-crisis characteristics due to the weighting.

1.5.1 Difference-in-differences estimation

Like in all DiD setups, the crucial assumption is the parallel trends assumption which says that in absence of the treatment the differences between the treatment and control groups are the same over time. However, the assumption needs to be adjusted in this analysis because the treatment, GVC-related trade, is continuous and a non-treatment group is not existent. Callaway et al. (2024) modify the assumption for continuous treatments and call it the strong parallel trends assumption, which must be met to identify an average treatment effect on the treated (ATT). Applied to this study, I assume that establishments with different levels of GVC-related trade would show the same trends in STW if they had been exposed to the same level of GVC-related trade and if the COVID-19 shock had not occurred. In other words, I could say that, in the absence of the COVID-19 crisis, STW would have followed parallel trends along all levels of GVC-related trade.

As a preliminary check for the assumption of parallel trends, I report leads of the effect of GVC-related trade on STW in an event-study plot and look for any recognizable differences. In addition, I alter the continuous treatment specification to a binary treatment specification (similar to Bauernschuster et al., 2016). This is done because the binary treatment specification relies on a weaker parallel trends assumption, since the identification of the effect only comes from a dichotomous change in the treatment. In contrast, the effect in the continuous specification comes from a level and a dose effect simultaneously (for a formal derivation, see Callaway et al., 2024). I generate a binary indicator equal to one if GVC-related trade is higher than a certain threshold. Then, one indicates sectors with high GVC-related trade, the treatment group, and zero indicates sectors with low GVC-

related trade, the control group. The TWFE model in the event-study design for the binary treatment specification is then given by:

$$STW_{it} = \sum_{t \neq 2020m2} \beta_t \mathbb{1}(t = T) \times \mathbb{1}(GVC_{s(i)}^v > T(p)) + \gamma_i + \tau_t + \epsilon_{it} \quad (1.3)$$

In Equation (1.3), STW_{it} is the share of short-time work in total employment in establishment i and month t .¹¹ $GVC_{s(i)}^v$ represents the GVC-related trade of an establishment with a partner country v . The value is assigned through the sector s of establishment i . $\mathbb{1}(GVC_{s(i)}^v > T(p))$ is an indicator function that is equal to one if GVC-related trade exceeds the threshold $T(p)$. Since there is no general rule for a threshold that defines low- and high-GVC-related trade, two different thresholds are defined: For p I use the 40th and the 66th percentile of GVC-related trade.¹² The indicator function $\mathbb{1}(t = T)$ is equal to one if the running index t is equal to the month T under consideration. February 2020, the month before the COVID-19 shock starts in Germany, serves as a reference. In addition, γ_i and τ_t are fixed effects for establishments and month-year pairs and ϵ_{it} is a white noise error term.

The binary DiD setup in Equation (1.3) identifies the so-called intention-to-treat effects (ITTs), the effect of the treatment assignment on the outcome. This is the case because I assign the treatment, high vs. low GVC-related trade via thresholds to the sectors (or rather the establishments) and do not use the variation within the two groups (Angrist et al., 1996). The different thresholds can also serve as a first test for the assumed linearity or rather monotonicity of the dose effect for the treatment (Callaway et al., 2024). The size of the ITTs should

¹¹I use a constant pre-crisis employment stock in June 2019 to calculate the share of short-time work.

¹²It is not possible to use thresholds lower than the 40th percentile. The 40th percentile is the lowest threshold where convergence in the binary model is achieved.

increase with higher thresholds, since sectors with higher exposure to GVC-related trade should be more affected.

A straightforward approach to get closer to the ATTs is to use the full variation of the treatment and use a continuous DiD specification (Bauernschuster et al., 2016). However, since the treatment, the GVC-related trade, is on the sector and not on the establishment level, the results do not perfectly represent the ATT.

$$STW_{it} = \sum_{t \neq 2020m2} \beta_t \mathbb{1}(t = T) GVC_{s(i)}^v + \gamma_i + \tau_t + \epsilon_{it} \quad (1.4)$$

Here, $GVC_{s(i)}^v$ is continuous and has any value between zero and one. In addition to the advantage that Equation (1.4) now exploits the entire variation of the treatment, it is not necessary to define an exact threshold for the division into control and treatment groups.

Numerous factors other than GVC-related trade can influence the level of STW during the crisis (see e.g., Bartik et al., 2020; Kim et al., 2022; Partridge et al., 2022). For this reason, it is only possible to assume parallel trends if all other possible influencing factors are controlled for. This assumption is referred to as the conditional independence assumption (CIA), which is also known as the sorting or selection problem. During the COVID-19 pandemic, establishments faced different restrictions depending on the region in which they were located. To account for this, I add additional time-varying controls at the labor market region level for each month directly in Equation (1.4):

$$STW_{it} = \sum_{t \neq 2020m2} \beta_t \mathbb{1}(t = T) GVC_{s(i)}^v + \sum_{l=1}^L \beta_l CONT_{lr(i)t} + \gamma_i + \tau_t + \epsilon_{it} \quad (1.5)$$

where $CONT_{li(r)t}$ represents all L time-varying control variables for establish-

ment i in region r . The controls are the COVID-19 infection rate, the policy response stringency index and regional mobility.¹³

1.5.2 Entropy balancing for pre-crisis establishments characteristics

In addition to the time-varying controls, entropy balancing is used to control for a broad range of pre-crisis controls on the establishment level. The dataset and the variables are described in Section 1.3.2. The reason to weight establishments by their pre-crisis characteristics is driven by the CIA and also by the stable unit treatment value assumption (SUTVA) (Rubin, 1980). There could be concerns that even within a sector, there are differences between establishments that have the same level of treatment. These differences could affect the level of STW. According to the CIA, the effects of GVC-related trade on STW can only be interpreted as causal if they are conditioned on relevant establishment characteristics. The SUTVA points in the same direction: It implies that each unit receives the treatment in homogeneous doses. Thus, with regard to differences in establishments within the sectors, it is necessary to control for different characteristics of the establishments. Moreover, the SUTVA also requires that there are no spillovers. This means that the integration of one establishment in GVC-related trade does not affect the STW of other establishments. This can only be partially corrected by entropy balancing. However, it is not possible with the available data to model how establishments interact with each other, e.g. via intermediate inputs or outputs. In some cases, the change in the value-added variable might help to reduce the problem related to spillover effects. The variable indicates the change in the gross value added of every industry caused by the closures of all other industries in Germany. This might capture some pre-crisis spillover effects on the industry

¹³See Section 1.3.1 for a detailed description of the variables.

level but it does not control for spillovers on the establishment level as well as for changes during the crisis. Further, the SUTVA assumes that there are no general equilibrium effects. In the sample period, which is three years or rather just under two years after the shock, it seems to be plausible that long-term adjustment effects play only a minor role, if any at all.

Hainmueller (2012) derived entropy balancing for binary treatment variables. It relies on a maximum entropy weighting scheme that calibrates weights so that the re-weighted control group is equal in predefined moment conditions of the covariate distributions of the treatment group.

Table 1.1: Balancing table for GVC-related trade with China (binary treatment)

	Mean differences			
	Pre p(40)	Post p(40)	Pre p(66)	Post p(66)
AKM firm-effects 2010-2017	-0.523	-0.000	-0.434	-0.000
Daily wage p(25)	-0.257	-0.000	-0.207	-0.000
Daily wage p(50)	-0.333	-0.000	-0.263	-0.000
Daily wage p(75)	-0.412	-0.000	-0.308	-0.000
Distance to Bergamo (km)	0.032	0.000	-0.024	0.000
Loss of value added	0.490	0.000	-0.915	0.000
Prop. business volume abroad	0.524	0.000	0.781	0.000
Prop. intermed. consump. of turnover(in %)	0.172	0.000	0.088	0.000
Share STEM occupations	-0.260	0.000	0.384	0.000
Share employees in highly complex tasks	-2.392	-0.001	-0.993	-0.001
Share high-skilled workers	-1.724	-0.001	-0.833	-0.001
Share managers	-0.615	-0.000	-0.420	-0.001
Share medium-skilled workers	0.214	0.000	0.147	0.000
Share professions with university degree	-14.265	-0.013	-14.438	-0.020
WfH Capacity	-0.289	-0.000	-0.103	-0.000

Note: The table shows the differences of the first moment (mean) between the treatment and the control group before and after entropy balancing. The first two columns show the differences when the treatment group is defined as GVC-related trade larger than the 40th percentile. Column three and four show the differences when the treatment group is defined as GVC-related trade larger than the 66th percentile.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

Table 1.1 shows the results of the entropy balancing for GVC-related trade with China in the binary treatment specification. The condition is that the difference

in the mean (first moment) of the treatment and the control group is minimized. Taking into account the weights obtained from entropy balancing, a synthetic control group is created that represents a near perfect image of the treatment group in terms of the establishment characteristics considered in the pre-crisis phase (post columns in Table 1.1).¹⁴

In the continuous case, I use entropy balancing for continuous treatments (EBCT) by Tübbicke (2021), which is an extension of the weighting procedure introduced by Hainmueller (2012). In the continuous case, the weighting uses only the variation of the treated observations, which is necessary in this analysis, since there are no untreated units. This has the advantage to balance the observations for certain doses of the treatment distribution (Tübbicke, 2021). EBCT first predicts GVC-related trade by using the characteristics of the establishment. Then, the algorithm iteratively minimizes the coefficient of determination (R^2) by assigning weights to each observation.

Further, the weights can also be interpreted in a slightly different way: Since the treatment is on the sector and not on the establishment level, I still identify an ITT of GVC-related trade on STW. This is the case because establishments within sectors still show different GVC integration. As EBCT explains the treatment by establishment characteristics, the weights could also be interpreted as a kind of inverse “compliance rate”. For example, the volume of business abroad or the dependence of an establishment on intermediate goods will influence its vulnerability when GVCs break down and cause differences even within the same economic sector. If differences in these characteristics between establishments are taken into account, it is more likely that the true ATT is identified.

To describe the results of EBCT, Figure 1.1 shows the correlations between

¹⁴The same holds in Table 1.E.1 in the appendix when the treatment is GVC-related trade with the world without China.

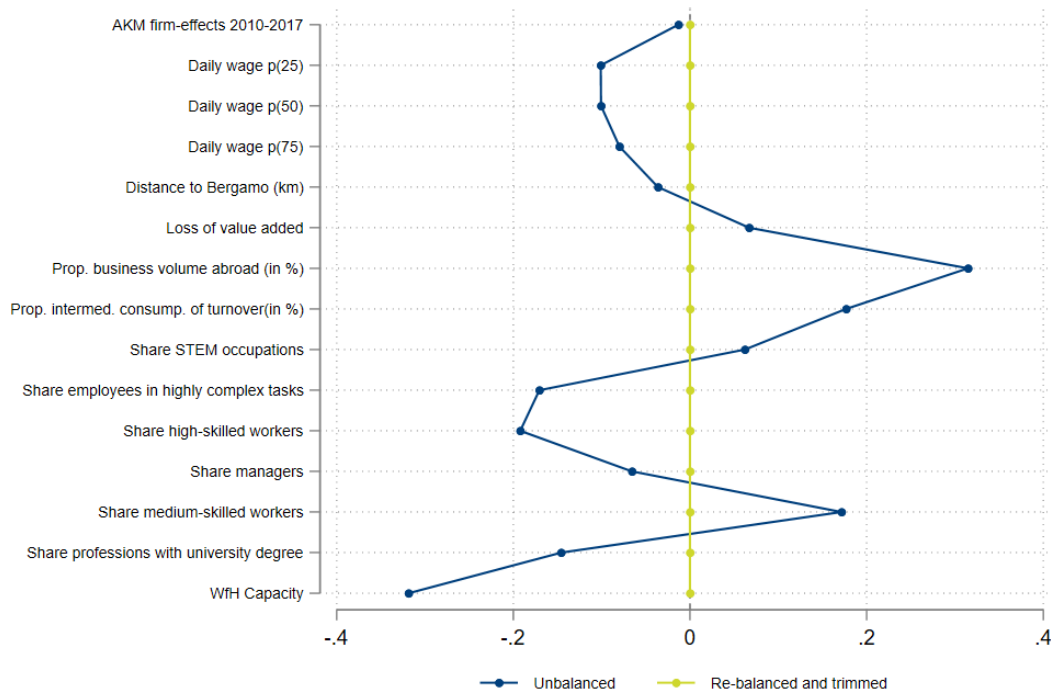


Figure 1.1: Correlations before and after entropy balancing for GVC-related trade with China

Note: The weighted correlations are shown after excluding the establishments with the 1% smallest and largest weights. The summary statistics of the variables are listed in Table 1.C.2.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

establishment characteristics and GVC-related trade with China before and after balancing. The blue line indicates the unweighted correlations. In the unweighted case, the R^2 is equal to 0.29. In contrast, the green line shows the correlations after weighting, which are all almost zero as the R^2 . Moreover, in the model after weighting, I cannot reject the null hypothesis of a Wald test that all coefficients in the model are equal to zero. Consequently, this indicates that EBCT weights the establishments in a way that all observed pre-crisis characteristics are not informative anymore with respect to the level of GVC-related trade.

The entropy balancing surely improves the identification of a causal effect of GVC-related trade, but it comes at some costs of another assumption: I have to

make sure that it is possible to calculate relevant inverse probability weights. Figures 1.E.2 and 1.E.3 show the weight distribution for GVC-related trade with China and the world without China. The results show that most of the weights lie in a compact band. This indicates that there is common support for most establishments. To ensure that the results are not driven by extreme weights, the sample is trimmed for the establishments with the 1% smallest and largest weights of the analysis (green markers) (Imbens, 2004; Tübbicke, 2021).

1.6 Results

1.6.1 Effects of GVC-related trade with China on STW

In this section, I investigate the relationship between GVC-related trade with China or the world (excluding China) and short-time work (STW). The results of the regression analysis are summarized in panel event study plots that show the estimated coefficients of GVC-related trade on STW from January 2019 to December 2021. In all plots, February 2020 is used as the reference month, and all variables are standardized with a mean of zero and a standard deviation of one. Furthermore, the bars around the point estimates indicate 95% confidence intervals and the standard errors are clustered on the sector level. The dependent variable is the percentage of workers in STW in a month using total employment in June 2019 as the denominator.

Figure 1.2 shows the relationship between STW and GVC-related trade with China in the continuous treatment specification of Equation (1.5). It includes the EBCT weights and the time-varying regional controls.¹⁵ Prior to the crisis, GVC-related trade does not have a significant effect on STW. Thus, there are no

¹⁵Figure 1.D.1 in the appendix shows the results of the continuous model from Equation (1.4) in Chapter 1.5 without EBCT.

major trends in the pre-crisis period, which supports the strong parallel trends assumption (Callaway et al., 2024). From April 2020 onward, the point estimates increase with a peak in June 2020 and remain statistically significant until October 2020. During this period, a 1 standard deviation increase in GVC-related trade with China increases the share of STW by on average 5.5 percentage points.

After the peak, the effects of GVC-related trade with China decline until winter 2020. From December 2020 until the end of the observation time, the point estimates constantly lie close to the zero-effect line.

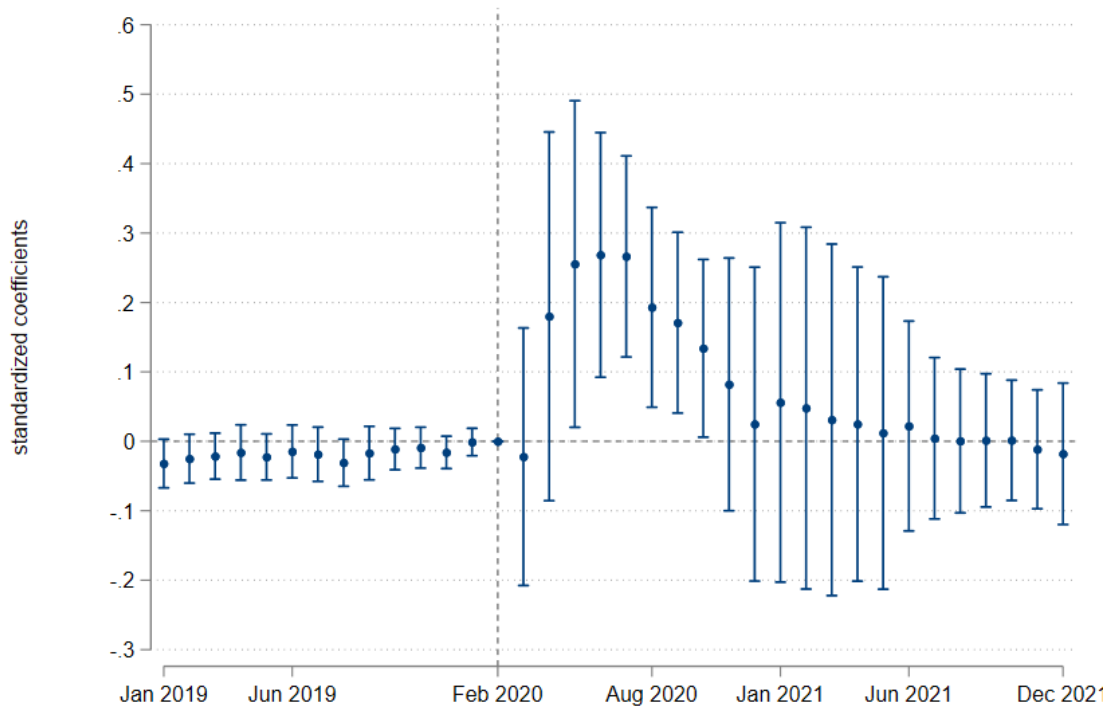


Figure 1.2: Event study plot for GVC-related trade with China and STW (continuous treatment)

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the sector level. EBCT weights are calculated for GVC-related trade with China. The top and bottom 1% firms are trimmed in the model. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

Since several controls for entropy balancing come from the establishment panel survey, this dataset has fewer establishment observations than the administrative dataset for STW information. In total, I can match 6,736 establishments. To make sure that the matched sample is still representative of all establishments in Germany, I reproduce the analysis with all establishments in Germany but with the drawback of fewer controls for the entropy balancing in Section 1.F in the appendix. The results show the same pattern of effects as in Figure 1.2.

To gain a deeper understanding of the economic meaning of the effects of GVC trade integration for Germany, the following back-of-the-envelope calculation is presented for the additional costs of STW. Table 1.2 shows additional information on the German labor market for the months in which the effect of GVC-related trade on STW, which can be seen in Figure 1.2, is positive and significantly different from zero. In May 2020 the number of workers in STW was around 5.7 million. In relation to all workers subject to social insurance contributions, these are 17% (Statistics of the Federal Employment Agency, 2024). The monthly standard deviations of the share of STW are presented in Column (4). The coefficients of Figure 1.2 are shown in Column (5).

Table 1.2: Additional information on the German labor market

	(1)	(2)	(3)	(4)	(5)
Month	Worker in STW	Employment	Share STW in Germany	sd STW in sample	Coefficients from model
May-20	5,714,840	33,328,050	0.171	0.314	0.255
Jun-20	4,452,280	33,322,950	0.134	0.265	0.269
Jul-20	3,305,890	33,233,140	0.099	0.272	0.266
Aug-20	2,537,050	33,482,210	0.076	0.251	0.193
Sep-20	2,229,430	33,791,870	0.066	0.22	0.171
Oct-20	2,020,650	33,862,040	0.06	0.204	0.134

Note: The table shows information for all months where the coefficients in Figure 1.2 are significantly different from zero at the 95% level (Further, the coefficients are listed in Table 1.D.1 in the Appendix B.

Source: Employment statistic provided by the Federal Employment Agency; own calculations.

With the information in Column (4) and (5) the monthly ceteris paribus effect of an increase of one standard deviation higher GVC-related trade with China on the share of STW can be calculated. For May, the effect is:

$$0.255 \times 0.314 = 0.080$$

This means that ceteris paribus establishments in industries with one standard deviation higher GVC-related trade with China show a roughly 8 percentage points (pp) higher share of STW in May 2020. If all establishments were one standard deviation more GVC-integrated with China, then the share of STW relative to all workers would increase from 17% to 25% in May 2020.

The increase in GVC-related trade with China by one standard deviation is equivalent to an increase of 11 pp and almost half the sample mean of 23%.¹⁶ This is roughly comparable to what would happen if the “*other transport equipment*” sector ($GVC^{CHN} = 0.391$) was as involved in GVC-related trade with China as

¹⁶The summary statistics can be found in Table 1.C.1 in the Appendix.

Table 1.3: Effects by an on standard deviation increase of GVC-related trade with China

Month	(1) Additional share STW	(2) Additional workers STW	(3) Additional wage payments	(4) Additional social security contributions payments
May-20	0.08	2,666,244	988,776,587 €	745,828,434 €
Jun-20	0.071	2,365,929	877,404,937 €	661,821,445 €
Jul-20	0.072	2,392,786	887,364,718 €	669,334,050 €
Aug-20	0.048	1,607,146	596,010,124 €	449,566,973 €
Sep-20	0.038	1,284,091	476,205,170 €	359,198,792 €
Oct-20	0.027	914,275	339,058,913 €	255,750,168 €
Sum		11,230,472	4,164,820,448 €	3,141,499,863 €

Note: The table shows the effects of a hypothetical increase of GVC-related exports with China of one standard deviation. One standard deviation is equal to 11% more GVC-related exports with China.

Source: Employment statistic provided by the Federal Employment Agency; own calculations.

the “computer, electronic and optical equipment” sector ($GVC^{CHN} = 0.509$).¹⁷ The corresponding effects for the other months are shown in Column (1) of Table 1.3. An increase in STW by 8 pp in Mai 2020 corresponds to 2,666,244 additional STW reports.

$$33,328,050 \times 0.080 = 2,666,244$$

For all months from May to October 2020, a one standard deviation increase in GVC-related trade with China would result in a total of around 11 million more STW reports (see Column (2) in Table 1.3.)

In 2020, in total, more than €22 billion was spent on state transfer payments for STW from which €12.5 billion was allocated to wage replacement benefits for cyclical STW and around €9.5 billion to social security contributions.¹⁸ In addition, the total number of monthly cyclical STW reports for the year 2020 is

¹⁷See Table 1.C.4 in the appendix for the values for all sectors.

¹⁸The actual amount of social security contributions for cyclical STW is slightly lower since the number also includes the social security contribution for seasonal STW benefits.

33,912,124. Assuming that each STW report has the same cost, each STW report would cost €650.73. Thus, €370.85 is charged for wage substitution benefits and €279.73 is for social security contributions (Statistics of the Federal Employment Agency, 2024). Using the number of hypothetical additional STW reports and the cost of a report, it is possible to calculate the cost of a one standard deviation increase in GVC-related exports with China during the crisis: for May 2020 the additional government transfer payments for wage substitutions would be:

$$2,666,244 \times €370.85 = €988,776,587$$

and government transfer payments for social security contributions would be:¹⁹

$$2,666,244 \times €279.73 = €745,828,434$$

In total across all months with significant coefficients, meaning from May to October 2020, the amount of hypothetical additional spending would be about €7.3 billion. This indicates that an increase of one standard deviation in GVC-related exports with China would lead to an additional expenditure of about €7.3 billion on STW, which is divided into approximately €4.2 billion for wage subsidies and €3.1 billion for social security contributions.

Figure 1.3 depicts the results for the binary treatment specification described in Equation (1.3) in Section 1.5.1. In particular, it shows the binary variable equal to one for establishments that are above the 40th percentile of the GVC-related trade with China distribution²⁰ (blue line) and for establishments that are above the 66% percentile (green line).

¹⁹For the government transfer payments of the other months see Table 1.3.

²⁰It is not possible to use thresholds lower than the 40th percentile. The 40th percentile is the lowest threshold where convergence in the binary model is achieved.

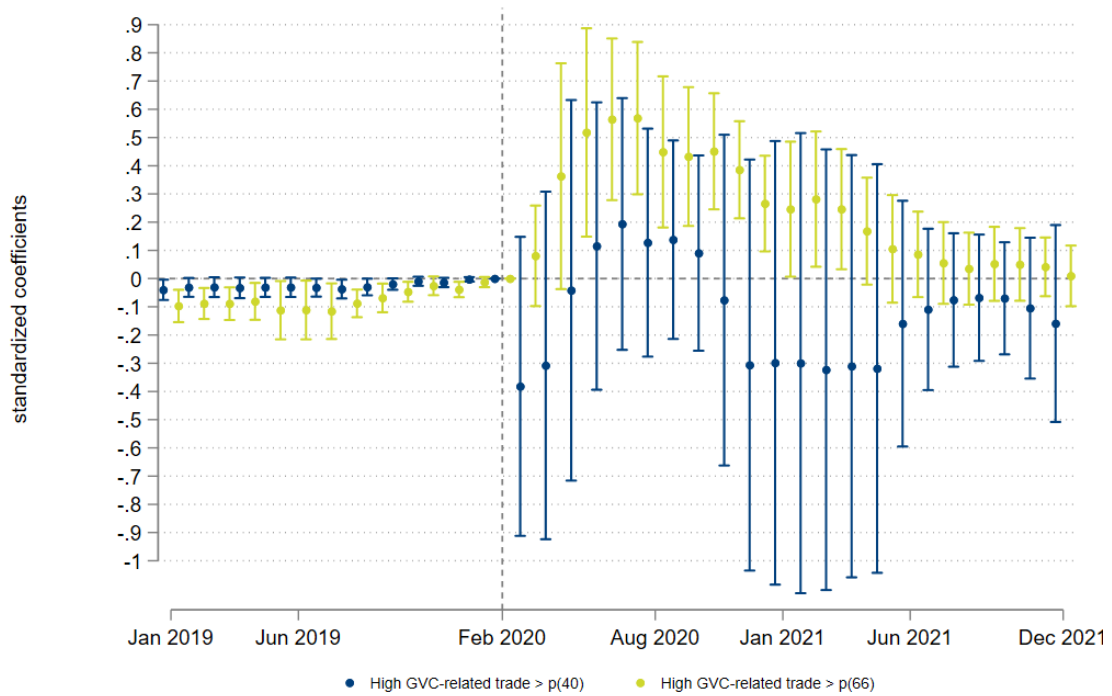


Figure 1.3: Event study plot for GVC-related trade integration with China and STW (binary treatment)

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0, \sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. It is not possible to use thresholds lower than the 40th percentile. The 40th percentile is the lowest threshold where convergence in the binary model is achieved. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019. The coefficients are estimated separately in two models.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

In the pre-crisis period, all point estimates are almost identical and close to zero. In the crisis period, the point estimates for the 40th percentile specification show an alternating pattern around the zero effect line. In all months, the effects are not significantly different from zero. However, the pattern for the 66th percentile specification is different: Starting in March 2020, the point estimates increase and reach a peak between June and July 2020. Furthermore, the effects are significantly different from zero from May 2020 to March 2021. This pattern

is similar to the continuous treatment specification in Figure 1.2. Comparing the two binary specifications indicates that the point estimates of the 66th percentile specification are always higher than those of the 40th percentile specification. This is an important finding for the identification of the continuous specification because it supports the assumption that the relationship between GVC-related trade with China and STW is linear or at least monotonic, since a change in GVC-related trade with China should always have effects that go in the same direction (Callaway et al., 2024). All in all, the results suggest that the continuous and binary treatment specifications lead to comparable results.

1.6.2 Effects of worldwide GVC-related trade on STW

The reason for changing the treatment to worldwide GVC integration is to check whether GVC-related trade with China is just a proxy for GVC integration in general. Therefore, Figures 1.4 and 1.5 show the results of worldwide GVC-related trade excluding China in the continuous and binary treatment specification. As in the previous section, the estimates for the pre-crisis period in the continuous specification do not suggest the presence of pre-crisis trends in Figure 1.4. In contrast to Figure 1.2, which shows the results for GVC-related trade with China, all confidence intervals intersect the zero effect line and the point estimates are smaller and often even negative in 2021.²¹ It can be concluded that the increase in the continuous model with the world excluding China as a trading partner is weaker and imprecisely estimated compared to the results with China as a trading partner. This finding is consistent with the evidence provided by Lafrogne-Joussier et al. (2023). They show for French firms that exports and domestic sales decline more in the early phase of the pandemic when the trading partner is China compared to other countries.

²¹Figure 1.D.2 in Appendix B shows the results of the continuous model from Equation (1.4) in Chapter 1.5 without EBCT.

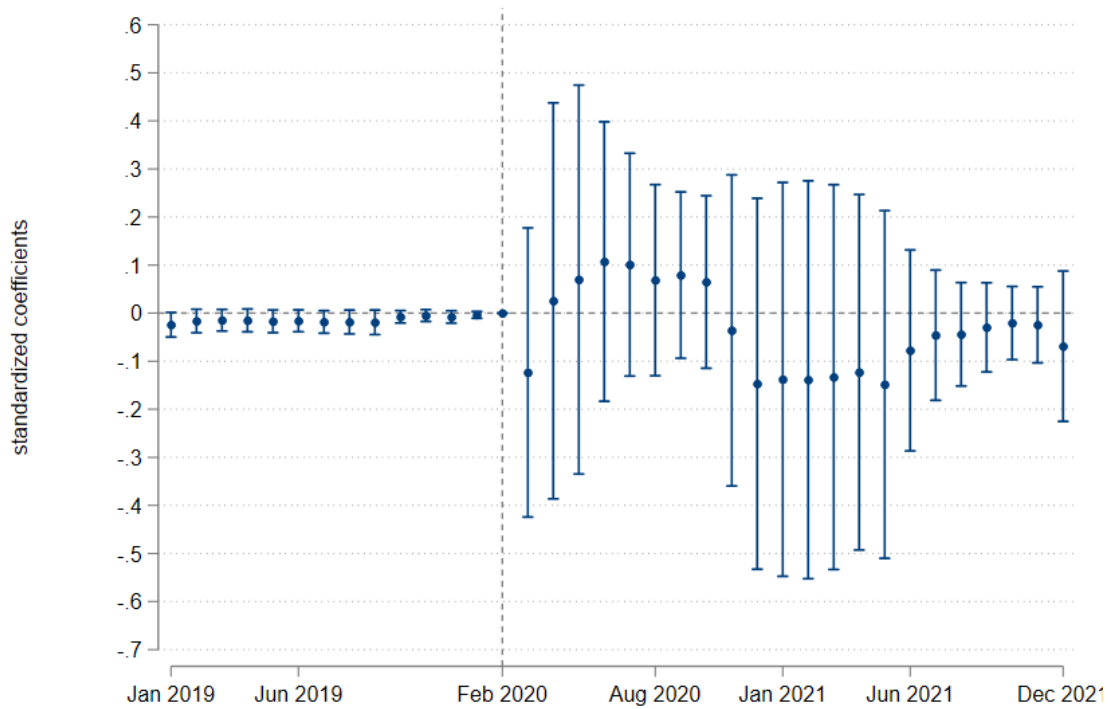


Figure 1.4: Event study plot for GVC-related trade with the world except China and STW (continuous treatment)

Note: : All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0, \sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the firm level. EBCT weights are calculated for GVC integration with the worlds except China. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

The results of the binary treatment specification are presented in Figure 1.5. For both specifications, the 40th and the 66th percentile, there are no significant effects in the pre-crisis period and all point estimates are close to zero. At the beginning of the pandemic, the point estimates increased slightly for both specifications. However, the effects are not significant from zero except for the 66th percentile specification in July 2020. In general, the point estimates for both specifications do not differ much, in particular during the first stage of the pandemic and do not always increase in size from the 40th to the 66th specification. Accord-

ingly, increasing the threshold for categorizing the control and treatment groups makes no difference to the effects on STW during the COVID-19 pandemic. This is different compared to the effects if the treatment is GVC-related trade with China. Likewise, the effects do not increase monotonically when the threshold is increased.

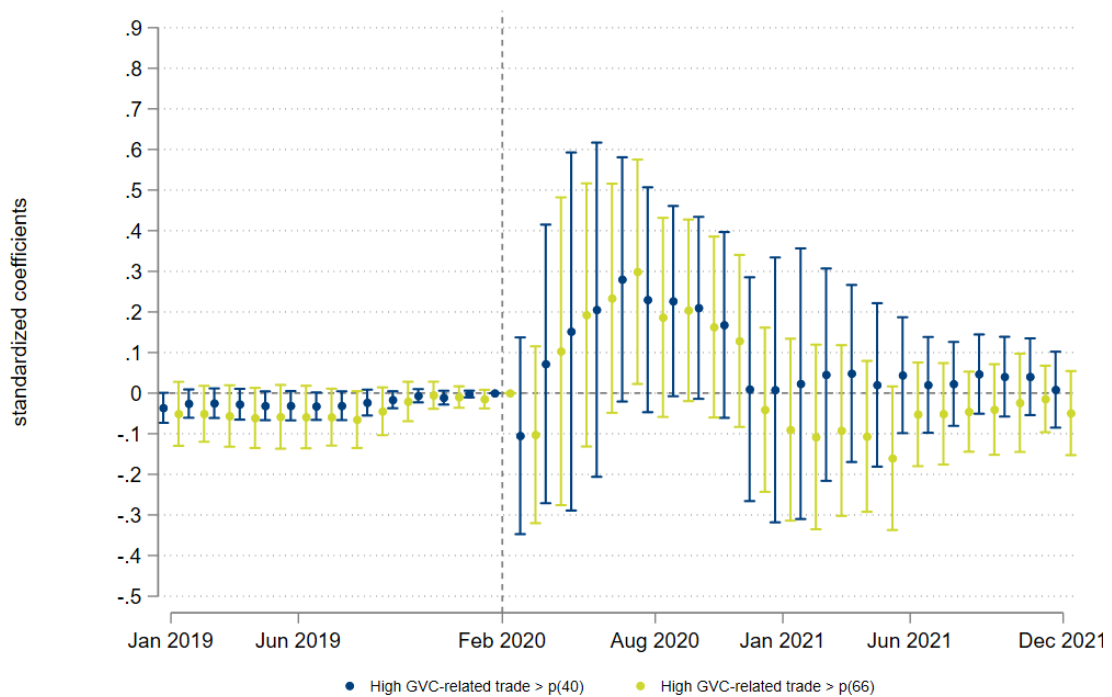


Figure 1.5: Event study plot for GVC-related trade integration with the world without China and STW (binary treatment)

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019. The coefficients are estimated separately in two models.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

1.7 Mechanism and Robustness

1.7.1 Importance of specific industries

As shown in the previous chapter, GVC-related trade with China on average has a significant positive impact on STW. Since GVC-related trade of establishments is measured at the industry level, it could be that specific industries drive the aggregate effect. For this reason, I stepwise exclude establishments from one industry section (ISIC classification) and compare the results of the reduced sample with the results of the entire sample (Figure 1.2). Figure 1.6 displays the correlations between the point estimates for the entire sample and the point estimates without establishments in one industry for the months March 2020 until December 2021. The correlations indicate that the subsample without the manufacturing sector (C) leads to a notable reduction in the correlation coefficient. This is interesting since Germany has a highly developed manufacturing sector and has become a key player in GVCs, particularly in high-tech industries such as automotive, chemical, and machinery (OECD, 2009).

Since establishments in the manufacturing sector seem to be the main driver of the effect on STW, Figure 1.7 plots the effects for the full sample (blue) and for the reduced sample without the manufacturing establishments (green). The confidence intervals indicate that the effects of the two samples are not significantly different. However, without manufacturing, the point estimates in the first part of the pandemic are now close to zero and are not significantly different from zero. Carefully interpreted, these findings suggest that primarily the relatively high share of GVC-related trade with China of the manufacturing sector in Germany, seems to cause the overall effect in the first phase of the pandemic.

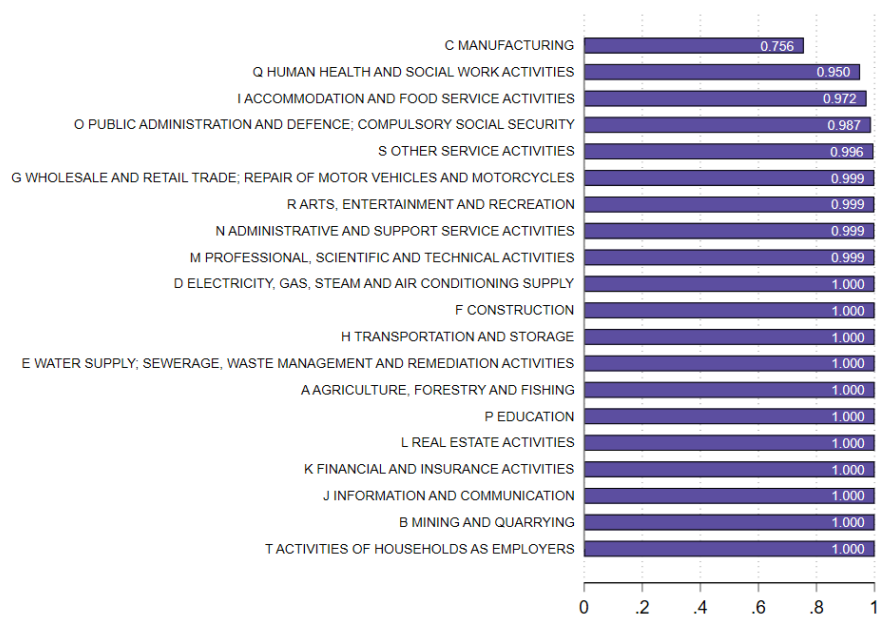


Figure 1.6: Correlations of effects from the full sample and effects without specific industries

Note: The figure shows the correlations between the coefficients in Figure 1.2 and the coefficients when the establishments of the 20 ISIC sections shown are excluded. The trade partner is China.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

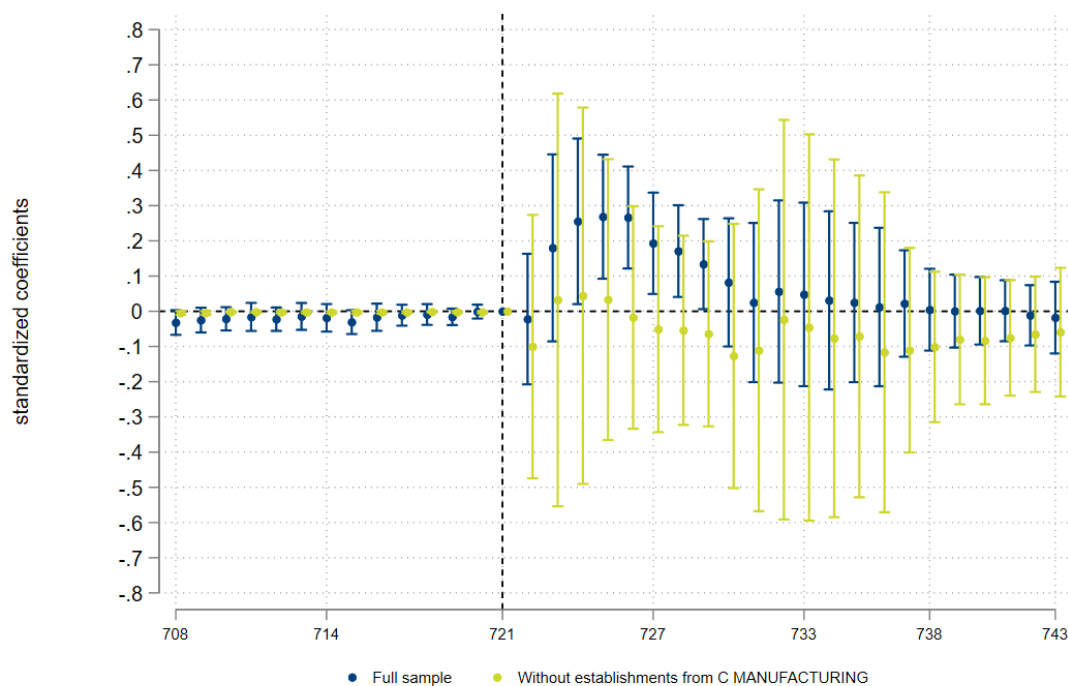


Figure 1.7: Effect with and without establishments from the manufacturing sector

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0, \sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. Short-time work rates are calculated as the number of workers using short-time work in a given month over the employment level in June 2019.

Source: Employment statistic provided by the Federal Employment Agency and OECD (2022); own calculations.

1.7.2 Robustness checks

This section summarizes additional robustness checks that are described in more detail in Appendix B. To check whether the mean imputation for the entropy balancing controls influences the results, Figure 1.D.3 in Section 1.B shows the results for GVC-related trade with China on STW with and without mean imputation. It can be seen that the results are similar, so any influence of the mean imputation for entropy balancing controls can be ruled out. Despite the similar results, the imputation is chosen since it has the advantage that the slightly positive trend in 2019 disappears. In addition, the confidence intervals decrease on average due to a higher number of observations (establishments) in 2019 and parts of 2020.

Section 1.F in the appendix shows that the sample of establishments used in the analysis is representative for all establishments in Germany. I reproduce the panel-event study for all establishments ($N = 2,445,010$) in Germany, but with a reduced number of explanatory variables for the entropy balancing. The results indicate that the sample used represents the entire population of all establishments in a suitable way.

Furthermore, Section 1.G shows the results for GVC-related trade on STW against a random treatment distribution. The results indicate that also for this “stricter” test, the results are significant for June and July 2020. Since the unit of observation in the dataset is the establishment, it is possible for a firm to have several establishments in different regions (multi-establishment firms). These firms tend to overreport STW because they may report STW for all their sub-firms (Kagerl et al., 2022). Chapter 1.H in the appendix shows that the effects without multi-establishment firms are almost identical.

1.7.3 GVC-related trade and supply problems for establishments

To learn more about the mechanism why establishments with high GVC-related trade with China used more short-time work during the first year of the pandemic, I use further information from the Establishment Panel (BP). The 2020 survey covers an additional section on the impact of the COVID-19 pandemic on establishments (Bellmann et al., 2022). Among others, it includes information on whether difficulties with the acquisition of inputs or with suppliers have a negative impact on the establishment during the pandemic in 2020.²²

Together with information on GVC-related trade for sectors, I can estimate a model with a binary variable that indicates problems with the acquisition of inputs or with suppliers as the dependent variable.²³ The hypothesis is that, on average, establishments belonging to sectors that are more integrated in GVCs should have more problems with inputs and suppliers due to the breakdown of international trade during the crisis (see Lebastard et al., 2023, for a comparable approach to firm exports).

$$Y_i = \beta_0 + \beta_1 GVC_{s(i)}^v + \sum_{k=2}^K \beta_k X_{ik} + \epsilon_i \quad (1.6)$$

where Y_i is the binary outcome for establishment i indicating whether establishments faces problems with the acquisition of inputs or with suppliers. The explanatory variable of interest is $GVC_{s(i)}^v$ which indicates the GVC-related trade

²²The original question is (question 1b, option C): “Which of the following negative impact did or does the Corona pandemic have on your establishment/office? — Pre-delivery difficulties of purchasing goods and services or difficulties with suppliers”. For more information on the questionnaires, see <https://fdz.iab.de/en/betriebsdaten/iab-establishment-panel-iab-bp-version-9321-v1/>.

²³The question about pre-delivery difficulties of inputs or difficulties with suppliers was answered by 10,698 (74%) in 2020. When I match the question to the dataset described in Section 1.A.1 I end up with 5,299 matched establishments (2,163 (41%) establishments affirmed the question, 3,136 (59%) did not).

of sector s to which establishment i belongs and with a trade partner v in the pre-crisis year 2019. Again, for v I use China and the world without China. The white noise error term is ϵ_i .

Using the indicator as outcome has to be treated with caution: If establishments state that they had difficulties with inputs or suppliers, then this can be driven by problems at home and abroad. To control for potential problems at home, I add all control variables X_{ik} from the dataset used for the entropy balancing described in Section 1.3.2 to the model.²⁴ The estimated parameter for GVC-related trade should give a good approximation whether higher integrated establishments face more problems during the first year of the pandemic or not.

Table 1.4 presents the results. Column (1) shows the effects of GVC-related trade with China on the negative impact on establishment during the pandemic with respect to the acquisition of inputs or with suppliers. The odds ratio of 1.337 implies that an establishment has a 33.7% higher chance of facing pre-delivery difficulties with goods or suppliers during the COVID-19 pandemic if its GVC-related trade with China increases by one standard deviation (equal to 11 percentage points).²⁵ The effect is significant at the 0.1% level. For example, this means that an establishment in the *"Electrical equipment"* sector ceteris paribus has roughly a 34% greater chance of facing supply problems during the COVID-19 pandemic compared to an establishment equal in all observed characteristics but in the *"Electricity, gas, steam and air conditioning supply"* sector. The reason is that the *"Electrical equipment"* sector has a 10.4 percentage points, almost one standard deviation, higher GVC-related trade with China compared to the *"Electricity, gas, steam and air conditioning supply"* sector.

²⁴Summary statistics of all variables are presented in Table 1.C.3 in the Appendix A.

²⁵GVC-related trade with China has a range from 0.054 until 0.65. This means that in the highest integrated sector, 65% of all exports from Germany to China are GVC-related.

Table 1.4: GVC-related trade and problems with inputs and suppliers

	(1) OR/Std. error	(2) OR/Std. error	(3) OR/Std. error
GVC-related trade (China)	1.337*** (0.107)		1.593*** (0.201)
GVC-related trade (world excluding China)		1.188** (0.087)	0.820 (0.106)
Constant	0.637*** (0.056)	0.649*** (0.058)	0.627*** (0.051)
Controls	Yes	Yes	Yes
Observations	5298	5299	5298
Pseudo R^2	0.0415	0.0346	0.0432
Log likelihood	-3433.7	-3459.2	-3427.5

Note: The table shows the results of a logistic regression with odds ratios (OR). The outcome variable is a binary variable indicating the answer to question 1b option C of the IAB Establishment Panel 2020. It asks whether difficulties with the acquisition of inputs or with suppliers have negative impact on the establishment during the pandemic in 2020. Since industry 5, "Mining support service activities" shows no gross exports with China, the number of observations reduces from 5299 to 5298 in Model (1) and (3). The complete model with all control variables is shown in Table 1.I.1. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with clustered standard errors at the industry level.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

In Column (2), the odds ratio for the worldwide GVC-related trade except China is 1.188 and significant at the 5% significant level. In this context, an establishment now faces only an 18.8% greater chance of supply problems during the crisis compared to an establishment that is equal in all observed confounders but in an industry with a standard deviation (10.4 percentage points) lower GVC-related trade with the world except China. The finding that GVC-related trade with China, in contrast to the worldwide integration (except China), is more relevant to explain supply problems is also underlined by the model "quality": The pseudo- R^2 and the log-likelihood show that including GVC-related trade with China leads to a "better model" than GVC-related trade with the world excluding China. Column (3) presents both indices in a single model. It shows that the odd ratios are significantly different when controlled for each other. The effect of GVC-related

trade with China is now even larger and still significant, but the effect for the world without China becomes smaller (even smaller than one) and is no longer significant.

The results indicate that during the COVID-19 pandemic, establishments in sectors that are more GVC-integrated with China have, on average, more difficulties with the acquisition of inputs or with suppliers. Thus, these problems may lead to production constraints during the crisis. One possible consequence of this would be an increased demand for short-time work for these establishments, which supports the results of Chapter 1.6.

1.8 Conclusion

This paper investigates the causal effect of GVC-related trade on short-time work during the COVID-19 crisis using a binary and continuous difference-in-differences approach combined with entropy balancing. Analyzing German establishment level data on a monthly basis from January 2019 until December 2021 it is possible to observe the initial shock as well as the medium-time period of the pandemic. The results provide evidence that a one standard deviation higher GVC-related trade with China as a trading partner leads to an increase by, on average, 5.5 percentage points in the shares of short-time work. However, the effects are only significantly positive for May until October 2020 and decline already during the second half of 2020. For months in which the effects are significant, an increase in one standard deviation in GVC-related trade with China would lead to an additional expenditure of about €7.3 billion on short-time work. In contrast to GVC-related trade with China, there is no significant relation between STW and worldwide (excluding China) GVC-related trade for German establishments during the pandemic.

An additional analysis of input supply problems of German establishments during the pandemic that makes use of survey data from the Establishment Panel supports the findings. The results indicate that in 2020, establishments that belong to sectors that are more GVC-integrated with China have on average more difficulties with the acquisition of inputs or with suppliers. Again, a higher worldwide (except China) GVC-integration shows no significant effects. Trade disruptions in GVCs, such as those that occurred at the onset of the pandemic, are not a one-time event. Russia's war against Ukraine and other growing geopolitical tensions are forcing companies and policymakers to continue to think about international supply chains. In this context, the findings of this paper support policy strategies to diversify GVCs. In the context of China, these strategies are commonly referred to in the media as "*decoupling from China*" or "*China plus one*" (The Economist, 2023). However, more research is needed to better measure the costs and benefits of GVCs and to assess specific strategies for robust GVCs.

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Appendix 1

1.A Sample restrictions

1.A.1 Dataset for the entropy balancing

- The Establishment History Panel (BHP) provides information on 3,069,299 establishments in 2019 with in total 38,780,805 employees.
- The Establishment Panel (BP) offers 19,501 unique establishment information in 2019.
- After linking the BP and the BHP via an unique identifier, I end up with 13,827 establishments in the year 2019.
- For the analysis, I only consider establishments which are observed from 2019 until 2021.
- 35 establishments are dropped since they switch the industry categorization within the three years.
- I end up with 6,736 establishments which I can observe over all three years and have a unique industry categorization.
- For the year 2019, the average establishment has 72 employees. The smallest establishment has one employee and the largest has 12,313 employees.

1.A.2 Monthly panel dataset from January 2019 until December 2021

- The number of establishments with at least one valid short-time work application from January 2019 until December 2021 in the dataset is 783,429.

- For 6,736 establishments I can find a match with the survey data from the BP.
- In the panel, I have 242,496 month-establishment observations from January 2019 until December 2021.
- Figure 1.A.1 shows the development of STW within the sample and the entire population in Germany over the three observed years.

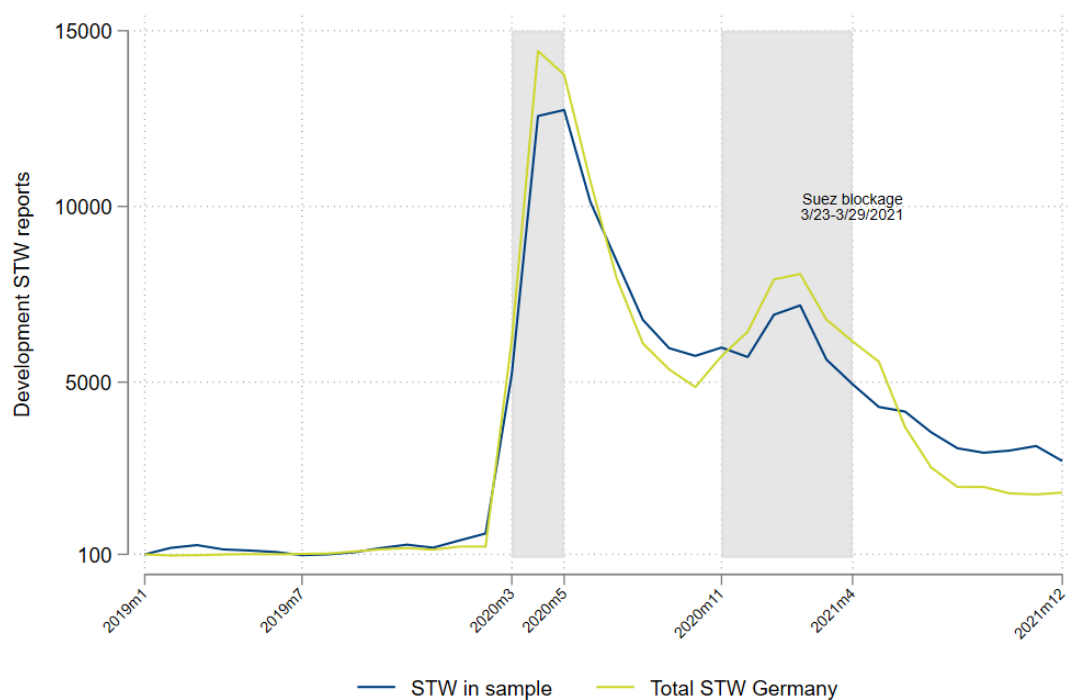


Figure 1.A.1: Development of short-time work in the sample and the entire population of establishments between January 2019 and December 2021

Note: The blue line indicates the development of the number of accepted STW applications from the 6,736 firms in the sample, the green line indicates the development for the total population. January 2019 serves as the reference (set to 100) and the y-line shows percentage changes. The gray bars indicate the lockdown periods in Germany.

Source: IAB Establishment Panel and Federal Employment Agency, Statistics/Labour Market Reporting (2016), own calculations.

1.B Imputation for control variables

Some explanatory variables have missing values. This is particularly the case for the proportion of intermediate consumption in turnover and the development of business volume from the current year to the previous year in the IAB Establishment Panel.²⁶ For the entropy balancing, each observation with missing values is neglected. As a consequence, it is not possible to calculate the weights of these observations. It could be that the relatively large amount of missing observations in single variables might lead to a biased and non-representative sample. To keep the information, I impute the missing information with the sample mean. The replacement of the missing observation with the sample mean of the corresponding variable means that the number of observation is not excluded, but the variable also does not contribute to the calculation of the weight. Table 1.B.1 shows the number of observations before and after the imputation. For all variables, the mean is rather constant, which implies that there should be no potential bias because of the imputation.²⁷

Table 1.B.1: Means before and after imputation

	N	N_imp	Mean	Mean_imp
Prop. intermed. consump. of turnover(in %)	4095	6736	46.581	46.353
Prop. business volume abroad (in %)	5278	6736	6.197	6.154
Share low-skilled workers	6691	6736	.097	.097
Share medium-skilled workers	6691	6736	.743	.743
Share high-skilled workers	6691	6736	.161	.161
Daily wage p(25)	5677	6736	87.091	87.041
Daily wage p(50)	5677	6736	97.448	97.41
Daily wage p(75)	5677	6736	111.714	111.741
AKM firm-effects 2010-2017	4331	6736	.206	.206

Note: Number of observations and means before and after imputation.

Source: IAB Establishment Panel, IAB Establishment History Panel; own calculations.

²⁶For more information, see Table 5 in Gensicke et al. (2022).

²⁷Furthermore, Figure 1.D.3 in the appendix shows the results that correspond to Figure 1.2 without mean imputation.

1.C Summary statistics

Table 1.C.1: Summary statistics for the monthly panel

	N	Min	Mean	Median	Max	SD
Share of short-time work	237600	0	0.047	0	16	0.19
GVC trade with China	237600	0.054	0.23	0.25	0.65	0.11
GVC trade with the World without China	237600	0.089	0.32	0.35	0.75	0.13
COVID-19 infections	237600	0	32.0	1.44	1797.5	126.2
Stringency index	237600	0	25.9	30.7	66.7	22.7
Regional mobility	237600	-0.57	-0.014	0	1.33	0.14

Note: The share of short-time work (STW) is calculated as the number of STW in the current month divided by the number of all workers in June 2019. The COVID-19 infections, the stringency index and the regional mobility are assigned to the establishments by the labor market region of their residence.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), Corona Datenplattform and Brockmann and Robert Koch Institute (2022); own calculations.

Table 1.C.2: Summary statistics to predict GVC integration with entropy balancing in 2019

	N	Min	Mean	Median	Max	SD
Share medium-skilled workers	6736	0	0.74	0.80	1	0.25
Share high-skilled workers	6736	0	0.16	0.073	1	0.23
Share STEM occupations	6736	0	0.016	0	1	0.072
Share professions with university degree	6736	0	0.016	0	1	0.074
Share employees in highly complex tasks	6736	0	0.098	0.0056	1	0.19
Share managers	6736	0	0.043	0	1	0.13
Daily wage p(25)	6736	3.55	87.0	86.8	893.7	32.2
Daily wage p(50)	6736	3.55	97.4	97.2	1270.3	39.3
Daily wage p(75)	6736	3.55	111.7	111.9	1647.0	50.4
AKM firm-effects 2010-2017	6736	-1.81	0.21	0.21	1.86	0.21
Prop intermed. consump. of turnover(in %)	6736	1	46.4	46	99	17.4
Prop. business volume abroad (in %)	6736	0	6.15	0	100	15.0
WfH Capacity	6736	0.30	0.55	0.54	0.89	0.13
Loss of value added	6736	-1	-0.22	-0.065	0	0.27
Distance to Bergamo (km)	6736	200.6	663.2	670.3	1025.4	187.5

Note: Missing values in the observations are mean value imputed. See Section 1.B for further information.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), Alipour et al. (2023) and OECD (2022); own calculations.

Table 1.C.3: Summary statistics for establishments and supply problems

	N	Min	Mean	Median	Max	SD
Pandemic Impacts: Problems supply chains and int. goods	5299	0	0.41	0	1	0.49
GVC CHN in share of GEXP	5298	0.054	0.24	0.25	0.65	0.11
GVC WLD in share of GEXP	5299	0.089	0.31	0.32	0.74	0.14
Number of employees	5299	1	87.0	16	44686	670.5
Share low-skilled workers	5299	0	0.11	0.053	1	0.17
Share medium-skilled workers	5299	0	0.74	0.79	1	0.25
Share high-skilled workers	5299	0	0.15	0.070	1	0.22
Share STEM occupations	5299	0	0.015	0	1	0.068
Share professions with university degree	5299	0	0.013	0	1	0.068
Share employees in highly complex tasks	5299	0	0.088	0.0034	1	0.17
Share managers	5299	0	0.031	0	1	0.095
Daily wage p(25)	5299	6.08	85.2	86.8	569.9	30.7
Daily wage p(50)	5299	6.08	95.6	97.2	681.3	37.1
Daily wage p(75)	5299	6.08	110.3	111.9	872.0	48.0
WfH Capacity	5299	0.30	0.54	0.54	0.89	0.12
Loss of value added	5299	-1	-0.25	-0.069	0	0.29
Distance to Bergamo (km)	5299	197.4	655.7	666.9	1025.4	190.1
Prop. intermed. consump. of turnover(in %)	5299	1	46.7	46	99	18.0
Prop. business volume abroad (in %)	5299	0	7.00	0	100	16.7
AKM firm-effects 2010-2017	5299	-1.81	0.20	0.21	1.73	0.22

Note: Missing values in the observations are mean value imputed. See Section 1.B for further information. Industry 5, "Mining support service activities" shows no gross exports with China and the number of observations reduces from 5299 to 5298.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023), OECD (2022) and World Bank (2024); own calculations.

Table 1.C.4: Indices for GVC-related trade by industry

	<i>GVC^{WLD}</i>	<i>GVC^{CHN}</i>
Agriculture, hunting, forestry	0.404	0.307
Fishing and aquaculture	0.541	0.271
Mining and quarrying, energy producing products	0.609	0.485
Mining and quarrying, non-energy producing products	0.513	0.239
Mining support service activities	0.557	.
Food products, beverages and tobacco	0.347	0.313
Textiles, textile products, leather and footwear	0.397	0.480
Wood and products of wood and cork	0.447	0.395
Paper products and printing	0.496	0.389
Coke and refined petroleum products	0.716	0.654
Chemical and chemical products	0.574	0.482
Pharmaceuticals, medicinal chemical and botanical products	0.309	0.254
Rubber and plastics products	0.547	0.464
Other non-metallic mineral products	0.396	0.313
Basic metals	0.741	0.598
Fabricated metal products	0.502	0.354

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Table 1.C.4: Indices for GVC-related trade by industry (continued)

	$GVC_{s(i)}^{WLD}$	$GVC_{s(i)}^{CHN}$
Computer, electronic and optical equipment	0.443	0.509
Electrical equipment	0.457	0.412
Machinery and equipment, nec	0.415	0.364
Motor vehicles, trailers and semi-trailers	0.438	0.346
Other transport equipment	0.481	0.391
Manufacturing nec; repair and installation of machinery and equipment	0.371	0.333
Electricity, gas, steam and air conditioning supply	0.440	0.308
Water supply; sewerage, waste management and remediation activities	0.377	0.271
Construction	0.392	0.283
Wholesale and retail trade; repair of motor vehicles	0.311	0.256
Land transport and transport via pipelines	0.358	0.280
Water transport	0.541	0.439
Air transport	0.404	0.349
Warehousing and support activities for transportation	0.461	0.311
Postal and courier activities	0.476	0.195
Accommodation and food service activities	0.144	0.143
Publishing, audiovisual and broadcasting activities	0.310	0.177
Telecommunications	0.290	0.184
IT and other information services	0.324	0.223
Financial and insurance activities	0.448	0.187
Real estate activities	0.0889	0.0790
Professional, scientific and technical activities	0.345	0.174
Administrative and support services	0.414	0.190
Public administration and defence; compulsory social security	0.192	0.124
Education	0.0996	0.0536
Human health and social work activities	0.159	0.138
Arts, entertainment and recreation	0.138	0.110
Other service activities	0.130	0.113

Note: Values can be interpreted as the share of exports that is GVC-related in relation to the total export of the industry. The derivation and an explanation of the indices can be found in Section 1.4. No values are available for the sector "D98: Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use".

Source: OECD (2022); own calculations.

1.D Additional regression results

Table 1.D.1: Coefficients from panel event study plot for GVC-related trade with China

Month	2019			2020			2021		
	Beta coefficient	95% confidence interval		Beta coefficient	95% confidence interval		Beta coefficient	95% confidence interval	
January	-0.032	-0.067	0.003	-0.001	-0.021	0.019	0.056	-0.203	0.315
February	-0.025	-0.06	0.01	ref.			0.048	-0.213	0.308
March	-0.021	-0.054	0.012	-0.022	-0.208	0.163	0.031	-0.222	0.284
April	-0.016	-0.056	0.024	0.18	-0.085	0.446	0.025	-0.201	0.251
May	-0.022	-0.056	0.011	0.255	0.02	0.491	0.012	-0.213	0.237
June	-0.015	-0.053	0.023	0.269	0.092	0.445	0.022	-0.129	0.173
July	-0.019	-0.058	0.02	0.266	0.122	0.411	0.004	-0.112	0.121
August	-0.031	-0.065	0.003	0.193	0.049	0.337	0.001	-0.103	0.104
September	-0.017	-0.055	0.022	0.171	0.041	0.301	0.001	-0.094	0.097
October	-0.011	-0.041	0.019	0.134	0.006	0.262	0.002	-0.085	0.088
November	-0.009	-0.039	0.02	0.082	-0.1	0.264	-0.011	-0.097	0.074
December	-0.016	-0.039	0.007	0.025	-0.201	0.251	-0.018	-0.12	0.084

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the firm level. EBCT weights are calculated for GVC-related trade with China. Top and bottom 1% firms are trimmed in the model. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

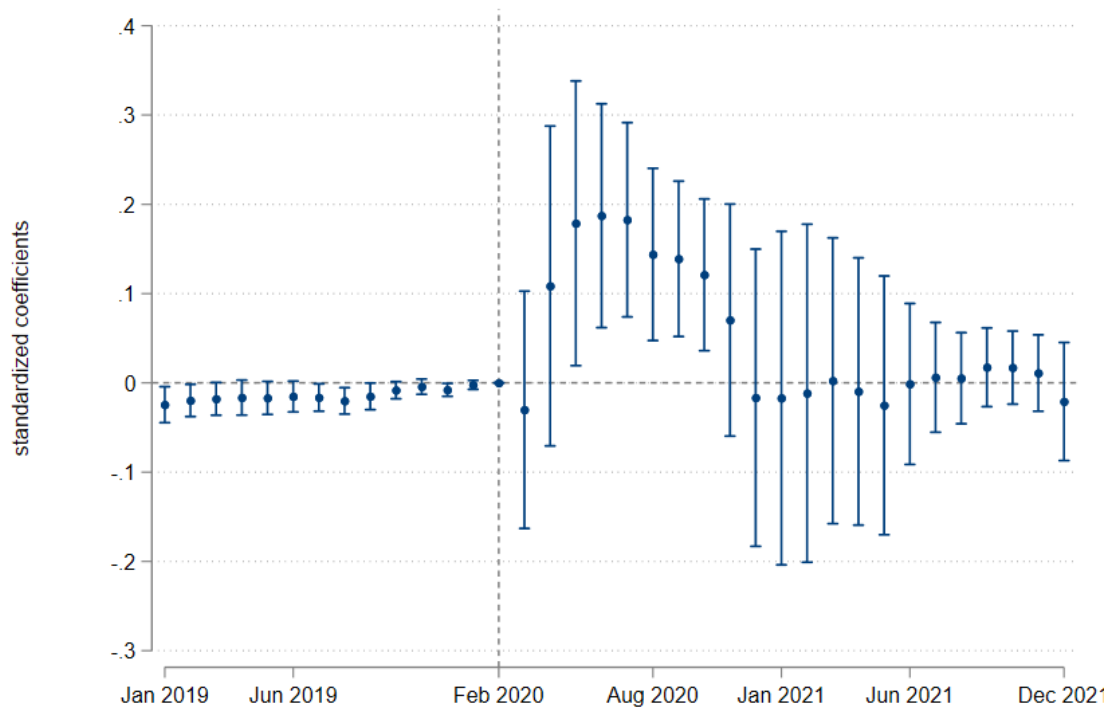


Figure 1.D.1: Baseline event study plot for GVC-related trade with China and STW (continuous treatment)

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016) and OECD (2022); own calculations.

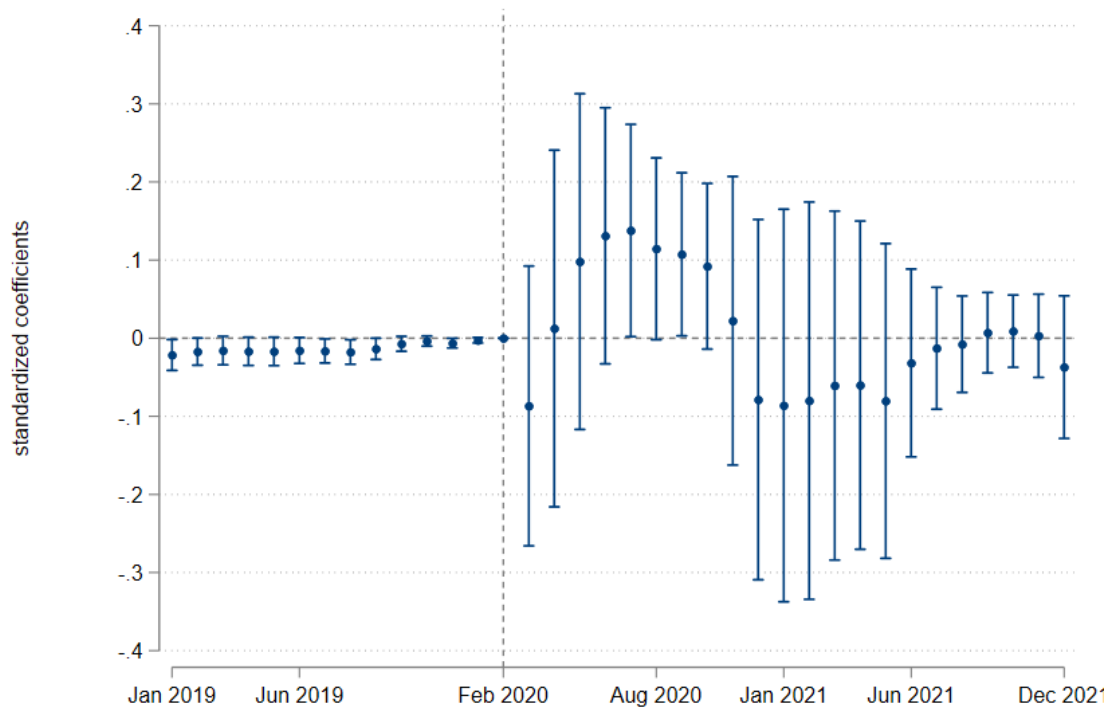


Figure 1.D.2: Baseline event study plot for GVC-related trade with the world without China and STW (continuous treatment)

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the firm level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016) and OECD (2022); own calculations.

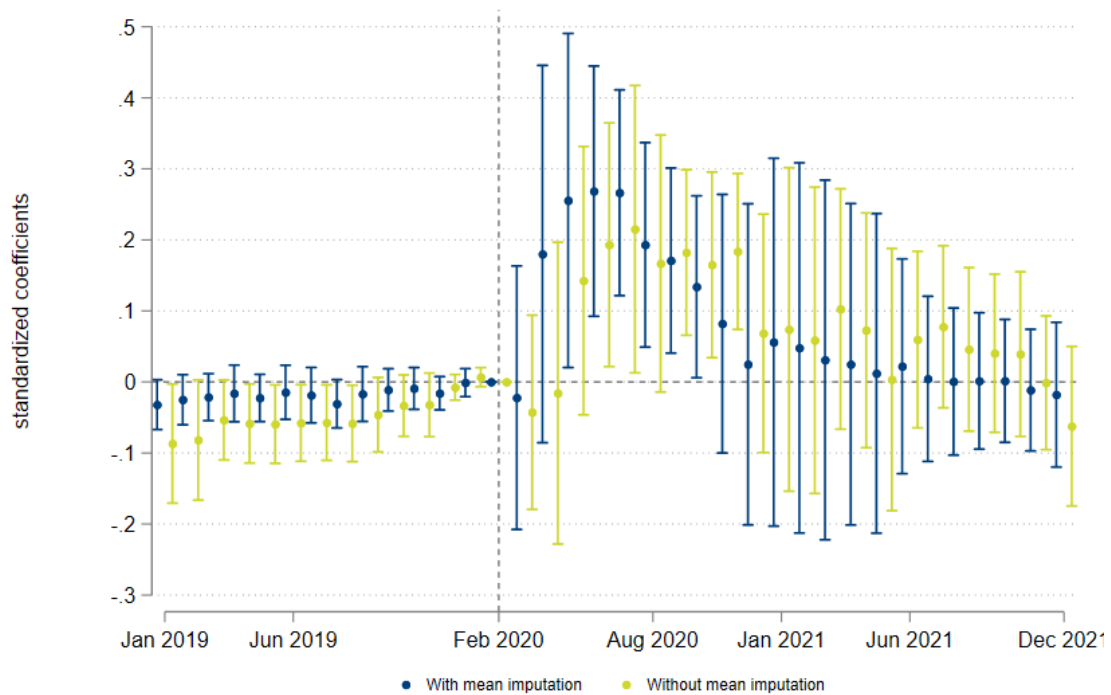


Figure 1.D.3: Event study plot with and without mean imputation for GVC-related trade with China and STW (continuous treatment)

Note: The blue line indicates the coefficients with mean imputation, and the green line without mean imputation. For further details on the imputation, see Section 1.B in the appendix. All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the firm level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

1.E Additional entropy balancing results

Table 1.E.1: Balancing table for GVC-related trade with the world without China (binary treatment)

	Mean differences			
	Pre p(40)	Post p(40)	Pre p(66)	Post p(66)
AKM firm-effects 2010-2017	-0.474	-0.000	-0.355	-0.000
Daily wage p(25)	-0.180	-0.000	-0.156	-0.000
Daily wage p(50)	-0.231	-0.000	-0.194	-0.000
Daily wage p(75)	-0.284	-0.000	-0.229	-0.000
Distance to Bergamo (km)	-0.009	0.000	-0.005	0.000
Loss of value added	0.101	0.000	0.520	0.000
Prop. business volume abroad (in %)	0.474	0.000	0.654	0.000
Prop. intermed. consump. of turnover(in %)	-0.017	0.000	0.013	0.000
Share STEM occupations	0.634	0.000	0.131	0.000
Share employees in highly complex tasks	-1.235	-0.000	-1.667	-0.000
Share high-skilled workers	-0.728	-0.000	-0.923	-0.000
Share managers	0.184	0.000	-0.332	-0.000
Share medium-skilled workers	0.131	0.000	0.144	0.000
Share professions with university degree	-7.731	-0.000	-18.989	-0.002
WfH Capacity	-0.136	0.000	-0.037	-0.000

Note: The table shows the differences of the first moment (mean) between the treatment and the control group before and after entropy balancing. The first two columns show the differences when the treatment group is defined as GVC-related trade larger than the 40th percentile. Column three and four show the differences when the treatment group is defined as GVC-related trade larger than the 66th percentile.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

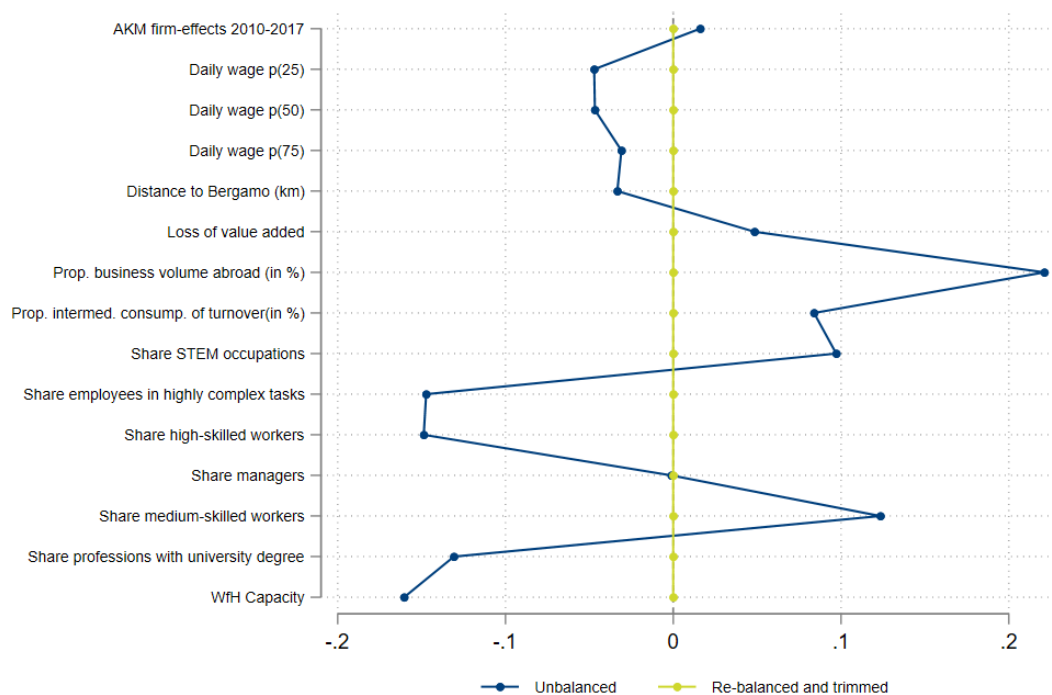


Figure 1.E.1: Correlations before and after entropy balancing for trade integration with the world without China

Note: The weighted correlations are shown after dropping the 1% smallest and largest firms regarding their weights. Further summary statistics of the variables are listed in Table 1.C.2.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

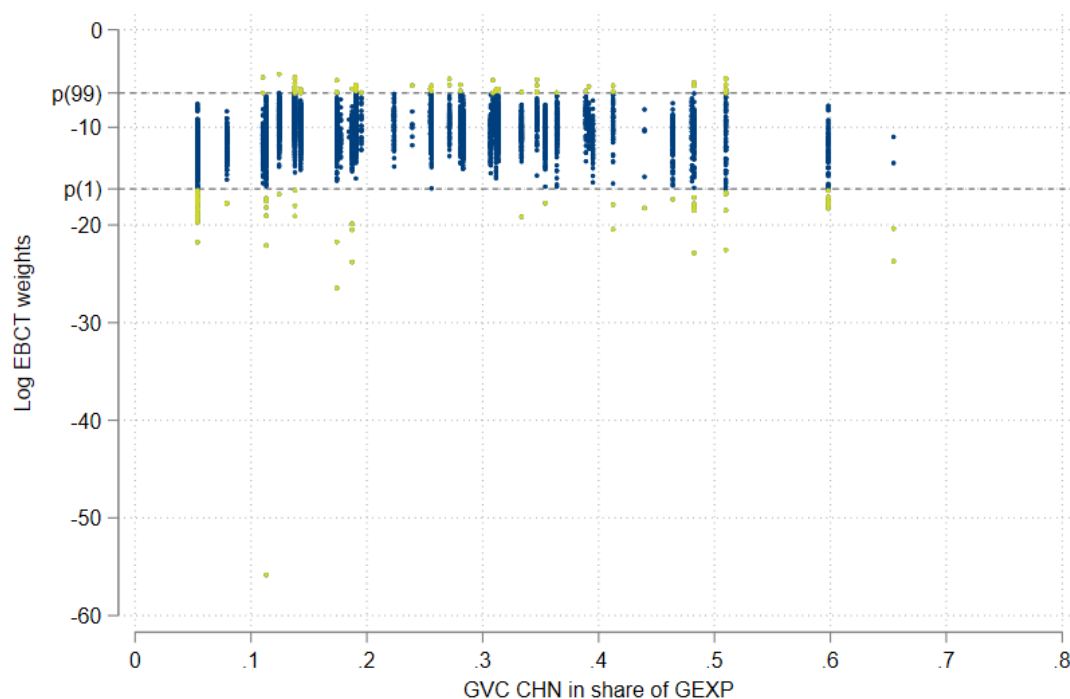


Figure 1.E.2: Entropy balancing weights for trade integration with China

Note: Firms are ordered by their GVC-related trade with China. Each dot represents the weight generated by EBCT with the variables presented in Table 1.C and for GVC-related trade with China as treatment variable. The green dots are the 1% smallest and largest firm-level weights which are trimmed in the following to guarantee common support.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

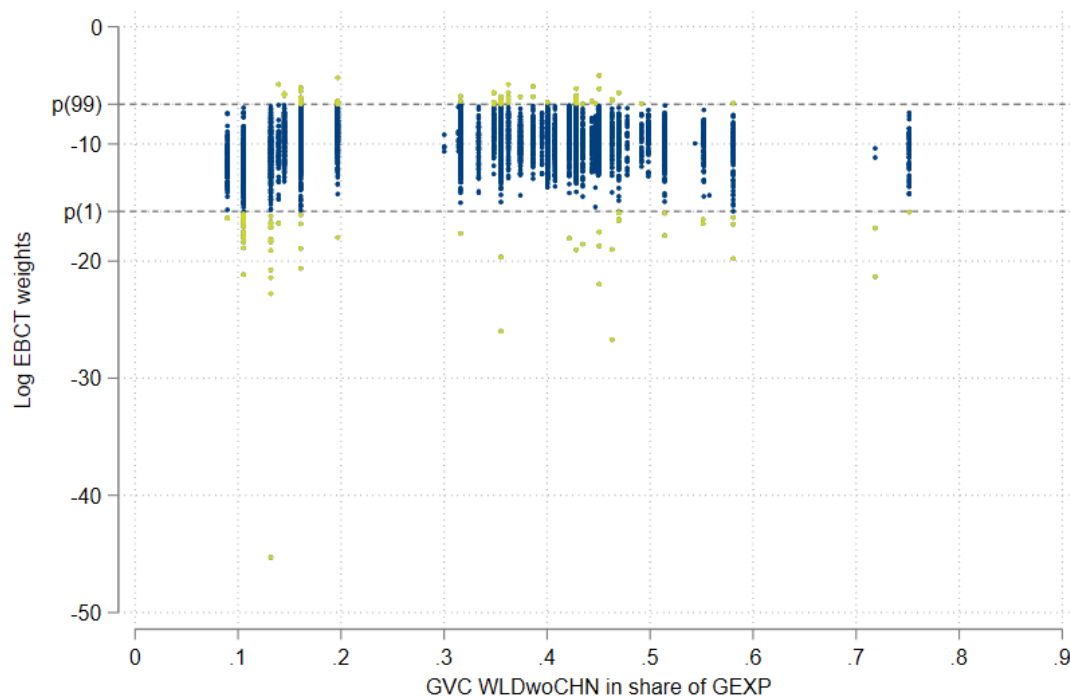


Figure 1.E.3: Entropy balancing weights for GVC-related trade with the world without China

Note: Firms are ordered by their GVC-related trade with the world without China. Each dot represents the weight generated by EBCT with the variables presented in Table 1.C.2 and for GVC-related trade with the world without China as treatment variable. The green dots are the 1% smallest and largest firm-level weights which are trimmed in the following to guarantee common support.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

1.F Representability of the matched sample

The dataset for the analysis consists of 6,736 establishments. To obtain representative results for all establishments in Germany, it is necessary that the industry distribution (treatment variation) in the sample and for all establishments in Germany is comparable. When aggregating all establishments to industries, the correlation of both industry distributions is $\rho = 0.829$ and is significant at the 0.1% level.

In addition, I use the entire establishment population in Germany that I can observe for the three-year period from 2019 until 2021 to estimate the model of Equation (1.5). In this dataset, I have 2,445,010 establishments for 36 months, which leads to 88,020,360 observations. Since I do not have survey information for almost all establishments I run an entropy balancing with a reduced set of control variables. I use the qualification structure, the shares of STEM workers, workers with university degree, employees in highly complex task and managers. Additionally, I use the wage percentiles, the work-from-home capacity, the loss of value added, and the distance to Bergamo of the establishment.

In Figure 1.F.1, the blue markers and confidence intervals show the relationship between STW and GVC-related trade with China for the matched sample of 6,736 establishments and the full set of entropy balance controls. The green line shows the effects for the full population of establishments with the reduced entropy balancing.²⁸ It is clear that the regression results are not significantly different. The green area around the line shows the confidence interval. Only the confidence interval is significantly larger in the model with fewer control variables.

²⁸For technical reasons, it is not possible to estimate the weights in the entropy balancing and the coefficients in the model with the full sample of 88,020,360 observations. For this reason, I divided the data set into 34 sub-samples. All samples have the same industry share distributions as the full dataset. The green line and area represent the mean coefficients of the 34 coefficients.

A possible explanation for the smaller confidence intervals in the matched dataset could be that the additional control variables in the survey dataset explain important differences between establishments within sectors that influence the level of STW. In summary, the reduced dataset could be considered as representative for all establishments in Germany.

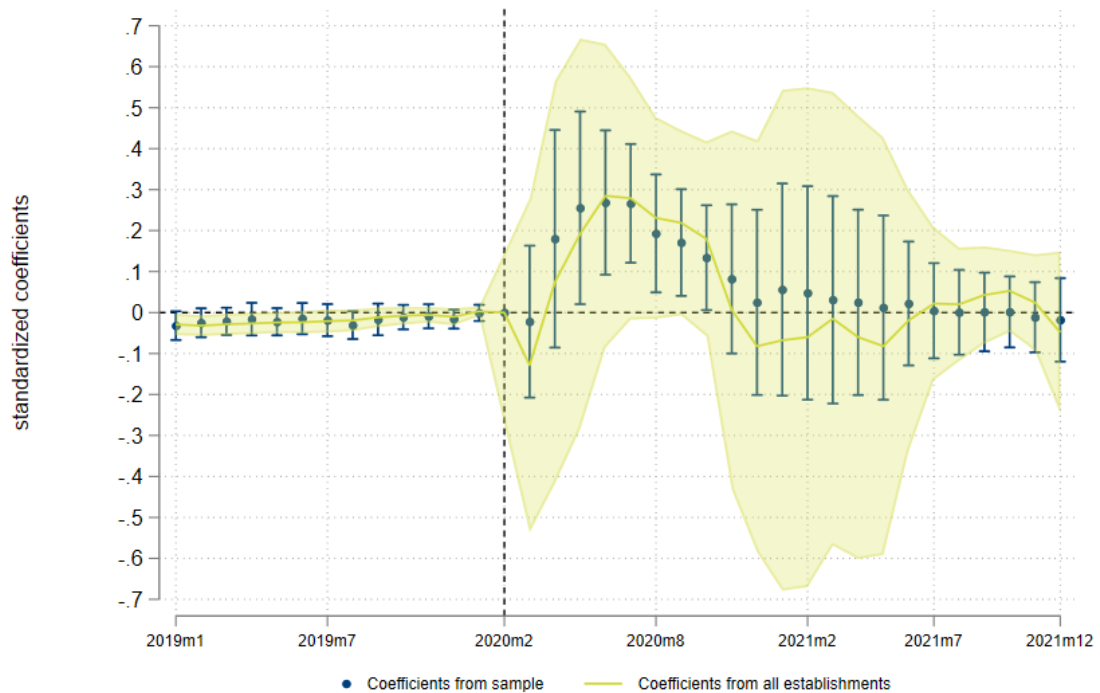


Figure 1.F.1: Effects for the entire establishments population in Germany

Note: All coefficients are in reference to February 2020. The blue line indicates the relationship between STW and GVC-related trade with China for the main dataset. The green line and area indicate the effects and confidence intervals derived from the dataset for the entire establishment population and a reduced entropy balancing. The standard errors for the 95% confidence intervals are clustered on the industry level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

1.G Random treatment specification

This robustness check tests the significance of the effects of GVC-related trade with China against a random treatment distribution. This approach can be interpreted as a more stringent test than testing the parameters against the null in the "normal" setting. To do so, I randomly draw the treatments 500 times from a normal distribution with mean and variance from the true GVC-related trade distribution:

$$GVC_{rand} \sim N(\mu_{GVC^{CHN}}, \sigma_{GVC^{CHN}}^2) \quad (1.7)$$

Figure 1.G.1 shows the means of the coefficients of the 500 draws in green and the coefficients from the specification from Equation (1.5) in blue for GVC-related trade with China. The true coefficients differ significantly from the coefficients of the random treatment distribution in the first part of the pandemic. Furthermore, the random coefficients all intersect the zero reference line and do not show any kind of pattern. This clearly indicates that the results not only significantly differ from zero but also from a randomly distributed potential treatment distribution.

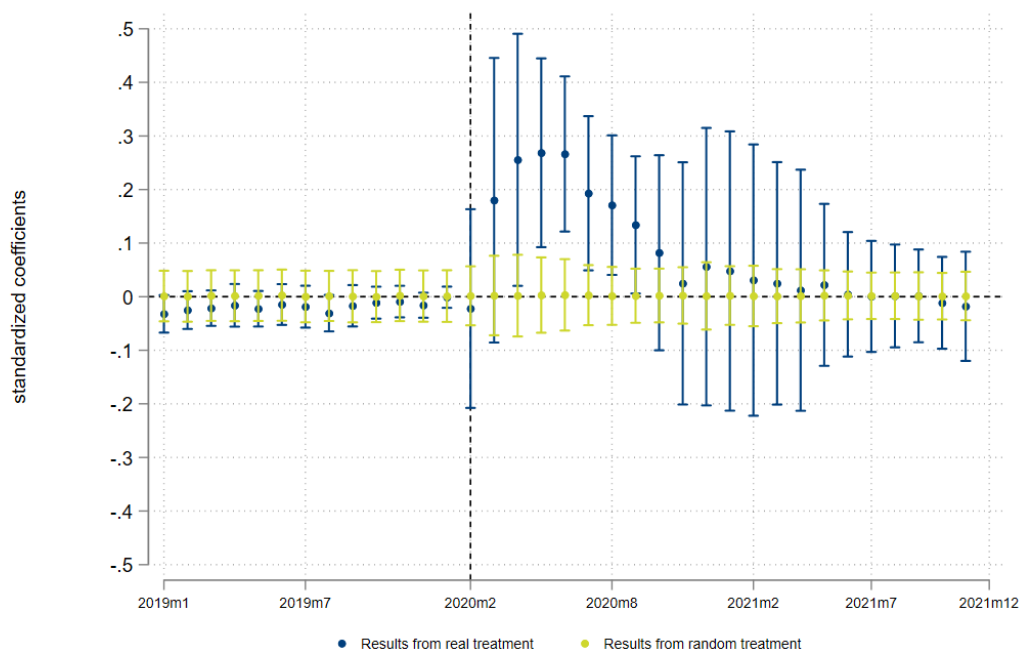


Figure 1.G.1: Randomization inference for GVC-related trade integration with China

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. EBCT weights are calculated for GVC-related trade with China. Top and bottom 1% firms are trimmed in the model. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019. The random coefficients are the means of the treatment coefficients that are drawn from a normal distribution ($GVC_{rand} \sim N(\mu_{GVC^{CHN}}, \sigma_{GVC^{CHN}}^2)$) with 500 repetitions.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023)

1.H STW reports on single-establishment level

As Kagerl et al. (2022) show that firms with several establishments often report STW at a central office which leads to problems in reporting and data generation. For this reason, I will review the STW reports during the crisis in different datasets.²⁹ Moreover, multi-establishment firms tend to over-report STW because they may report STW for all their sub-firms. For this reason, in Figure 1.H.1 I run the model on the subsample of firms with only one establishment. It is clear that including or excluding multi-establishment firms in the sample has almost identical effects.³⁰

²⁹See Section 1.A in the appendix for a detailed description. Further, the development of STW in the sample looks very similar to the development of STW of the entire population, see Figure 1.A.1.

³⁰Many thanks to Christian Kagerl for the explanation and the guidance on this topic.

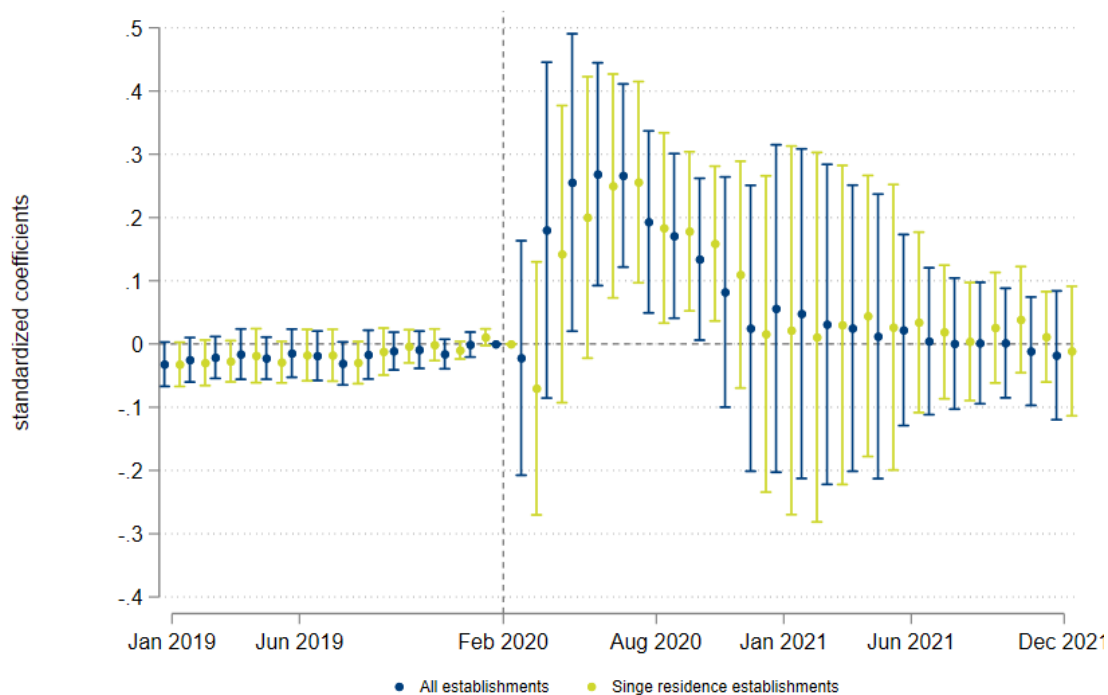


Figure 1.H.1: Effects for single residence establishments

Note: All coefficients are in reference to February 2020. GVC-related trade index is standardized ($\mu = 0$, $\sigma = 1$). The standard errors for the 95% confidence intervals are clustered on the industry level. Short-time work rates are calculated as the number of workers in short-time work in a given month over the employment level in June 2019.

Source: Federal Employment Agency, Statistics/Labour Market Reporting (2016), IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

1.I Regression results for input supply problems

Table 1.I.1: GVC-related trade and supply problems (table with controls)

	(1) OR/Std. error	(2) OR/Std. error	(3) OR/Std. error
GVC-related trade (China)	1.337*** (0.107)		1.593*** (0.201)
GVC-related trade (world excluding China)		1.188** (0.087)	0.820 (0.106)
Number of employees	1.000 (0.000)	1.000 (0.000)	1.000 (0.000)
ref: share low-skilled workers			
Share medium-skilled workers	0.976 (0.046)	0.994 (0.051)	0.970 (0.043)
Share high-skilled workers	0.909* (0.047)	0.910* (0.047)	0.902** (0.047)
Share STEM occupations	1.100** (0.041)	1.120** (0.050)	1.109*** (0.043)
Share professions with university degree	1.066 (0.043)	1.060 (0.042)	1.065 (0.043)
Share employees in highly complex tasks	0.966 (0.071)	0.954 (0.070)	0.956 (0.071)
Share managers	0.963 (0.065)	0.968 (0.071)	0.975 (0.067)
Daily wage p(25)	0.776* (0.104)	0.780* (0.103)	0.785* (0.105)
Daily wage p(50)	1.238 (0.295)	1.177 (0.284)	1.239 (0.299)
Daily wage p(75)	1.042 (0.133)	1.082 (0.139)	1.034 (0.136)
Prop. intermed. consump. of turnover(in %)	1.110** (0.046)	1.140*** (0.052)	1.098** (0.045)
Prop. business volume abroad (in %)	1.091** (0.044)	1.141*** (0.049)	1.082* (0.042)
WfH Capacity	0.835 (0.095)	0.786** (0.093)	0.855 (0.091)
Loss of value added	1.055 (0.113)	1.097 (0.120)	1.045 (0.107)
Distance to Bergamo (km)	1.040 (0.040)	1.036 (0.040)	1.041 (0.040)
AKM firm-effects 2010-2017	1.163 (0.262)	1.156 (0.261)	1.190 (0.270)
Constant	0.637*** (0.056)	0.649*** (0.058)	0.627*** (0.051)
Observations	5298	5299	5298
Pseudo R^2	0.0415	0.0346	0.0432
Log likelihood	-3433.7	-3459.2	-3427.5

Note: The table shows the results of a logistic regression with odds ratios (OR). The outcome variable is question 1b option C of the IAB Establishment Panel 2020. It asks whether difficulties with the acquisition of inputs or with suppliers have negative impact on the establishment during the pandemic in 2020. Industry 5, "Mining support service activities" shows no gross exports with China, the number of observations reduces from 5299 to 5298 in Model (1) and (3). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ with clustered standard errors at the industry level.

Source: IAB Establishment Panel, IAB Establishment History Panel, Alipour et al. (2023) and OECD (2022); own calculations.

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Chapter 2

Welcome back! The impact of ‘return initiatives’ on return migration to rural regions*

Moritz Meister Anja Rossen Jan Cornelius Peters

Abstract This paper studies the effect of return initiatives in rural regions of Germany on interregional return migration. The initiatives aim to increase return migration by, amongst other things, providing information on local employment opportunities and personal support to workers interested in returning to find a job in the former rural region of residence. Analyzing administrative data on individual labor market biographies through survival analysis and difference-in-differences estimation, we find that return initiatives, on average, promote interregional return migration. Among the considered workers, particularly those in the middle and at the top of the wage distribution, are more likely to return.

*A slightly different version of this chapter is published in the *Journal of Economic Geography*, Volume 24, Issue 5, September 2024, Pages 759–784, DOI: <https://doi.org/10.1093/jeg/lbae028>

A former version of the chapter is available as: *Welcome back! The impact of ‘return initiatives’ on return migration to rural regions*. Vfs Annual Conference 2022 (Basel): Big Data in Economics, Verein für Socialpolitik. URL: <https://ideas.repec.org/p/zbw/vfsc22/264134.html>.

We would like to thank the German Federal Rural Development Scheme as part of the project “*The spatial mobility of workers over the course of individual working lives – Analyses for rural areas in Germany*” (No. 2817LE054) for financial support.

2.1 Introduction

Demographic change leads to a significant decline in the supply of labor in many remote regions of OECD countries (OECD, 2020). One driver of this development is that in particular young, high ability workers tend to leave rural areas and move to agglomerated local labor markets (see, e.g., Behrens and Robert-Nicoud, 2015; Combes et al., 2008; Costa and Kahn, 2000; De la Roca, 2017; Glaeser and Resseger, 2010; OECD, 2020; Simon, 2019).² Several scholars argue that this net out-migration and the associated sorting of workers with different skill-levels across space diminishes the future prospects of peripheral regions, as the endowment with human capital is thought to be a crucial factor for regional development (see, e.g., Chen and Rosenthal, 2008; Faggian and McCann, 2009; Gennaioli et al., 2012; Rodríguez-Pose and Ketterer, 2012). Recent results by Fajgelbaum and Gaubert (2020) for the U.S. indicate that also aggregate welfare might be reduced by a too high concentration of economic activity across space and too few high skilled workers in smaller cities, from which the lower skilled may benefit due to spillover effects.

Against this background, this paper studies – based on administrative micro-data – the impact of a regional policy measure, so-called return initiatives, on return migration to rural regions in Germany. These return initiatives have been established by local stakeholders in several peripheral regions in the last two decades to address declining local labor supply and associated shortages of skilled labor (Stiller and Ohlhoff, 2021). Specifically, a return initiative aims to promote interregional return migration of former inhabitants to the region, in which the

²We use the terms ‘rural regions’, ‘peripheral regions’ and ‘remote regions’ interchangeably throughout the paper to improve readability.

initiative is situated.³ A key instrument is typically publishing information on local employment opportunities, such as vacancies and potential employers on their website. Furthermore, the initiatives often provide additional personal support to workers who are interested in returning to find a job in the former rural region of residence, among other things.

By analyzing whether the existence of a return initiative in a former region of residence increases the probability of return migration, our study is, to our knowledge, the first to provide insights on the effect of this kind of policy intervention, even though the first return initiatives in Germany were established about 20 years ago. More generally, our analysis also contributes to the growing literature on the role of spatial search frictions for interregional labor migration by providing new suggestive evidence. We presume that an important mechanism underpinning the positive effect of return initiatives on return migration, which we detect, is a reduction of the search frictions that workers likely face, when looking for a job in the former rural region of residence.

Recent studies indicate that labor market frictions significantly impact internal migration of workers. For instance, based on French data, Schmutz and Sidibé (2018) find that mobility cost estimates are smaller by one order of magnitude, if spatial search frictions are taken into account. Similarly, Balgová (2019; 2022) estimates that in the U.S. it is even for employed college educated workers about 1.5 times harder to search for a job in another region than locally, despite the fact that this group of workers face the lowest spatial search frictions compared to other types of labor in the U.S.⁴ Furthermore, according to her model, a reduction

³Potential reasons for return migration discussed in the literature refer to a correction of a previous migration decision, an optimized individual life-cycle plan and migration as signal for skills unobservable by firms before hiring (Borjas and Bratsberg, 1996; De la Roca, 2017; Knauth and Wrona, 2018).

⁴Further recent studies that emphasize the significance of spatial search frictions and information about employment opportunities for labor mobility are Ransom (2022), Schluter and Willems (2019), and Wilson (2021).

of spatial search frictions specifically increases non-speculative migration, that is, migration with a position already secured. The reason is that lower frictions facilitate achieving a good job-match in another region without *ex ante* moving there. Balgová (2022) points out that in some models of interregional migration, like the ones by Harris and Todaro (1970), Kennan and Walker (2011), and Kline and Moretti (2013), it is assumed that workers can only search for a job after moving (see also De la Roca, 2017). In contrast, in other models, for instance those by Amior (2015), Beaudry et al. (2014), Epifani and Gancia (2005), and Lutgen and Van der Linden (2015), it is assumed that workers only move given they achieve a match in another region (*ibid.*). Balgová (2022) herself develops a theoretical model in which workers can move with and without a job. Furthermore, she detects that about two third of interstate moves in the U.S. are associated with cross-regional job match (non-speculative migration) and only about one third of the mobile workers move to search. Interestingly, non-speculative moves might be of particular importance for migration to peripheral areas, including return migration. By contrast, speculative migration is likely to be relatively unattractive for at least some workers due to the rather low probability of achieving a (high-quality) match in a small local labor market even after moving there (see, e.g., Di Addario, 2011; Duranton and Puga, 2004; Fontagné and Santoni, 2018), which diminishes the expected return of speculative migration to a rural region. This paper contributes to the literature on spatial search frictions and labor migration by providing robust evidence on the impact of regional policy interventions, that aim to foster return migration by increasing the chance that workers, who are interested in returning, achieve a sufficiently acceptable job-match in the respective former region of residence, so that they indeed return.

Our results indicate that the considered return initiatives, on average, promote return migration. However, the estimates also point to heterogeneous effects be-

tween workers. For those individuals who moved to another local labor market immediately after the end of vocational training – about one third of all considered workers – we do not observe any significant impact. In contrast, for workers who acquired further work experience after the completion of vocational training before moving, we do find a significant effect of the return initiatives on return migration, on average. A further differentiation indicates that workers in the middle and at the top of the wage distribution drive this result. For these individuals, we observe a statistically and economically significant impact of return initiatives on the likelihood to return, while for workers at the bottom of the wage distribution, who arguably possess rather low abilities and less specialized skills, we do not. Depending on the exact specification, the estimated average treatment effect on the treated (ATT) in the case of workers in the middle of the wage distribution is about 21 percent to 25 percent which means that the return initiatives increase the likelihood to return by about 21 percent to 25 percent. For those workers with the highest wages in our sample, the point estimates suggest an increase in the probability to return by about 24 percent to approximately 38 percent. The increase in return migration, however, seems to occur not immediately in the year in which a return initiative is established, but with a time-lag of two to three years.

For our analysis, we merge administrative information on individual labor market biographies from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) with novel data on the establishment and existence of return initiatives in German regions provided by Stiller and Ohlhoff (2021). We consider the universe of all workers who completed vocational training in Germany in the period 2000 to 2014 and moved to another local labor market in the years thereafter. Based on this sample of 405,320 workers, we examine the likelihood of return migration to the local labor market in which vocational training was completed, and whether it is positively affected by the existence of a

return initiative at the former residential location.

Our identification strategy rests on exploiting the spatio-temporal variation in the establishment of return initiatives at NUTS 3-level and information on individual return migration decisions. Specifically, we combine event history analysis and difference-in-differences estimation in a panel event study framework. In this setup, we estimate the effect of a return initiative on the individual likelihood to return conditional on indicators for the ability level of a worker and the individual labor market success prior to and after initial migration. Furthermore, we control for important time-varying regional characteristics, which likely determine migration decisions such as skill-level and occupation specific regional labor market conditions and (positive) local labor demand shocks caused by newly founded establishments. To confirm the robustness of our results, we, among other things, apply matching and entropy balancing (Hainmueller, 2012) to generate a synthetic control group that is as similar to the treatment group as possible.

The paper proceeds as follows. In Section 2.2 we describe the data and provide information about the return initiatives examined in this analysis. In Section 2.3 we explain our empirical strategy and in Section 2.4 we present and discuss the results of our analyses. Finally, in Section 2.5 we set out our conclusions.

2.2 Data and descriptive analysis of return migration

For our empirical analyses, we mainly use two data sources. The first is the Integrated Employment Biographies (IEB, Version 13.01.00-181010), which capture individual labor market biographies, including annual information on individual places of residence. We merge these data with new information on return ini-

tatives in Germany provided by Stiller and Ohlhoff (2021). The combination of both data sets enables us to study individual decisions on return migration, depending on the existence of a return initiative in the former residential region. Furthermore, we use the IEB to generate important control variables referring to the individual labor market biography and to precisely measure regional labor market conditions.

2.2.1 Construction of an annual worker panel

The IEB covers microdata on employment, unemployment, job searches, benefit receipt, and participation in measures of active labor market policy on a daily basis for the universe of all labor market participants in Germany, as long as workers are not exempt from social security contributions, such as civil servants and self-employed persons (about 12 percent of the labor force). Because the IEB is constructed from administrative records, including health, pension and unemployment insurance notifications, it contains very reliable information on all periods of labor market participation.⁵

From 1999 onwards, the individual spells in the IEB, i.e. observations covering a span of time, provide information on the municipality of residence. Employment spells contain precise information on a range of areas, including employment status, occupation, gross daily wage, and the location of employment at the municipality level, in addition.⁶ Based on individual employment and unemployment spells, we construct an annual worker panel, which captures information on individual labor market participation and remuneration, as well as the last residential information per worker and year.

Our analysis, and thus the annual worker panel, is restricted to medium-skilled

⁵For a more detailed description of the IEB see Frodermann et al. (2021).

⁶Information on place of birth is not available in the IEB.

workers, i.e. workers who completed dual vocational training that comprises (a) practical training in a firm and (b) vocational education at a vocational school. We focus on these workers because for this group we observe all residential locations starting with the take-up of vocational training (provided a worker remains in the labor market). In Germany, workers with a vocational training degree represent by far the largest group of employees. The share of former apprentices in regional employment in many rural local labor markets is particularly high. At the same time there is a lack of medium skilled labor in Germany such as craftsmen, or agricultural, technical, medical and nursing professionals (Bossler and Popp, 2022; Cedefop, 2016).⁷

Specifically, we consider all medium skilled workers who finished the apprenticeship between 2000 and 2014 in Germany. Among these workers, we focus on those who moved from the local labor market of residence during vocational training to another part of Germany in subsequent years (until 2014).⁸ After imposing some additional restrictions on the sample (see appendix, Section 2.B.1), the number of individuals in our annual worker panel amounts to 405,320 potential return migrants. For them, the panel comprises all worker-year observations between initial migration after the completion of vocational training and the year in which a worker drops out of the sample at risk because she (a) returns, (b) is not observed in the IEB for at least 2 years, e.g., because the person (temporarily)

⁷See appendix, Section 2.A for some key facts about the German dual apprentice system. For a more detailed description of vocational education and training (VET) in Germany, please refer to Deissinger (2015) and Cedefop (2020). The share of workers with a vocational training degree in total employment (with known level of qualification) is 69 percent (June 30, 2017; own calculation). Similarly, the share of VET occupations in total employment in Germany was 62.4 percent in 2020, according to Cedefop (2022) (see Figure 2.A.1 in the appendix).

⁸To define the local labor market in which a worker was living as apprentice, we trace a circle with a radius of 50 km around the geographic center of the municipality of residence during vocational training. This radius is in line with findings by Manning and Petrongolo (2017) for the size of local labor markets using data for the UK. Furthermore, Dauth and Haller (2018), who provide evidence on commuting distances in Germany, find that less than 10 percent of them exceed 50 km (driving distance by car).

leaves the German labor market or (c) the end of the observation period (end of 2017) is reached. The number of these observations is 2,532,971.

Return migration is defined as moving back to the local labor market of residence during vocational training. More precisely, we consider all workers who move to a municipality that is less than 50 km apart from the municipality of residence during vocational training (until December 31, 2017) to be return migrants. This amounts to 92,639 people. More than 50 percent even move back to the municipality they lived in during vocational training. The 75th percentile of the distance between the locations of residence during vocational training and after return migration at municipality level is 15 km and the 90th percentile is 35 km.⁹

Based on the individual spells in the IEB, we generate additional variables that contain time-invariant information on each worker in our sample (e.g., municipality of residence during vocational training, degree level and average wage between the end of vocational training and initial migration) and annual information on (occupation-specific) local labor market conditions (e.g., wage level, unemployment rate and local labor demand shocks caused by newly founded establishments), respectively. We merge this information with the annual worker panel.¹⁰

Finally, in order to study heterogeneous effects of return initiatives on return migration, we define different groups of workers. For the human capital endowment of a region, the skill level of (return) migrants is of particular importance.

⁹As a robustness check, we define return migration as moving back to the NUTS 3-region (county) of residence during vocational training. 75 percent of all municipalities in Germany are at most 40 km² large and the maximum size is 894 km² (Berlin), which corresponds to a radius of 3.6 km, and 16.9 km, respectively if the municipalities were circular.

¹⁰To differentiate occupations, we use the two-digit occupational group level of the German Classification of Occupations (2010) which is similar to the international ISCO-08 classifications and contains 36 occupations in our case. For a list of considered control variables, definitions and summary statistics, see Section 2.B.3 in the appendix.

Moreover, spatial mobility varies significantly with individual ability levels. We use information on full-time wages as an indication of the individual ability level and to define distinct groups of workers (cf., Matano and Naticchioni, 2016). Specifically, we consider the average worker wage before initial migration similar to De la Roca (2017) and differentiate between workers at the bottom, in the middle and at the top of the wage distribution (see appendix, Section 2.B.2 for details). For about one third of the workers in our sample, we do not observe full-time wages between the end of vocational training and initial migration, often because these individuals moved rapidly after graduation (more than 75 percent until the end of the calendar year, in which vocational training ended, see Appendix 2.B.2 for details). These workers are considered as an additional group. It includes an above-average number of women and vocational training graduates with *Abitur* (higher education entrance qualification). As most of them emigrate immediately after completing their training, they are also younger at the time of emigration than those who gain work experience beforehand (see Table 2.B.1 in the appendix). This might be an explanation as to why their wages in the first year after initial migration are on average lower than wages of those who emigrate later. As regards employment status in the destination of initial migration, there are, in contrast, only minor differences between the two groups (see Table 2.B.2 in the appendix).

As a robustness check, we also use information on the individual school-leaving diploma distinguishing between *Abitur* and lower degrees. In our entire sample, 19 percent of the considered employees have a high school diploma, 81 percent have a lower school degree. Among workers with high wages, 33 percent have a high school diploma and 67 percent do not (see Table 2.B.1).

2.2.2 Frequency and spatial pattern of return migration

In this section, we provide some descriptive information on return migration in Germany based on the sample of workers as defined above. Figure 2.2.1 indicates that about 30 percent of all former apprentices, who moved to another local labor market after completion of vocational training for at least two years¹¹, return in subsequent years. Consistent with findings by De la Roca (2017) for Spain, workers with higher wages prior to initial migration – arguably those with relatively high abilities – tend to return less often than workers with lower wages. Furthermore, we also observe a slightly smaller proportion of return migrants among workers for whom a full-time wage prior to initial migration is not observed. Quantitatively, however, the differences in return migration rates between the groups considered are rather small.

¹¹We exclude very short temporal migration, that is, workers, who return within the first year after initial migration (see appendix, Section 2.B.1).

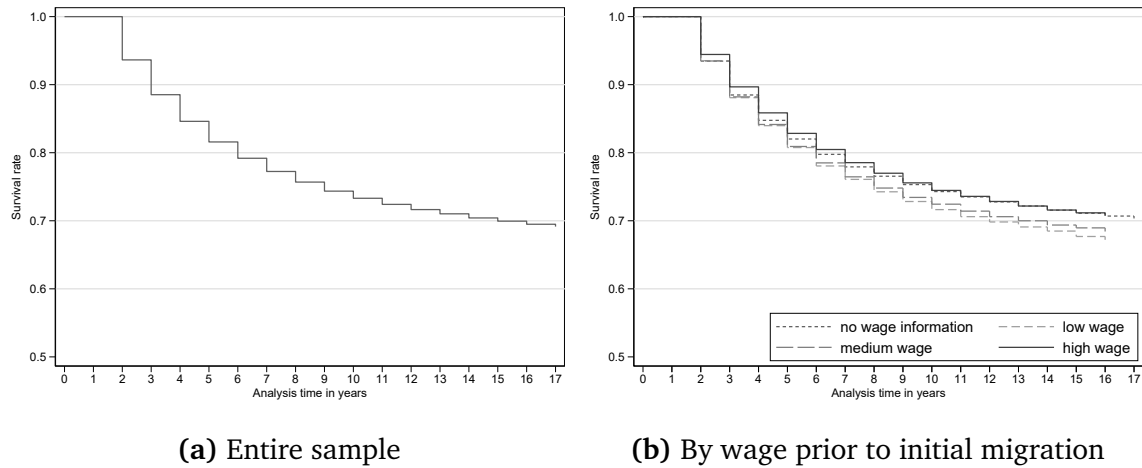


Figure 2.2.1: Frequency of return migration

Notes: The figure illustrates Kaplan-Maier estimates of return migration as defined in Section 2.2.1. In Figure (b), the average wage in full-time employment between the end of vocational training and initial migration serves as proxy variable for the individual ability level. The first and third quartile of observed full-time wages are used as thresholds. Corresponding wages are not available (category “no wage information”) in particular for workers, who left the local labor market rapidly after the end of vocational training. Since this latter group also comprises workers, who initially moved in the year of graduation, we observe some of these individuals for 17 years. Source: IEB, own calculations.

Likewise, Figures 2.C.1a and 2.C.1b in the appendix indicate that the share of return migrants amongst initial migrants varies only little between regions with high and low labor market density. While this applies in particular if the density at the origin of initial migration is considered (Figure 2.C.1a), a differentiation according to the density at the destination of initial migration shows that migrants who initially moved to high-density locations tend to have higher return migration rates over time by around four percentage points than migrants who initially moved to labor markets with a below-average density (Figure 2.C.1b). A potential explanation is that highly dense labor markets may lead to more failed experimentation.

Figure 2.2.2 focuses on the spatial pattern of initial and return migration. In line with findings by e.g. De la Roca (2017), the destination of initial migration is to higher density regions and, thus, this type of migration is relatively more

likely to occur at the expense of rural labor markets (see also Figure 2.C.2 in the appendix). The destination of return migration is most often low density regions and return migration tends to be associated with moving down the urban hierarchy.

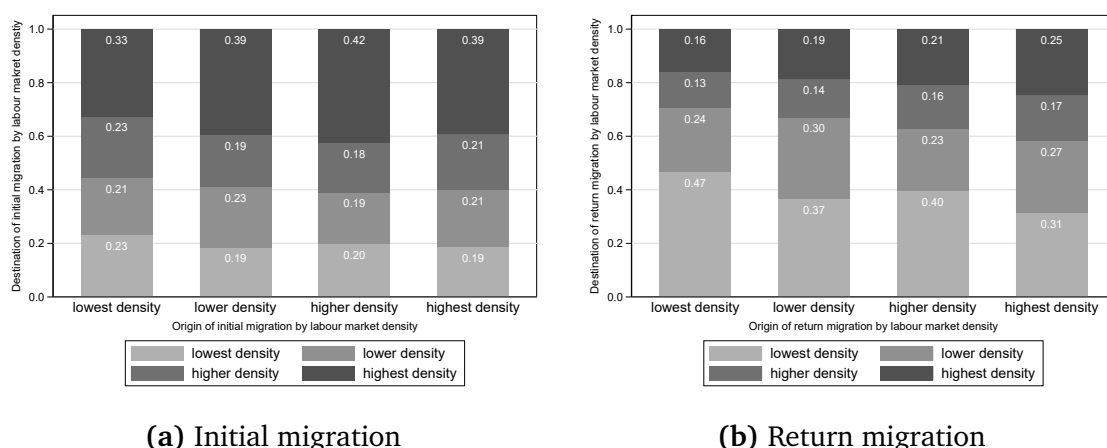


Figure 2.2.2: Spatial pattern of initial and return migration

Notes: Initial migration refers to migration events of medium-skilled workers in the years after the completion of vocational training if the worker moves for the first time to a municipality that is at least 50 km apart from the location of residence during vocational training (N= 405,320). Return migration refers to the first move back to a municipality that is less than 50 km apart from the municipality of residence during vocational training (N= 92,639). The four types of labor markets are defined based on the quartiles of local labor market size (average number of jobs within 50 km in the period 1999-2017) such that all workers subject to social security in Germany are equally distributed across the four categories. Thresholds of local employment density are 53.86 jobs per km², 85.22 jobs per km² and 144.89 jobs per km². Source: IEB, own calculations.

2.2.3 Return initiatives

The second data source we use is the study by Stiller and Ohlhoff (2021), which provides information on the establishment and existence of different types of return initiatives in Germany. In our analysis, we focus on return initiatives that operate at the level of NUTS 3-regions and that are maintained throughout the whole year.¹² We consider all return initiatives that were established until the end of our observation period (the year 2017). This amounts to 39 initiatives and they cover 65 of the 401 German NUTS 3-regions since some neighboring regions cooperate.

Figure 2.2.3 shows that the first return initiatives were established in East Germany. They were implemented to address the significant outflow of workers from East to West Germany in years after unification in 1990.¹³ “Sachse komm zurück” (“Saxon come back”), for example, is the title of the initiative founded in 2004. In more recent years, a significant number of return initiatives have been established in West German regions as well. Nevertheless, regions with return initiatives are still over-represented in East Germany. Furthermore, the regions are rural and economically rather weak, i.e., on average they show a lower employment density, lower wage level, lower net migration rate and higher unemployment rate than regions without a return initiative. However, the initiatives were established in rather good economic times in terms of employment and wage growth and a decline in unemployment compared to regional conditions in previous years. This

¹²Table 2.B.5 in the appendix lists all the initiatives and their specifications we consider. In few NUTS 3-regions, more than one initiative has been established in the observation period that aims at fostering return migration. In these rare cases, the earlier return initiative defines the treatment in our analysis. There also exist other types of return initiatives in Germany. We do not consider those which focus on the return of former inhabitants to a certain municipality nor return initiatives that exist at the NUTS 3-level, but are occasionally active within a year only. For instance, in some regions a so-called “returnee-day” is organized once a year like a job fair. Finally, we do not consider related programs of East German *Länder* (NUTS 1-regions).

¹³See, e.g., Hunt (2006) for an analysis of the East-West migration in the 1990th.

suggests a relative increase in regional labor demand in the years of implementation (details of the levels and trends of regional characteristics are provided in panel A of Table 2.3.1 in Section 2.3.3).

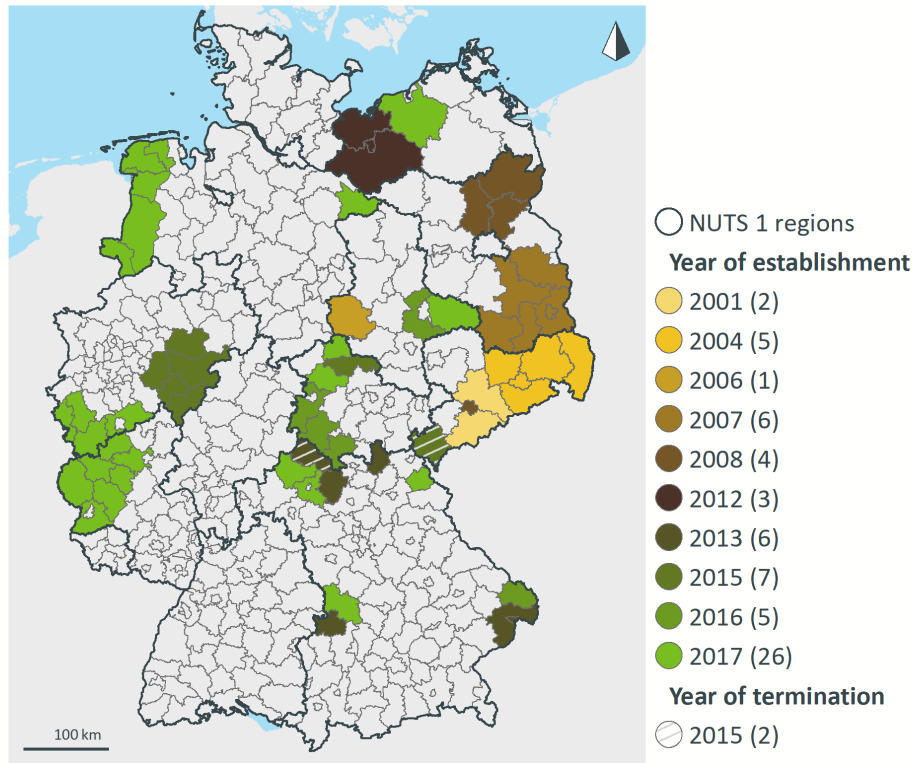


Figure 2.2.3: NUTS 3-regions with return initiatives by the year of establishment (and termination)

Notes: The map refers to all return initiatives that operate at the level of NUTS 3-regions and are maintained throughout the whole year. The number in parentheses refers to the number of NUTS 3-regions. Two return initiatives were only active until 2015, all others exist till 2017, the end of our observation period.

Source: Stiller and Ohlhoff (2021), own illustration.

Return initiatives are one-stop agencies that fulfill a network function and close the gap between various actors in the region such as economic development agencies, companies and business associations, employment agencies, administrations, as well as other regional initiatives and networks (Kreuser, 2023). As an example, the initiative Heimvorteil HSK¹⁴ located in the region Hochsauerlandkreis (HSK) is described by the OECD (2023, p. 41) to be “a full-fledged agency for returnees, offering an exclusive career network, information about work and life in HSK through a blog and social media. Interested parties can find a steadily growing list of contacts for return and relocation initiatives throughout the region, to exchange suggestions and know-how.”

In this vein, Table 2.2.1 gives an overview of the offerings the considered initiatives often provide, although the design and exact features vary between initiatives. The key elements are the provision of information on local vacancies and employers. Further, they provide consulting services for people interested in returning and some offer a newsletter that people considering moving to the region can subscribe to.¹⁵ In addition, return initiatives also provide information on housing, infrastructure, public services, etc.

¹⁴A direct translation of ‘Heimvorteil’ is ‘home advantage’ referring to “the psychological and physiological advantage that the home team has over the visiting team in sports” (OECD, 2023, p. 41).

¹⁵Some initiatives also send newsletters to firms with information about potential return migrants seeking a job in the former region of residence. This may facilitate matches between workers and firms, even if the firm had not advertised a role.

Table 2.2.1: Features of return initiatives

	yes	no	#regions
Consultation services	47 73.44	17 26.56	64
Local employers	36 56.26	28 43.75	64
Vacancies	58 90.63	6 9.38	64
Housing	59 92.19	5 7.81	64
Newsletter	16 25.00	48 75.00	64

Notes: The first line per feature shows the number of treated regions that have the corresponding characteristic (yes) or not (no). The respective share in percent can be found in the second line. ‘Consultation services’ indicates whether the return initiative provides personal counseling of people interested in returning. ‘Local employers’ indicates whether the return initiative provides information on local companies on their website. ‘Vacancies’ indicates whether the return initiative provides specific job offers on their website. ‘Housing’ indicates whether the return initiative provides information on the housing market and general information about life in the region. ‘Newsletter’ indicates whether the return initiative provides a newsletter. We do not have information on the type of initiative for one treated region. The characteristics of the initiatives were collected in and refer to January/February 2023.

Source: own data collection and calculations based on Stiller and Ohlhoff (2021).

Even though the initiatives do not exclusively provide their services to former inhabitants, they typically have a particular focus on these workers which often also reflects in their names such as “Comeback Elbe-Elster” and “Heimvorteil HSK”. The initiatives explicitly target former residents of the region because these regions often experience a significant outflow of young people. At the same time, however, these individuals already have established connections to the region and less information deficits about it compared to people who have not previously lived in the region, as pointed out by Kreuser (2023).

Meister et al. (2020) show that in rural regions the percentage of returnees in the labor force immigration typically surpasses the national average of 27 percent, and in some instances, it exceeds 40 percent (see Figure 2.C.3 in the appendix). This phenomenon is particularly pronounced in regions with low overall immi-

gration rates, which apparently are relatively unattractive to workers in general. However, former residents may still consider moving there due to a general regional attachment and family or social ties. A prerequisite for a return may be that they find a suitable job in advance in the region of their former residence. Here, return initiatives may help as they provide low-threshold additional and up-to-date knowledge about local businesses and employment opportunities, as noted by Kreuser (2023).

2.3 Empirical strategy and identification

We examine the impact of return initiatives on return migration using microeconomic techniques. The survival analysis of return migration, on which all our estimates are based, is described in the following Subsection 2.3.1. We then outline in detail in Subsection 2.3.2 how we account for return initiatives in our regressions, and in Subsection 2.3.3 we explain how we construct a synthetic control group based on matching and entropy balancing to account for the fact that return initiatives were not established randomly in space and time.

2.3.1 Survival analysis

When studying (return) migration in the course of individual working lives, one needs to take into account that workers migrate at different points in time and that some never move (back) in the period of observation, but maybe later. The data are thus right censored. This is typically addressed by applying survival analysis, also known as event history analysis. van den Berg (2001) points out that this type of analysis is also particularly useful for studying treatment effects because the relationship between treatment timing and events such as return migration is explicitly analyzed.

In our study, the unit of observation is a worker-year pair and an event is defined as returning to the local labor market, which has been left after completing vocational training (see Section 2.2 for details).¹⁶ The economic rationale of our analysis is based on the assumption that after initial migration individuals maximize their utility by deciding to stay away from or to return to the former residential location. Specifically, we assume, similar to De la Roca (2017), that the corresponding hazard rate $h_{i,t}$ is given by Equation (2.1). It indicates the probability of return migration in the t^{th} year after the initial migration, provided the individual has not returned to the vocational training region by year t . Depending on the calendar year of worker i 's initial migration, the t^{th} year after initial migration corresponds to calendar year y .

$$h_{i,t} = P(T_i = t | T_i \geq t; Z_{i,y(i,t)}) = F(\beta_t + Z_{i,y(i,t)}). \quad (2.1)$$

T_i is a discrete random variable that represents the year worker i returns to the labor market that she left after vocational training (possibly never). $F(\cdot)$ is assumed to be a cumulative logistic probability function and β_t refers to the probability of returning t years after initial migration. It takes into account in a non-parametric and thus very flexible way that return migration rates are lower the longer time has elapsed since initial migration (see Figure 2.2.1). $Z_{i,y}$ captures that the probability of returning depends on individual and regional characteristics that may vary over time, in addition. Specifically, we assume $Z_{i,y}$ to be given by:

¹⁶Our model can be interpreted as a single-exit duration model with return migration as the single event (exit). As a robustness check, we also estimate a discrete multiple-exit model and differentiate between (i) return migration, (ii) staying in the destination of initial migration and (iii) onward migration to a third region.

$$\begin{aligned}
Z_{i,y} = & \alpha X_{i,y-1} + \delta M_{r(i),y-1} + \phi N_{s(i,y),y-1} + \mu_{r(i)} + \theta_{s(i,y)} \\
& + \nu_y^e I(r(i) \in \text{East}) + \nu_y^w I(r(i) \in \text{West}) + RI_{r(i),y}
\end{aligned} \tag{2.2}$$

where $X_{i,y-1}$ is a set of (time-varying and constant) individual characteristics of worker i lagged by one year (e.g., wage, sex, education, occupation). $M_{r(i),y-1}$ and $N_{s(i,y),y-1}$ are one year lagged regional characteristics referring to the local labor markets of residence during vocational training, $r(i)$, and the residence in the year of observation, $s(i, y)$, respectively. ν_y^e and ν_y^w represent year fixed effects for East and West Germany. $I(\cdot)$ denotes an indicator function that captures whether the residential location during vocational training, r , is in East or West Germany. We consider separate year fixed effects for both parts of the country to account for potentially different time patterns in East and West Germany caused by the significant East-West migration in the aftermath of the German reunification discussed by, e.g. Hunt (2006). $\mu_{r(i)}$ and $\theta_{s(i,y)}$ are NUTS 3-region fixed effects for the location of residence during vocational training and the residential location in calendar year y . $RI_{r(i),y}$ is the treatment. Specifically, it captures the effect of a return initiative in the NUTS 3-region that was left after vocational training. We estimate different specifications with respect to the treatment that are laid out in section 2.3.2.

To determine the parameters of the hazard rate and how it is affected by return initiatives, we estimate a *discrete* survival model. It takes into account that information on residential locations and return initiatives is only available annually, which means the data have an interval-censored structure, and return migration events are heavily tied, that is, we observe several events at the same time (see Figure 2.2.1: the survival rate does not decrease steadily, but in steps).¹⁷

The log-likelihood function L of our discrete duration model for N workers is given by (see De la Roca, 2017; Jenkins, 1995):

$$L(\Omega) = \sum_{i=1}^N \left[(1 - R_i) \sum_{t=1}^{T_i} \log(1 - h_{i,t}) + R_i \left(\sum_{t=1}^{T_i-1} \log(1 - h_{i,t}) + \log h_{i,t=T_i} \right) \right] \quad (2.3)$$

where Ω is a vector that captures all the parameters the hazard rate depends on (see Equations (2.1) and (2.2)), R_i is equal to one if the worker returns to the vocational training region during the observation period and zero otherwise. $t=1$ denotes the first year in which a worker is a potential return migrant because she left the region of residence during vocational training. Like shown by Jenkins (1995) and De la Roca (2017) this model can be rewritten and regarded as a sequence of discrete choice binary models. To estimate the parameters of this model, we apply a logit model on a panel of workers with an indicator equal to one in the year in which the workers return to the region of vocational training.

¹⁷Chalita et al. (2002) suggest using the proportion of ties as a guide for the decision whether a discrete or a continuous model should be applied. The results indicate that the estimation of discrete models is appropriate, although they do not clearly reject the estimation of continuous ones (see Table 2.C.1 in the appendix).

2.3.2 Difference-in-differences

To identify the effect of return initiatives on return migration, we apply difference-in-differences (DiD) estimation and use the spatio-temporal variation in the establishment of return initiatives and return migration events. In the first DiD specification, we set up our model as a panel event study similar to, e.g., McHale et al. (2022). We are interested in the evolution of the likelihood to return to a treated region (relative to return to a non-treated region) over time, and replace $RI_{r,y}$ in Equation (2.2) by:

$$RI_{r,y} = \sum_{\tau=2}^J \gamma_{-\tau} I(y = y_0(r) - \tau) + \sum_{\tau=0}^K \gamma_{+\tau} I(y = y_0(r) + \tau) \quad (2.4)$$

where $y_0(r)$ denotes the calendar year in which the return initiative is implemented in region r . The last year before the establishment of a return initiative, $y_0 - 1$, serves as a reference. Hence, the probability of return migration is normalized such that the probability of returning to a treated region one year before the treatment equals – conditional on covariates – the average probability of return migration to the non-treated regions (across all years). $\gamma_{+\tau}$ is the average treatment effect on the treated (ATT) τ years after a return initiative has been established. It is expected to be significantly larger than zero if return initiatives positively affect return migration. Estimates for $\gamma_{-\tau}$ indicate whether the (conditional) likelihood of return migration follows a similar or different pattern over time in treated regions prior to treatment compared to untreated regions (cf. Angrist and Pischke, 2009).

In our second DiD specification, we pool individual years before and after treatment to assess the average effect of a return initiative in the short and medium term. Specifically, based on the results from Equation (2.4), we distinguish three

different time phases: (i) the pre-treatment phase capturing the years without initiatives in the former region of residence, (ii) the implementation phase (*imp*) comprising the year of establishment, $y_0(r)$, and ϵ years thereafter, and (iii) the medium term phase (*med*) which covers all years in the observation period after the implementation phase. The specification is given by:

$$RI_{r,y} = \gamma^{imp} I(y_0(r) \leq y \leq y_0(r) + \epsilon) + \gamma^{med} I(y > y_0(r) + \epsilon). \quad (2.5)$$

By distinguishing the immediate effect γ^{imp} and the medium term effect γ^{med} , we allow for a potential time lag in the effect of return initiatives on return migration because it might take some time for the initiatives to become effective. It may take some time for the initiatives to build up relevant networks, and workers might need some time to actually move back to the former region of residence (Kreuser, 2023). One advantage over our first treatment specification (Equation (2.4)) is that in Equation (2.5) we now test whether the parameters $\gamma_{+\tau}$ in the implementation and the medium term phase, respectively, are jointly significant. Estimating the treatment effect separately for each year after implementation might result in rather imprecise estimates because of the comparatively low number of potential return migrants per year. This might be particularly an issue if subsamples of workers are considered (see Table 2.B.1 in the appendix).

For a causal interpretation of the estimated effect of a return initiative on the probability of return, two major requirements have to be met (Abbring and van den Berg, 2003). Amongst others, the treatment must not be anticipated. In our case, it requires that individuals either have no access to information on the establishment of a return initiative up to its implementation or that individuals do not act on that information. We presume that this assumption is met in our case. An initiative provides information that can lead to a return. However, this informa-

tion is only provided after the implementation of the initiative, meaning that even knowing about a planned launch does not provide any benefits for potential return migrants. Furthermore, we observe individuals who are affected by a treatment at the regional level. Individual workers who plan to return but have not yet done so are unlikely to influence the implementation of a return initiative in the region they previously left.

The more critical assumption is the conditional independence assumption, which means in our case that conditional on observable characteristics, return initiatives are randomly assigned to regions (Cunningham, 2021). We would face a selection problem that results in biased estimates if there are *time-varying* factors besides the characteristics we control for that influence the establishment of initiatives and individual return migration. All relevant *time-invariant* characteristics affecting return migration are captured by the region fixed effects.

Table 2.3.1 in Section 2.3.3 shows that the initiatives considered were established on average in rather good economic times (compared to previous years). This could in principle account for an increase in return migration in the years after an initiative is established, meaning that more frequent return migration may not be due to the initiatives themselves, but due to improved labor market conditions, for instance. To account for this pattern and reduce the risk of an omitted variable bias, we include both individual and regional characteristics that might influence the decision to return and be correlated with the establishment of a return initiative.

At the individual level, we control for potential composition effects by considering, among other things, the individual ability level and success in the labor market before and after initial migration. These factors affect return migration as shown by De la Roca (2017) and workers with certain ability levels and/or certain

degrees of success in the labor market may not be randomly distributed in regions and years. To account for regional characteristics, we include time-varying indicators (lagged by one year) for (i) local labor market conditions (wage and unemployment rate) that we measure occupation- and skill-specific, (ii) the composition of the local labor market with regard to occupations and industries and (iii) overall regional attractiveness as reflected in the skill-specific net migration rate. Furthermore, we explicitly address positive local labor demand shocks due to the establishment of new firms. Regions in East Germany in particular were characterized by the settlement of companies at the beginning of the 2000s, the time at which the first return initiatives were established (see Figure 2.2.3 in Section 2.2.3). Therefore, we consider regional employment growth related to new firms.¹⁸

The treatment specification from Equation (2.5) shows the likelihood of return migration before and after a return initiative has been established. This will help us to examine whether regions with and without return initiatives were comparable in outcome dynamics pre-treatment conditional on covariates (Cunningham, 2021). However, even if we observe a similar pattern before the treatment and despite the fact that we control for important determinants of migration decisions at the individual and regional levels, we cannot completely rule out the possibility that there are contemporaneous unobserved shocks that influenced both the decisions to implement a return initiative and to return to the treated regions. Hence, our analysis could potentially still suffer from omitted variable bias, especially if unobserved shocks were not or only weakly correlated with regional labor market conditions and regional net migration rates for which we control. In case of shocks *correlated* with the considered variables, the latter should at least partly

¹⁸We are grateful to Christian Leßmann for pointing out the possible impact of newly established firms on return migration to East German regions. For details about the considered variables, see Section 2.B.3 in the appendix.

also control for omitted effects.

To test the sensitivity of our estimation results with regard to the consideration of observable regional characteristics, we estimate our model with and without the corresponding set of covariates. This may help us to evaluate the risk of biased treatment effects due to unobservable factors. By omitting the time-varying regional variables, we also take into account that they might be ‘bad controls’ because they are on the same level and timing as the treatment (Angrist and Pischke, 2009).¹⁹

2.3.3 Matching and balancing

To account for the fact that return initiatives were not established randomly across regions and time and to further test the robustness of our baseline results where workers from all non-treated regions serve as control group, we apply matching and entropy balancing. In the first step, we define a reduced control group based on k -nearest neighbor matching at the regional level. Specifically, we aim to reduce the control group to workers who – during their vocational training – lived in never-treated regions that share similar characteristics to the treated regions, which, on the one hand, are correlated with the establishment of a return initiative and, on the other hand, may be important determinants of return migration. For this purpose, we use panel data for German NUTS 3-regions generated based on the IEB and covering the years 2000–2017. Specifically, we consider the following characteristics: unemployment rate, net migration rate, regional wage level (all referring to medium skilled workers with completed vocational training), employment density, and an indicator variable for East/West Germany.

¹⁹We gratefully thank an anonymous referee and the editor for pointing to the risk of biased estimates due to unobserved shocks and the potential disadvantage to include time-varying regional characteristics.

Our matching algorithm uses both levels and trends of the regional characteristics. It is our goal to identify never-treated regions that are similar to the treated regions in the year prior to the implementation of a return initiative. Therefore, we apply nearest neighbor matching separately for each year in which return initiatives are established and consider in each iteration the region-year observations of the respective previous year.²⁰ All workers who lived in the matched regions during vocational training define our reduced control group.

Considering the regional wage, employment density and the East/West-indicator simultaneously causes severe multicollinearity problems in the regression that we estimate to obtain propensity scores. Therefore, we do not run the matching based on the levels and trends of all five regional characteristics at the same time, but apply different specifications with subsets that include three or four of the five regional characteristics. Estimating different variants provides information on the sensitivity of the regression results with respect to the regional characteristics the matching is based on, in addition. We also let the number of selected neighbors vary between one and four, and for some variants we require common support, while for others we do not.²¹ In total, we apply 48 different matching specifications (see Table 2.C.3 in the appendix).

In panel (a) of Table 2.3.1, we compare the treated with all non-treated regions focusing on the most recent year prior to the implementation of a return initiative, respectively. The regions with return initiatives differ statistically significantly from the regions in the unrestricted control group, i.e. all never-treated

²⁰As an example, in Görlitz, a return initiative was founded in 2004. The pool from which we select control regions for Görlitz consists of the 336 never-treatment regions with their regional characteristics in 2003 (the year before the foundation in Görlitz). We do not apply matching to the two regions where a return initiative was established in 2001. The regions are excluded because data availability does not allow us to calculate the change in all regional characteristics over the previous three years.

²¹If we impose common support, treated regions are excluded if the propensity score is outside the range of values of the propensity scores of the control regions.

regions, in terms of average levels and trends of almost all considered regional characteristics as indicated by the t-tests and discussed before.

Panel (b) refers to matched region-year observations only and shows that the matching approach applied leads to an alignment of the treatment and control groups as intended. The statistics refer to our preferred matching specification where we (i) consider the East/West-indicator, employment density, unemployment rate and the net migration rate, (ii) select one neighbor per treated region and (iii) impose common support. The average levels and trends are no longer statistically significantly different from each other, and the biases have been substantially reduced. This does not only hold for the characteristics the matching is based on, but also to the regional wage.²²

²²The treatment group in panel (b) comprises 61 of the 63 regions treated between 2004 and 2017. The other two regions are excluded since we impose common support. The control group includes 51 of the 335 non-treated regions. Some non-treated regions are selected as neighbors more than once.

Table 2.3.1: Balance table

	Mean		%bias	%reduction	t-test	
	Treated	Control		bias	t	p> t
A: Before matching						
Levels (t ₀ -1)						
East Germany	0.460	0.137	75.1		7.31	0.000
Employment density	70,796	216,030	-62,0		-3,68	0,000
Unemployment rate	0.086	0.069	29.2		2.93	0.003
Net migration rate	-0.001	0.000	-19.8		-1.58	0.114
Gross daily wage	82.881	94.255	-83.2		-6.91	0.000
Past trends (t ₀ -4 → t ₀ -1)						
Employment density	2.719	2.041	11.6		0.97	0.332
Unemployment rate	-17.851	-6.326	-53.5		-3.62	0.000
Net migration rate	0.001	0.000	32.2		2.35	0.019
Gross daily wage	2.568	0.757	54.9		4.65	0.000
B: After matching						
Levels (t ₀ -1)						
East Germany [†]	0.443	0.410	7.6	89.9	0.36	0.717
Employment density [†]	72.482	62.478	4.3	93.1	0.57	0.569
Unemployment rate [†]	0.087	0.087	0.3	99.0	0.01	0.989
Net migration rate [†]	-0.001	-0.001	6.3	68.1	0.36	0.721
Gross daily wage	83.383	85.214	-13.4	83.9	-0.69	0.493
Past trends (t ₀ -4 → t ₀ -1)						
Employment density [†]	2.859	3.580	-12.3	-6.4	-0.65	0.515
Unemployment rate [†]	-17.060	-15.694	-6.3	88.1	-0.44	0.663
Net migration rate [†]	0.001	0.001	11.4	64.7	0.55	0.586
Gross daily wage	2.576	2.622	-1.4	97.5	-0.08	0.940

(Continued on next page)

Table 2.3.1: Balance table (continued)

	Mean		%reduction		t-test	
	Treated	Control	%bias	bias	t	p> t
C: After matching and balancing						
Levels (t_0-1)						
East Germany [†]	0.443	0.443	-0.0	99.9	-0.00	0.999
Employment density [†]	72.482	72.460	0.0	100.0	0.00	0.999
Unemployment rate [†]	0.087	0.087	-0.0	99.9	-0.00	0.999
Net migration rate [†]	-0.001	-0.001	0.0	99.9	0.00	0.999
Gross daily wage	83.383	83.748	-2.7	96.8	-0.14	0.890
Past trends ($t_0-4 \rightarrow t_0-1$)						
Employment density [†]	2.859	2.858	0.0	99.9	0.00	1.000
Unemployment rate [†]	-17.06	-17.062	0.0	99.9	0.00	1.000
Net migration rate [†]	0.001	0.001	-0.0	100.0	-0.00	0.999
Wage level	2.576	2.695	-3.6	93.5	-0.19	0.847

[†] Variables considered in matching and entropy balancing.

Notes: In each panel, the statistics of the treatment group refer to the previous year of the year t_0 in which a region was treated. In panel A, the control group includes the observations of all 336 non-treated regions that refer to the last year before the establishment of a return initiative in one of the treated regions. In panels B and C, the control group includes matched region-year observations of 51 non-treated regions. The number of treated regions in panel A is 63 and in panels B and C it is 61. Two treated regions are excluded in panels B and C since we impose common support in matching. Both regions treated in 2001 are excluded in each panel due to limited data availability. Employment density is measured in terms of workers per km². The wage level refers to gross daily wages in full-time employment and Euro. The unemployment rate is the fraction of the unemployed in the sum of the registered unemployed and employees subject to social security. The net migration rate refers to workers subject to social security and is measured in terms of net-immigration per worker living in a region. Wage, unemployment rate and net migration rate refer to medium-skilled workers. Past trends in unemployment rate, wage and employment density are measured as relative change in percent and the trend in net migration rate is measured as absolute change. Both refer to the change over the previous three years.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Despite the similarity of the treatment group and the reduced control group in panel B, the sample means of the regional characteristics still differ to some extent. In some cases, the bias amounts to more than ten percent. To compensate for

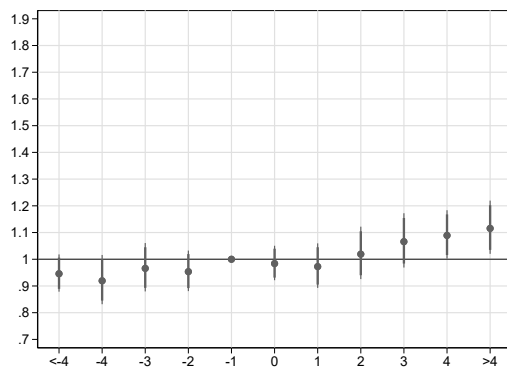
these differences, in the second step, we apply entropy balancing using the code provided by Hainmueller and Xu (2013). We determine region-specific weights for the matched region-year observations, so that the moments of the aforementioned regional characteristics are as equal as possible in the treatment and the reduced control groups.

Taking into account the weights we obtain from entropy balancing, a synthetic control group is created that represents a near perfect image of the treatment group in terms of the regional characteristics considered one year before the return initiatives were established and past trends (see panel (c) in Table 2.3.1). We merge the region specific weights to our individual data set and weight the observations in the reduced control group, that comprises only workers from the non-treated regions matched in step one, accordingly.

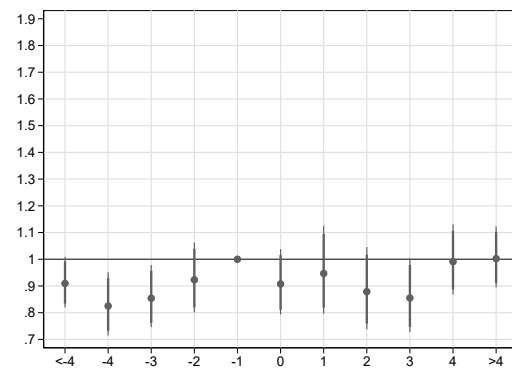
2.4 Results

2.4.1 Patterns of return migration prior to and after the establishment of a return initiative

Figure 2.4.1 illustrates the results of our survival analysis (Equation (2.3)) if we apply the event study treatment specification described by Equation (2.4) and consider workers from all non-treated regions as control groups. Different samples of workers with vocational training degree are examined to analyze potential effect heterogeneity between groups.

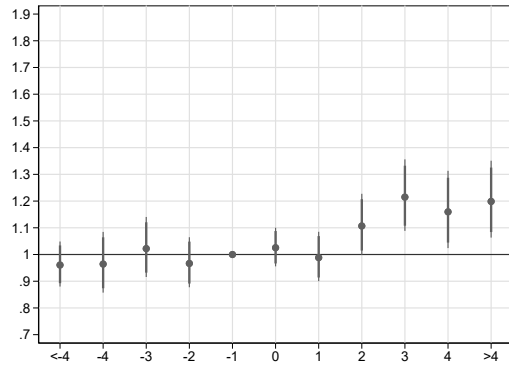


(a) Entire sample ($N = 2,532,971$)

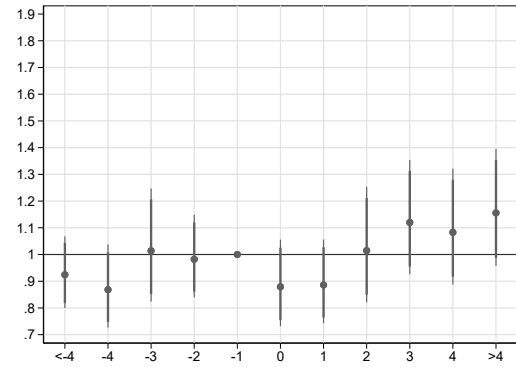


(b) Workers *not* employed prior to initial migration ($N = 950,705$)

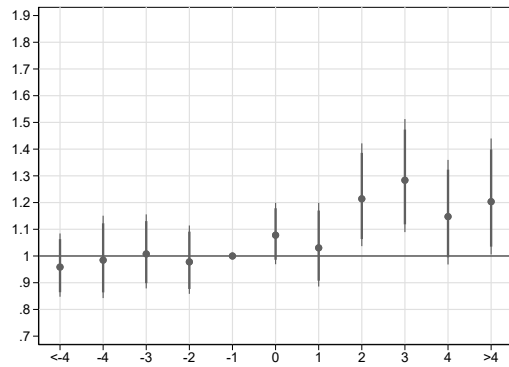
Figure 2.4.1: Likelihood of return migration before and after a return initiative has been established



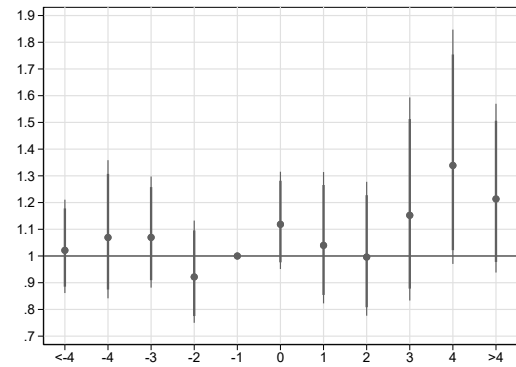
(c) Workers employed prior to initial migration ($N = 1,582,266$)



(d) Workers employed prior to initial migration, low wage ($N = 393,160$)



(e) Workers employed prior to initial migration, medium wage ($N = 799,860$)



(f) Workers employed prior to initial migration, high wage ($N = 388,719$)

Figure 2.4.1: Likelihood of return migration before and after a return initiative has been established (continued)

Notes: Odds ratios (exponentiated coefficients) are reported referring to the likelihood of return migration of medium-skilled workers and Equations (2.1), (2.2) and (2.4). Unit of observation is worker-year pair. 95%- and 90%-confidence intervals are reported that are based on robust standard errors, which are clustered at the level of NUTS 3-regions of residence during vocational training. On the horizontal axis, 0 denotes the year in which return initiatives are implemented. All models include fixed effects for the occupation of vocational training, the industry, the NUTS 3-regions of residence during vocational training and the current residential location, the number of years since initial migration as well as the calendar year of observation differentiating between time fixed effects for East and West Germany. Furthermore, the following sets of control variables are included: (i) individual characteristics including indicators for labor market success prior to and after initial migration (ii) time-varying characteristics of the local labor market of residence during vocational training and (iii) time-varying characteristics of the local labor market of current residence. For details refer to Table 2.C.2 in the appendix. In (b) we only consider workers who were not employed between the end of vocational training and initial migration or only part time. In (c), (d), (e) and (f) only workers are considered that were employed full-time between the end of vocational training and initial migration. In (d), (e) and (f) workers are distinguished based on the average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Panel (a) refers to the entire sample and therefore denotes the average effects between all considered workers. The first subsample, panel (b), comprises only workers who were not employed full-time prior to the initial migration. Most of these workers left the local labor market immediately after completing their vocational training (see Section 2.2.1). In panels (c)-(f), we only consider workers who were employed full-time between the end of vocational training and the initial migration. On average, these workers initially migrated about 5 years after the completion of vocational training and are therefore more likely to be attached to the local labor market, in which they lived during vocational training, than the workers considered in panel (b). While panel (c) is based on all of these workers, panels (d)-(f) focus on further subsamples. We use the average individual wage prior to initial migration as a proxy variable for the individual ability level (cf., De la Roca, 2017; Matano and Naticchioni, 2016) and distinguish workers at the bottom, middle and top of the wage distribution.

Figure 2.4.1 shows the pre-treatment leads and the post-treatment lags of all subgroups conditional on covariates. First, we evaluate the pre-treatment leads to check whether the regions with and without return initiatives were comparable in outcome dynamics before treatment (year 0). Altogether, the estimates do not point to deviating patterns in return migration rates conditional on covariates before the considered initiatives were established. Even in the year of implementation and the first few years thereafter, there are no significant differences between the treated and non-treated regions with regard to return migration. However, the post-treatment lags increase over time and are significantly larger than one in the fourth year after the implementation of the return initiatives and in subsequent years on average if the entire sample is concerned. The odds ratio to return to a region in which a return initiative exists is then about 1.1 and thus approximately 10 percent higher compared to a counterfactual scenario without a return

initiative indicating that return initiatives foster return migration as intended. We interpret the observed time lag to reflect the fact that it may take some time for a return initiative to become effective. For instance, it may take some time to build relevant networks with potential employers in the region and become known to potential returnees. Furthermore, workers might need some time to move to the former region of residence.

Comparing the results summarized in panels (b) and (c) points out heterogeneous treatment effects between groups. Specifically, the results indicate that the increase in return migration is driven by those workers who were employed prior to initial migration and stayed in the local labor market of residence during vocational training for a relatively long time before emigrating, on average, suggesting a relatively strong attachment to the region (panel (c)). By the third year after the return initiatives were established, the probability of return for this group increases by about 20 percent and remains at this higher level in subsequent years. In panel (b), we neither detect a statistically significant nor a size-relevant effect. Hence, workers who moved to another local labor market quite rapidly after the completion of vocational training are apparently not more likely to return if a return initiative is established.

If we distinguish the workers considered in panel (c) according to their position in the wage distribution prior to initial migration, we find indications for further effect heterogeneity. For low-wage workers, the odds ratio increases only by about 10 percent in the medium term, but the increase is not statistically significantly different from zero (panel (d)). For workers with medium wages, we observe a statistically significant increase in the probability of return migration by about 20 percent in the second year, already (panel (e)). And for high-wage workers (panel (f)), the results are somewhat ambiguous. On the one hand, the

estimated odds ratios also vary around a value of 1.2 from the third year onwards. On the other hand, the effects are less precisely estimated: the confidence intervals in panel (f) are more than twice as large as the ones in panel (e). One likely reason is the lower number of workers in the subsample considered in panel (f). Since year-by-year treatment effects refer only to workers who were potential return migrants to the treated regions in a given year, imprecise estimation results are more likely with a smaller sample (the numbers of observations per year are reported in Table 2.B.4 in the appendix).

Panels (e) and (f) also suggest that a higher probability to return sets in one year later in the case of workers at the top of the wage distribution (if at all). For these workers, we observe an increase in the point estimate in the third year after treatment. Workers with medium wages are more likely to return already in the second year. One reasonable explanation for the longer time lag is that workers at the upper end of the wage distribution might have more special skills and specialized knowledge. Supporting them to find a suitable job may therefore require being able to draw on a larger network and a larger pool of vacancies that take more time to be created.²³

2.4.2 Average effects in the short and medium term

To increase the precision of the estimate of treatment effects shown in Figure 2.4.1, we pool certain years as described by Equation (2.5) and estimate average short-term and average medium-term effects of the return initiatives. Specifically, we distinguish the pre-treatment period (reference), an implementation phase and a medium term phase. For their definitions, we take into account that it apparently takes different lengths of time for return initiatives to have a

²³This argument is related to the one put forth by the literature on matching advantages in big cities which argues that the local number of jobs increases the quality of job matches in the case of workers with specialized skills and specific labor requirements by firms (cf., Kim, 1990).

positive impact on the likelihood of return migration for different groups of workers. Specifically, we assume that the implementation phase is two years in the case of workers with medium wages and three years in the case of workers with high wages and all other samples (cf. Figure 2.4.1).²⁴

The results summarized in Table 2.4.1 confirm that return migration rates do not immediately increase if return initiatives are established, or at most to a relatively small extent compared to the medium-term effects. Only for workers in the middle of the wage distribution, we obtain an odds ratio significantly larger than one at the 5 percent level. It is about 1.08 meaning that the odds to return increase by about 8 percent in the implementation phase (Column (5)).

²⁴We are aware that the return initiatives of 2016 and 2017 do not contribute to the identification of the medium term phase effects since the observation period ends in 2017. If we exclude all workers who lived in those regions during vocational training, that were treated in 2016 or 2017, from our analysis, this does not substantially impair our regression results (compare Table 2.4.1 with the lower panel in Table 2.C.5 in the appendix).

Table 2.4.1: Average effects of return initiatives on return migration in the short and medium term

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration [†]		Wage prior to initial migration [‡]		
	All	No	Yes	Low	Medium	High
Implementation phase ($t_0 \leq t \leq t_0 + \epsilon$)	1.029 (0.025)	0.994 (0.044)	1.053** (0.027)	0.946 (0.049)	1.084** (0.043)	1.059 (0.071)
Medium term phase ($t_0 + \epsilon < t$)	1.136*** (0.037)	1.055 (0.045)	1.202*** (0.048)	1.142* (0.081)	1.234*** (0.060)	1.243** (0.135)
Observations	2,532,971	950,705	1,582,266	393,160	799,860	388,719
Individuals	405,320	135,851	269,469	65,843	136,216	67,328
Pseudo R2	0.0510	0.0691	0.0433	0.0474	0.0476	0.0471

[†] Indicator for full-time employment between the end of vocational training and initial migration.

[‡] Average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

Notes: Odd ratios (exponentiated coefficients) are reported that have been estimated based on Equations (2.1), (2.2) and (2.5) and refer to the likelihood of return migration of medium-skilled workers. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels. All models include fixed effects for the occupation of vocational training, the industry, the NUTS 3-regions of residence during vocational training and the current residential location, the number of years since initial migration as well as the calendar year of observation differentiating between time fixed effects for East and West Germany. The following sets of control variables are included in all models: (i) individual characteristics including indicators for labor market success prior to and after initial migration (ii) time-varying characteristics of the local labor market of residence during vocational training and (iii) time-varying characteristics of the local labor market of current residence. For details refer to Table 2.C.2 in the appendix. For the medium wage group, ϵ is set to 1, for all other groups, it is set to 2 (cf. results in Figure 2.4.1).

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

In the medium term, the increase amounts to more than 23 percent and 24 percent for workers in the middle or at the upper end of the wage distribution (Columns (5) and (6)). Both effects are statistically significant. This also applies to the overall effect of about 14 percent (Column (1)). For workers at the bottom of the wage distribution (Column (4)), we detect only a weakly significant effect of about 14 percent and for workers, who emigrated from the region of vocational training quite rapidly without further prior employment, we again do not find any indication that their return is promoted by the considered initiatives (Column (2) in Table 2.4.1, compare also panel (b) in Figure 2.4.1). Together, the results in

Table 2.4.1 indicate that return initiatives have a positive impact on return migration on average. However, they appear to take some time to take effect and their impact varies between different groups of workers.

One possible explanation for the heterogeneous effects of return initiatives between wage groups is that workers in the middle and top of the wage distribution likely possess higher abilities and more specialized skills than individuals with low wages. Therefore, workers with a medium or high wage level, in particular, arguably suffer from a small local labor market in a rural area with regard to the chance of finding a match that makes a return attractive (see discussion of heterogeneous gains from agglomeration by, e.g., Behrens and Robert-Nicoud, 2015; Kim, 1990). A return initiative could help workers with relatively high abilities to find the few employment opportunities available in their former region of residence.

2.4.3 Robustness checks

To ensure that the estimated effects of return initiatives on return migration are robust, we estimate alternative specifications. In the following, we present the results that we obtain when (i) omitting the regional control variables and (ii) using a control group that is generated by applying matching and entropy balancing. Furthermore, we summarize the results of additional robustness checks included in the appendix (Sections 2.C–2.E).

Omitting regional control variables

The first robustness check deals with two econometric issues: unobserved shocks and bad controls. In our main analysis, we include one-year lagged regional characteristics of the former and of the present local labor market of residence to account for potential changes in regional attractiveness over time that may affect return migration and coincide with the establishment of a return initiative (wage level, unemployment rate, employment growth related to the establishment of new firms, occupational and sectoral specialization of the local economies, net migration rate). However, these characteristics potentially do not fully capture relevant changes in regional attractiveness. There may have been contemporaneous unobserved shocks that influenced both the decision to implement a return initiative and the decision to return. Furthermore, the inclusion of regional characteristics might also have a disadvantage, as they could be bad controls in the sense that they may be simultaneously determined with return migration by the return initiatives.

Table 2.4.2 provides regression results where we omit all time-varying regional characteristics. The estimated odds ratios denoting the impact of return initiatives on return migration are very similar to our benchmark results reported in Table 2.4.1. This leads to the conclusion that the regional characteristics under

consideration do not simultaneously explain the establishment of a return initiative and return migration. Moreover, we interpret this as an indication that our main results do not suffer significantly from unobserved effects or bad controls. Omitting the regional control variables would most likely lead to different estimation results if there were other regional characteristics and shocks that significantly affected the previous regression results, at least as long as the relevant omitted regional characteristics and unobserved shocks were correlated with the considered indicators of regional labor market conditions and/or the net migration rate of a region.

Table 2.4.2: Average effects of return initiatives on return migration in the short and medium term when omitting regional control variables

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration		Wage prior to initial migration		
	All	No	Yes	Low	Medium	High
Implementation phase	1.033 (0.025)	0.996 (0.044)	1.057** (0.027)	0.949 (0.050)	1.085** (0.043)	1.072 (0.072)
Medium term phase	1.138*** (0.038)	1.055 (0.046)	1.206*** (0.049)	1.146* (0.081)	1.245*** (0.061)	1.262** (0.137)
Observations	2,532,971	950,705	1,582,266	393,160	799,860	388,719
Individuals	405,320	135,851	269,469	65,843	136,216	67,328
Pseudo R2	0.0508	0.0688	0.0431	0.0471	0.0474	0.0463

Notes: Like Table 2.4.1, but without time varying regional characteristics (wage, unemployment rate, sectoral and occupational specialization, net migration rate and employment growth) as control variables. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Matching and entropy balancing

Table 2.4.3 summarizes the regression results of a second robustness check where we use a reduced and weighted control group generated by *k*-nearest neighbor matching and entropy balancing as described in section 2.3.3. Further results are summarized in Table 2.C.3 in the appendix. The latter are based on alternative matching specifications. The results confirm our previous finding that return

initiatives promote return migration in the medium term and that, in particular, workers who did not immediately leave the region of vocational training after graduation with medium and high wages are more likely to return (Columns (5) and (6)). In general, the odds ratios reported in Table 2.4.3 for the different samples are very similar to the results in Table 2.4.1 and also vary only moderately depending on the additional entropy balancing (compare the top and bottom panels in Table 2.4.3). The medium-term effect on return migration of workers with high wages (Column (6)) is even somewhat larger in Table 2.4.3 than in Table 2.4.1. However, the standard error is relatively large and the point estimate also varies to some extent depending on the matching specification (see Table 2.C.3 in the appendix). Nevertheless, the vast majority of specifications yield an odds ratio at least as large as that in Table 2.4.1 of 1.243. For workers at the lower end of the wage distribution, in contrast, we do not even find a weakly significant effect based on reduced control groups as in Table 2.4.3.

Table 2.4.3: Average effects of return initiatives on return migration in the short and medium term after applying nearest neighbor matching and entropy balancing

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration		Wage prior to initial migration		
	All	No	Yes	Low	Medium	High
<i>without entropy balancing after matching</i>						
Implementation phase	1.015 (0.026)	0.959 (0.047)	1.054* (0.029)	0.955 (0.055)	1.087** (0.045)	1.049 (0.074)
Medium term phase	1.106*** (0.040)	0.980 (0.055)	1.208*** (0.054)	1.138 (0.090)	1.245*** (0.066)	1.357** (0.174)
<i>with entropy balancing after matching</i>						
Implementation phase	1.007 (0.028)	0.967 (0.049)	1.037 (0.029)	0.929 (0.056)	1.064 (0.047)	1.053 (0.074)
Medium term phase	1.106*** (0.040)	1.019 (0.066)	1.187*** (0.042)	1.107 (0.083)	1.207*** (0.067)	1.383** (0.189)
Observations	935,211	351,714	583,381	177,837	290,421	113,578
Number of individuals	143,458	48,553	94,891	28,543	47,159	18,952

Notes: Like Table 2.4.1, but with reduced control group that has been generated based on nearest neighbor matching at the regional level as described in Section 2.3.3. For each region we consider the first neighbor and common support is imposed. Results based on alternative matching specifications are summarized in Table 2.C.3 in the appendix. Here, the treatment group comprises workers from 61 of the 65 treated regions and the control group comprises workers from 51 of the 336 non-treated regions (some regions were selected more than ones in matching). Results in the lower panel are obtained if we weight the observations in the reduced control group with region specific weights that we obtain based on entropy balancing (see Section 2.3.3). Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

With heterogeneous time trends and excluding very early and very late treated regions

Section 2.C in the appendix contains results of additional robustness checks. Table 2.C.4 summarises the treatment effects of the return initiatives that we obtain when we include separate linear time trends for treated/non-treated regions and region-specific trends, respectively. We still observe significant medium-term effects of return initiatives on return migration. The odds ratios are again even somewhat larger in the case of workers at the upper end of the wage distribution compared to our baseline result in Table 2.4.1 (1.416 and 1.395 vs. 1.243), but

at the same time they are less precisely estimated in the specification with region specific linear time trends. Excluding workers from regions that were treated at the very beginning or at the very end of the observation period and thus contribute only partially to the identification of the short-term and medium-term effects of the return initiatives does not significantly change the estimates either (Table 2.C.5).

By school-leaving degree and considering return migration at NUTS 3-level

Results in Table 2.C.6 point to heterogeneous effects among workers in line with our results for the different wage groups. On average, return initiatives have a greater impact on return migration of those workers who have completed vocational training and have a high school diploma than on those with lower school-leaving certificates. When we define return migration at the NUTS 3-region level rather than based on distance from the former municipality of residence, the estimates for the impact of return initiatives on return migration are very close to our baseline results in the previous subsection (Table 2.C.7).

Staggered treatment

We also test whether our results are affected by the implementation of staggered treatment, i.e., return initiatives were established in different regions in different years. This pattern can in principle result in biased treatment effects since the early treated regions are part of the control group of the later treated regions. Therefore, the parallel trend assumption might be violated (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021). However, the estimates summarized in Table 2.C.8 do not indicate that this is a serious problem in our case. The average effects are about the same size as our baseline results if we group the treated regions by the year in which the return initiatives were established and estimate their impact on return migration separately for each group. The small size of the treatment

group relative to the control group may contribute to this (see Table 2.B.4 in the appendix).²⁵

Placebo experiment

A placebo experiment where we estimate our regression model 1,000 times and randomly assign the treatment to NUTS 3-regions in each iteration indicates that the odds ratios consistently vary around one if the treatment is assigned randomly across space and time. The medium-term effects of return initiatives that we obtain for the actual treatment are larger than the 95th percentile of the estimated effects that are based on the random treatment (see Figure 2.C.4) indicating that our results for the actual treatment are most likely not random.

Multiple-exit model

Complementing the results described so far, Table 2.C.9 in the appendix summarizes results of a multiple-exit model where we differentiate between three alternatives: staying at the destination of initial migration (reference), moving back to the local labor market of residence during vocational training, and onward migration to a third local labor market. We investigate whether the probability of choosing these alternatives is affected by a return initiative in the region where a person lived during training. The results confirm our previous findings that return initiatives foster return migration. In contrast, the risk of onward migration relative to non-migration changes slightly at most in the implementation and medium-time phase. This implies that the increased return migration to the region of training after a return initiative is established there occurs both at the expense of remaining at the destination of the initial migration and at the expense of onward migration to a third region.²⁶ This holds for the medium- and high-wage

²⁵One disadvantage of estimating the treatment effects separately for each group of region is that the standard errors become very large due to a rather low number of workers in the considered treatment groups.

²⁶This is confirmed by specifications where we use “return migration” as the reference. Results are available from the authors upon request.

groups as well as for the entire sample.

Effects on location choice more generally and on gross value added growth

Throughout this article, we identify the impact of return initiatives on return migration by comparing return migration to the regions in which an initiative was established, with return migration to non-treated regions. In Section 2.D of the appendix, we, in contrast, study the effect of return initiatives on location choice more generally. We examine two different cases: (1) Whether regions with a return initiative attract vocational training graduates from other regions by analyzing graduates' choice of location from the end of training until they leave the local labor market in which they lived as an apprentice (possibly never), and (2) whether mobile workers, those who moved after graduation, are more likely to reside in a treated region in the years after the initial migration. Here we distinguish between the effect of a return initiative in the former region of residence (to consider again the impact on return migration) and the influence of return initiatives in other regions on the individual's residential choice.

The results for our first case indicate that a return initiative does not increase immigration of graduates from other regions, but those with medium wages are more likely to stay if a return initiative exists in the region of residence. Some graduates may use the information provided by a local return initiative to inform themselves about the labor market and potential future employers in the region, among other things, and might be more likely to decide to stay based on this information. For mobile workers who have emigrated after graduation and currently live in another region (our second case), the initiatives appear to have no influence on the choice of location, unless there is a return initiative in the previous region of residence. Then, these workers are more likely to move to the treated region making them return migrants. This is particularly evident for people with medium

to high wages who did not leave their former region of residence immediately after completing their vocational training, but acquire additional work experience beforehand. This is in line with the findings of our main analysis that the initiatives promote return migration in general and of these workers in particular.

A possible explanation for why return initiatives promote the influx of former residents, but apparently have no significant influence on the regional choice of other (mobile) workers is that spatial search frictions, which the initiatives are designed to alleviate, play a greater role in whether former residents of a rather peripheral rural region move back than they do in the potential inflow of workers from other regions. Workers who come from a peripheral region may have an interest in moving to the remote region because of family and/or social ties or regional attachment, for example. However, from the point of view of many workers without corresponding ties, the region may be rather unattractive, which is why they do not even look for an employment opportunity there. This would mean that the effectiveness of return initiatives is limited as they only reach certain potential immigrants. The results in Section 2.E of the appendix point in a similar direction. There, we examine the development of regional characteristics following the establishment of a return initiative. Although we find some indication that return initiatives positively affect the regional migration balance to some extent, in terms of the growth rate of gross value added, return initiatives show no significant influence on regional economic development. One possible reason is that the stronger return migration resulting from return initiatives is too small to have a noticeable impact on regional economic growth. However, in terms of the cost efficiency of return initiatives, it should be noticed that the costs of the initiatives probably only account for a small fraction of the regional gross value

added and are also low compared to other spatially effective means.²⁷ In addition, the return of previously emigrated workers can have non-economic benefits, such as caring for elderly family members in remote rural areas.

2.4.4 Heterogeneity between initiatives

So far, we studied the average effect of the return initiatives that have been established until 2017 in German regions. Although all return initiatives are similar in their core features (providing information and support to former residents and other potential immigrants), there are differences in their design and location (see Table 2.2.1 in section 2.2.3). An in-depth analysis of heterogeneous effects of different return initiatives goes beyond the scope of this article and is left for future research. To provide some initial insights, though, we distinguish the treated regions according to some characteristics of the initiatives. However, it is important to note that almost all considered characteristics of the initiatives are potentially time varying (despite the remoteness of a region) and we gathered the relevant information in January/February 2023, i.e. six years after the end of our observation period. The characteristics of an initiative may have changed within the observation period and thereafter.

We first distinguish regions with return initiatives according to their distance from the nearest agglomeration to compare the effects of initiatives in more remote and less remote regions.²⁸ Second, we differentiate the initiatives according

²⁷We do not have comprehensive information on the costs of the individual return initiatives, but the 2021 annual report of the initiative “Wendlandleben” shows a total budget for the period 1.2.2017 to 31.1.2022, which corresponds to an average of around €174 thousand per year. The gross value added in the associated Lüchow-Danneberg district is €1.1 billion per year.

²⁸To distinguish between more remote and less remote regions, we take into account all the municipalities in which the workers lived during their vocational training. Based on this, we calculate the average distance of the municipalities per NUTS 3-region to the nearest large city with at least 100,000 inhabitants weighted by the number of workers per municipality. A region is considered more (less) remote if the average distance between the municipalities of the region and the nearest large city is more (less) than 63 km which is the 75th percentile.

to the service they offer. We have created five different categories into which the initiatives have been grouped. Individual categories refer to the following questions: (1) Do the initiatives offer personal advice? (2) Do they provide information on potential employers located in the region on their website? (3) Do they publish specific job offers on their website? (4) Do they provide information on the housing market and general information on living in the region? (5) Do they offer a newsletter that returnees can subscribe to and through which job postings are sent out, for example?

Table 2.C.10 in the appendix summarizes the corresponding regression results. In each specification, we consider the treatment variable distinguishing between pre-treatment phase (reference), implementation phase and medium term phase separately for the return initiatives with / without a certain characteristic. The null hypothesis is that, in each case, the considered subsample of return initiatives does not increase return migration in the short and medium term, respectively. We further test whether the two estimated medium term effects are statistically different from each other or not. We focus on workers with medium and high wages since they are the ones for which we detect significant effects of return initiatives on average.

Altogether, the results for medium-wage workers (upper panel in Table 2.C.10) do not point out that certain subsamples of return initiatives considered drive the overall significant effect on return migration that we detect for these workers. In each specification, the two odds ratios indicating the medium term effects are statistically larger than one at conventional levels of significance. Furthermore, the t-tests at the bottom of the upper panel do not show that the two medium term effects are statistically significantly different from each other.

For workers with high wages (lower panel in Table 2.C.10), we find some weak

indication that features of the return initiatives could play a role for the initiatives' effectiveness. The results suggest that particularly initiatives in less remote regions drive the overall significant effect in the medium term with regard to the considered group of workers. The odds ratio denoting the medium term effect of initiatives in more remote regions is relatively small and not statistically significantly larger than one. However, the null hypothesis that the medium-term effects of initiatives in less remote and more remote regions are the same cannot be rejected either. Likewise, the specifications where we differentiate according to characteristics related to the labor market (Columns (2)-(4)) suggest that those initiatives that offer a certain service which might reduce search frictions and help to find a job in the region are the ones which foster return migration. However, again, we cannot reject the hypothesis that the two medium term effects per specification are the same from a statistical point of view. This also applies to the distinction between providing information on housing and providing a newsletter.

Overall, in particular, the results for high-wage workers suggest that certain features of return initiatives could determine their effectiveness. However, due to the fact that we do not have precise information on when the initiatives offered which services and the data at hand refer to the status quo, our results should not be over-interpreted, but rather serve as a starting point for future research.

2.5 Conclusions

In this paper, we study whether the probability of return migration increases by the existence of a return initiative in the region from which a worker initially emigrated. Return initiatives aim to foster the return of former inhabitants by providing information on, amongst other things, vacancies and firms located in the region on their website and often also personal support in the job search to work-

ers interested in returning. To our knowledge, it is the first time that the impact of such a policy measure has been the focus of a solid scientific analysis. To study the effect of return initiatives, we combine event history analysis and difference-in-differences estimation in a panel event study framework. Our analysis is based on administrative information on individual labor market biographies of former vocational training graduates that we merge with novel information about return initiatives in Germany provided by Stiller and Ohlhoff (2021).

Our results indicate that the considered return initiatives on average foster return migration after few years of implementation. However, we detect heterogeneous effects across different types of workers. While we observe no significant effects for workers at the bottom of the wage distribution, the estimated average treatment effect on the treated (ATT), i.e., the increase in the odds to return due to a return initiative, is about 21 percent to 25 percent in the case of workers with medium wage level, depending on the exact specification of the regression model. For those workers with the highest wages in our sample, the effect is about 24 percent to 38 percent. One potentially important underlying channel is the reduction of spatial search frictions by return initiatives. This interpretation of our results is in line with recent findings by, e.g., Wilson (2021) and Balgová (2022) who highlight the role of information (deficits) about local employment opportunities and spatial search frictions for interregional labor migration, respectively.

The fact that return initiatives have a greater effect on workers with arguably relatively high abilities could be particularly advantageous for rural regions often facing a lack of skilled labor. These regions might also benefit from increased return migration due to a potential transmission of (tacit) knowledge from workers who acquired work experience in, for instance, urban areas in the meantime (cf., Choudhury, 2015; De la Roca, 2017; Peters, 2020). Furthermore, results by Fa-

Jorgelbaum and Gaubert (2020) suggest that also overall welfare might in principle increase if return initiatives contribute to the redistribution of more able workers to rather peripheral areas. At least for the U.S., the authors observe that the share of high skilled labor is too low in small cities from which lower skilled workers in these cities might benefit through spillover effects. It should be noted, however, that although we identify a significant increase in return migration to rural areas due to the initiatives, supplementary analyses do not indicate an important impact on regional growth of gross value added. Hence, as the initiatives do not appear to significantly promote regional economic development on their own, they may be best considered as part of a package of measures to tackle economic challenges in rural areas rather than as a main instrument of choice.

The results of this article leave space for further research. In this study, we focus on the average effect of all return initiatives that were established at the district level in Germany. Hence, an important question for future research is whether there are certain features or activities of return initiatives that make them particularly successful in terms of promoting return migration. Our first analyses on effect heterogeneity between types of initiatives could serve as a starting point for such an investigation. Corresponding analyses might also provide additional insights on the significance of potential underlying mechanisms. Future research should also try to look more closely at whether the benefits of the initiatives outweigh their costs. Our first assessment of the impact on the growth of regional gross value added does not show an economically substantial effect. However, if the costs of the initiatives are low in relation to regional gross value added, even very small potential increases in value creation could outweigh their costs.

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Appendix 2

2.A Key facts about the German apprenticeship system

Table 2.A.1: Key facts about the German apprenticeship system

	2017	Comments
Total number of apprentices in dual vocational training	1,323,894	Inhabitants of Germany (Dec. 31, 2017): 82.8 million
Number of new training contracts	515,679	
Number of training occupations	325	247 trained for three years
Sector in the economy with majority of new training placements	302,940	Industry and Commerce
Training quota	19.8%	Share of companies that are engaged in training
Success rate of training	92.8%	
Average age of new apprentices (years)	19.9	p25: 17 years, p50: 19 years, p75: 21 years
New apprentices with low school qualification	24.7%	Share holding a 'Hauptschulabschluss'
New apprentices with intermediate school qualification	42.3%	Share holding a 'Realschulabschluss'
New apprentices with higher education entry qualification	29.2%	Share with permission to study
Training occupation with highest share of school leavers with a higher education entry qualification	73.7%	Banking clerk
Training occupation with highest share of school leavers with a low school qualification	65.8%	Shop assistant (food)

Source: Federal Institute for Vocational Education and Training (BIBB) (2019), representation as with Deissinger (2015, Table 1).

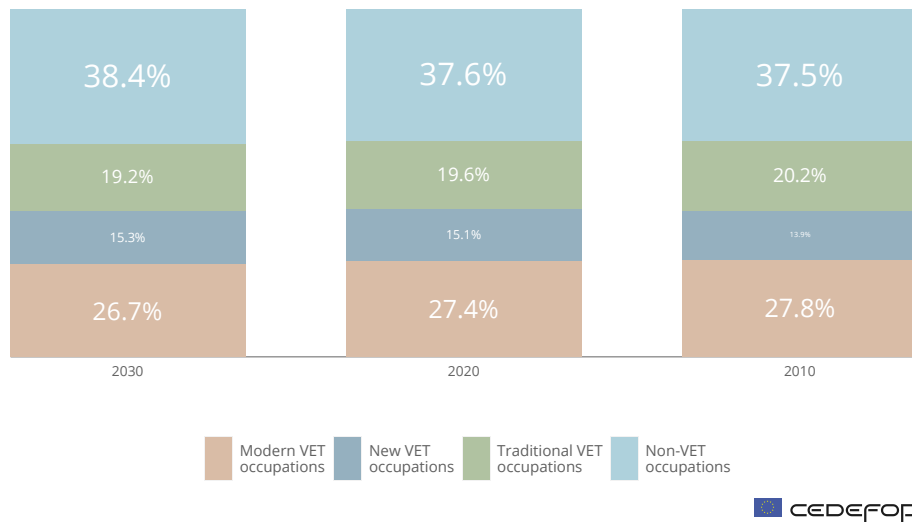


Figure 2.A.1: Importance of VET occupations in employment in Germany

Notes: Based on Cedefop Skills Forecast, indicator: Future of VET occupations. VET: vocational education and training
Source: Cedefop (2022).

2.B Further information about the data used in the empirical analysis

2.B.1 Sample restrictions

In addition to the sample restrictions discussed in the main part of the article (Section “Data”), we impose further restrictions due to different reasons.

- For workers with more than one vocational training, we consider only the first one since this denotes individual labor market entry (number of workers: 8,519,466).
- We only keep workers whose vocational training lasts between 2 and 5 years (remaining workers: 6,184,696, about 73%). The restriction takes into account that the data at hand does not contain information about the success of the vocational training. Official apprenticeships last on average 3 years,

although there are also apprenticeships that only last 2 years or 3.5 years (Federal Institute for Vocational Education and Training (BIBB), 2018). In addition, if you have the appropriate prior knowledge, you have the option of shortening the training or, in the event of difficulties, extending the training.

- We only keep persons between 15 and 25 years of age when they start their vocational training (remaining workers: 6,036,736, about 98%) in order to make the sample more homogeneous.
- We only keep persons with a known (official) vocational occupation (remaining workers: 5,622,320, about 93%).
- We exclude workers for whom we have no information about the places of work and residence during the vocational training and who commute longer than 100 km during vocational training (remaining workers: 5,477,588, about 97%). Commuting such a large distance every day is unrealistic, in particular with regard to apprentices. Hence, we have no reliable information on the location of residence for these people. In our final sample, that we use for our analysis, the 50th percentile of the commuting distance at municipality level during vocational training is 6.8 km and the 75th percentile is 18.7 km.
- We only keep persons who stay in the labor market after vocational training, i.e., we need to observe an employment spell subject to social security within the first year after the end of vocational training (remaining workers: 4,686,397, about 86%). Applying this restriction, we exclude workers who, for example, study after their vocational training.
- Applying these restrictions, we end up with 4,686,397 vocational training graduates. Of these, we focus on persons, who leave the local labor mar-

ket of residence during vocational training until 2014 and thereby become potential return migrants. Their number amounts to 666,152 workers.

- We exclude workers for whom we do not observe any spells after their initial migration (remaining workers: 658,875, about 99%).
- We exclude all workers with a gap in the labor market biography in the IEB of more than one year between the end of vocational training and initial migration, e.g., because the person (temporarily) leaves the German labor market or become self-employed for some time. For women whose gap is related to the birth of a child, the gap is allowed to be up to 3 years long, provided the place of residence before and after the gap match. By excluding these workers, we ensure that we correctly determine the year of initial migration for all workers in our final sample and, thus, the year in which they become potential return migrants. To precisely measure the year in which a worker is at risk for the first time is important in order to estimate a proper hazard rate in a discrete survival model (cf. Jenkins, 1995) (remaining workers: 619,727, about 94%).
- For the same reason, it is necessary that we observe each worker every year after initial migration until the individual drops out of the sample at risk. Therefore, we exclude all subsequent worker-year observations if there is a gap in the individual labor market biography in the IEB of two or more years after initial migration. Since in some cases the gap starts in the first year after initial migration, this further reduces the number of workers considered in the analysis (remaining workers: 607,131, about 98%).²⁹

²⁹If there is a gap of only one year, we fill the gap by adding a corresponding worker-year observation. In doing so, we take over the place of residence before the gap. For women whose gap is related to the birth of a child, we fill gaps of up to three years, provided the place of residence before and after the gap match.

- We exclude workers, who move back to the local labor market of residence during vocational training about one year after initial migration to exclude very short temporal migration; recall that we observe only one place of residence per worker and year (remaining workers: 519,306, about 86%).
- We only consider workers for which we observe at least one wage in full-time employment after initial migration (prior to dropping out of the sample at risk) that we may use to determine the individual position in the (occupation specific) regional wage distribution, which we use as proxy for individual labor market success after initial migration as with De la Roca (2017) (445,459 workers, 86%).
- Finally, we only retain workers who do not work within the local labor market of residence during vocational training one year after initial migration. Thereby, we ensure that the potential return migrants completely left the former region of residence. We end up with 405,320 potential return migrants.

2.B.2 Definition of subsamples

To study heterogeneous effects of return initiatives on return migration, we define different groups of workers. Specifically, we consider the average wage of a worker between the end of vocational training and initial migration to gauge the individual ability level. In the IEB, only daily wages are available, but no information on hourly wages or the exact number of hours worked. Therefore, we only use wages associated with full-time employment to approximate the ability level of a worker. Considering the first and third quartile of observed (full-time) wages as thresholds, we define groups of workers with low, medium and high wages, respectively. Workers, for which no wage information prior to initial migration is available, are assigned to a fourth group. The latter group in particular com-

prises workers who migrated to another local labor market rather rapidly after the completion of vocational training and those, who only worked in part-time prior to initial migration. More than 75 percent of all workers for which we do not observe full time employment prior to initial migration, moved to another local labor market until the end of the calendar year, in which vocational training ended and at least 95 percent stayed in the local labor market, in which they lived as apprentice, for at most 3 years after the end of vocational training. In contrast, former apprentices, for which we observe full time employment and wages prior to initial migration, moved on average 5 years after vocational training to another local labor market.

As a robustness check, we also use information on the individual school-leaving diploma distinguishing between *Abitur* (higher education entrance qualification) and lower degrees. Table 2.B.1 shows the share of workers with *Abitur* per sample, amongst other indicators. As expected, the share is highest among workers at the upper end of the wage distribution. Table 2.B.2 provides information on labor market outcomes in the first year after initial migration, in addition.

Table 2.B.1: Composition of the entire sample and subsamples including destination of initial migration

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration [†]		Wage prior to initial migration [‡]		
	All	No	Yes	Low	Medium	High
Age after initial migration						
15-24 years	33.1	59.8	19.6	27.7	20.0	10.9
25-29 years	50.6	38.0	57.0	56.7	58.6	54.0
30-34 years	14.5	2.1	20.8	14.4	19.4	29.6
≥35 years	1.8	0.1	2.7	1.2	2.0	5.5
Gender						
male	46.2	36.9	50.9	44.9	50.9	56.6
female	53.8	63.1	49.1	55.1	49.1	43.4
Mother						
no	93.0	94.5	92.3	91.0	92.4	93.1
yes	7.0	5.5	7.7	9.0	7.6	6.9
Nationality						
German	96.3	96.7	96.2	96.1	96.0	96.6
Foreign	3.7	3.3	3.8	3.9	4.0	3.4
High school degree						
no	81.2	77.4	83.1	92.8	86.3	67.2
yes	18.8	22.6	16.9	7.2	13.7	32.8
labor market density at the destination of initial migration						
lowest density	20.7	22.5	19.8	23.8	19.9	15.5
lower density	21.2	21.6	21.0	22.5	21.0	19.6
higher density	20.9	20.7	21.1	20.3	21.4	21.2
highest density	37.1	35.2	38.1	33.4	37.6	43.8
Number of individuals	405,320	135,851	269,469	65,843	136,216	67,410

[†] Indicator for full-time employment between the end of vocational training and initial migration.

[‡] Average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

Notes: The figures indicate the percentage of all individuals per (sub)sample that fall into the respective category.

Source: IEB, own calculations.

Table 2.B.2: Labor market outcomes in the first year after initial migration

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration [†]		Wage prior to initial migration [‡]		
	All	No	Yes	Low	Medium	High
Deflated gross daily wage	79.88 (33.59)	71.43 (26.30)	84.15 (35.98)	63.09 (33.09)	79.58 (25.90)	113.95 (37.23)
Months employed	10.14 (3.6)	10.09 (3.49)	10.13 (3.58)	9.61 (3.90)	10.13 (3.63)	10.69 (3.22)
Months vocational training	0.16 (1.27)	0.12 (1.06)	0.17 (1.37)	0.30 (1.78)	0.16 (1.32)	0.07 (0.91)
Months unemployed	0.79 (2.14)	0.85 (2.11)	0.77 (2.16)	1.21 (2.68)	0.75 (2.11)	0.37(1.54)
Months no labor market participation	0.70 (2.20)	0.70 (2.15)	0.70 (2.23)	0.73 (2.20)	0.72 (2.26)	0.65 (2.21)
Number of individuals	405,320	135,851	269,469	65,843	136,216	67,410

[†] Indicator for full-time employment between the end of vocational training and initial migration.

[‡] Average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

Notes: The table shows the mean and standard deviation in parentheses per variable and sample.
Source: IEB, own calculations.

2.B.3 Information on variables, summary statistics and number of observations

Supplementary information on variables used in the analysis and listed in Table 2.B.3:

- ^a **Firm tenure:** For almost all persons, firm tenure refers to periods of employment beginning after the end of vocational training. Only 2.37% of the considered individuals continue to work in the training establishment after initial migration. This establishment is located between 50 and 100 km away from the municipality of residence during training since we (i) exclude all workers who move, but continue to work in the former local labor market of residence and (ii) exclude all individuals who commuted during vocational training more than 100 km.
- ^b **Wage:** The individual wage is considered in logarithmic terms and relative to the occupation-region specific wage level in former and current region of residence, respectively. About 20% of all considered worker year-observations do not contain information about wage in the previous year since the person was not employed full-time in the respective year. However, it is necessary to observe each worker every year after initial migration until the individual drops out of the sample at risk in order to estimate a proper hazard rate in a discrete survival model (Jenkins, 1995). Therefore, we impute these missing wages based on a regression with worker fixed effects and the occupation specific regional wage level, age, age², experience, experience², tenure, tenure² and the individual share of unemployment in the previous year. The (imputed) wage serves as proxy for the (hypothetical) individual position in the occupation specific regional wage distribution

because we consider it relative to the occupation-region specific wage level (see discussion by De la Roca, 2017). Individual wage differentials due to different region-occupation specific wage levels are captured by the regional occupation-specific wage information. The degree of individual labor market participation is captured by the variables that refer to the employment status in the previous year.

^c **labor market status between end of vocational training and initial migration:** Average over the years between the end of vocational training and initial migration.

^d **Local labor market characteristics:** Regional wage level, unemployment rate and specialization are considered in logarithmic terms and relative to the rest of Germany (cf. Mitze, 2019). All regional variables, except the net migration rate, are calculated at the level of (overlapping) local labor markets, that we define by tracing circles with a radius of 50 km around the centers of the municipalities in Germany, based on the IEB. The net migration rate refers to NUTS 3-regions (counties) and has been provided by Meister et al. (2019). For the unemployment rate, we divide the number of medium-skilled registered job seekers in local labor market r and occupation j by the number of medium-skilled (un)employed workers living in region r and working or seeking a job in occupation j . Employment growth due to newly founded firms is computed based on information provided by the Establishment History Panel (EHP) of the IAB (see Eberle and Schmucker, 2017). Specifically, we use the identifier for new firms in the EHP and compute, at the level of the considered (overlapping) local labor markets, the region specific number of new jobs created in the first year after firm birth by new establishments classified as “new establishment start-up (medium/large)” or “spin-off of part of an existing establishment” relative to total regional em-

ployment in the previous year.

Table 2.B.3: Summary statistics - continuous control variables

	Obs.	Mean	Std.dev.	Min.	Max.
labor market biographies					
Firm tenure since beginning of vocational training (in months) ^a	2,532,971	32.498	33.813	0	247.800
Experience since end of vocational training (in months)	2,532,971	75.077	42.961	0.033	206.800
Employment before vocational training (in months)					
outside labor market of residence during voc. training	2,532,971	1.266	5.528	0	120.767
in labor market of residence during voc. Training	2,532,971	3.029	8.091	0	119.667
Years till initial migration since end of vocational training	2,532,971	3.274	2.554	1	15
labor market status in previous year					
Months employed	2,532,971	9.973	3.871	0	12
Months minor employed	2,532,971	0.401	1.778	0	12
Months unemployed	2,532,971	0.659	2.133	0	12
Months no labor market participation	2,532,971	0.968	2.672	0	12
Months employed public sector	2,532,971	0.433	2.219	0	12
Daily gross wage ^b	2,532,971	-0.132	0.405	-2.666	6.041
labor market status between end of vocational training and initial migration^c					
Months employed	2,532,971	9.767	2.353	0.921	12
Months minor employed	2,532,971	0.171	0.690	0	10.060
Months unemployed	2,532,971	0.515	1.086	0	10.751
Months no labor market participation	2,532,971	1.547	1.700	0	9.508
Months employed public sector	2,532,971	0.185	1.154	0	11.200
Daily gross wage ^b	1,582,266	-0.301	0.363	-7.898	2.958
Characteristics of the local labor market of residence during vocational training^d					
Median daily gross wage (occupation specific)	2,532,971	-0.076	0.164	-1.160	0.652
Unemployment rate (occupation specific)	2,532,971	0.035	0.436	-3.300	1.816
Sectoral specialisation (emp. share of individual VET sector)	2,532,971	0.046	0.457	-7.162	3.718
Occupational specialisation (emp. share of individual VET occup.)	2,532,971	-0.004	0.353	-4.647	3.581
Net migration rate (in 1,000)	2,532,971	-0.470	4.111	-32.538	26.915
Employment growth due to newly founded firms	2,532,971	0.013	0.004	0.004	0.066
Characteristics of the local labor market of current residence^d					
Median daily gross wage (occupation. specific)	2,532,971	0.005	1.132	-0.908	0.655
Unemployment rate (occupation specific)	2,532,971	-0.098	0.408	-3.321	1.808
Sectoral specialisation (emp. share of individual VET sector)	2,532,971	-0.014	0.436	-6.984	3.552
Occupational specialisation (emp. share of individual VET occup.)	2,532,971	0.009	0.332	-5.030	3.101
Net migration rate (in 1,000)	2,532,971	-1.105	4.803	-32.538	26.915

Notes: Information on the variables is given in the list above this table.

Source: IEB, own calculations.

Table 2.B.4: Number of worker-year observations in treatment and (unrestricted) control group

		All	Medium wage	High wage
Treated regions: observations (=potential return migrants) by (year of observation - year of treatment)	i-4	108.534	32.333	13.035
	-4	27.761	9.075	3.766
	-3	31.894	10.514	4.378
	-2	36.072	11.929	5.037
	-1	44.444	14.649	6.344
	0	42.561	14.101	6.051
	1	26.540	8.335	3.390
	2	25.187	7.745	3.134
	3	21.019	6.169	1.902
	4	23.042	6.820	2.115
	>4	184.289	52.849	15.977
	Total	571.343	174.519	65.129
Non-treated regions: worker-year observations		1.961.628	625.341	323.590
Total		2.532.971	799.860	388.719

Notes: The treated regions are all 65 German counties (NUTS 3-regions) in which a return initiative has been established in the observation period and the non-treated regions are all other 336 German counties. Unit of observation is worker-year pair. 'Medium wage' and 'High wage' refer to workers who were employed full-time prior to initial migration and whose average daily wage was between the first and third quartile / higher than the third quartile.

Source: IEB, own calculations.

2.B.4 Considered return initiatives

Table 2.B.5: List of return initiatives

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Boomerang Lausitz / Fachkräfteportal	BB and SN	Oberspreewald Lausitz, Görlitz, Bautzen, Elbe-Elster, Dahme- Spreewald, Oder-Spree, Cottbus, Spree-Neiße	2007	ongoing	https://www.fachkraefteportal-brandenburg.de/
Comeback Elbe-Elster / Willkommensagentur Elbe-Elster	BB	Elbe-Elster	2012	ongoing	https://www.comeback-ee.de/
Zuhause in Brandenburg e.V.	BB	Uckermark, Oberhavel, Barnim	2008	ongoing	www.zuhause-in-brandenburg.de
Rückkehrernewsletter	BB	Cottbus, Dahme-Spreewald, Spree-Neiße, Oberspreewald- Lausitz, Elbe-Elster	2015	ongoing	https://www.arbeitsagentur.de/vor-ort/cottbus/rueckkehrer
Mehr als du erwartest	BY	Freyung-Grafenau	2016	ongoing	https://www.mehralsduerwartest.de/

Table 2.B.5: List of return initiatives (*continued*)

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Hast scho g'hörd?	BY	Haßberge	2013	ongoing	https://www.vhs-hassberge.de/
Am Main daheim	BY	Schweinfurt (LK), Haßberge	2017	ongoing	https://www.am-main-daheim.de/
Heimatpost	BY	Donau-Ries	2017	ongoing	https://www.donauries.bayern/region/regional-und-konversionsmanagement/regionalmanagement/heimatpost/
Come back Passau	BY	Passau, Passau (LK)	2013	ongoing	https://www.kuwi.de/
Das Passauer Land - da packmas hin	BY	Passau, Passau (LK)	2014	ongoing	http://www.pa-ck-mas.de/
Club der Rückkehrer	BY	Rhön-Grabfeld	2013	2015	
Chance Heimat	BY	Kronach	2013	ongoing	https://www.regionalmanagement-landkreiskronach.de/projekt/chance-heimat/
Newsletter "Durchstarten im Landkreis Dillingen"	BY	Dillingen	2013	ongoing	https://www.facebook.com/Wirtschaftsfoerderung.dlg/

Table 2.B.5: List of return initiatives (*continued*)

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Willkommen Daheim - Willkommen in deinem Landkreis	BY	Bad Kissingen	2017	ongoing	https://www. landkreis-badkissingen.de/ wirtschaft/index.html
Willkommensagentur Fichtelgebirge #freiraumfürmacher	BY	Wunsiedel im Fichtelgebirge	2017	ongoing	https:// freiraum-fichtelgebirge.de/
Pendlerpost	MV	Ludwigslust-Parchim, Northwest- mecklenburg, Schwerin	2012	ongoing	https://www.invest-swm.de/ arbeiten-leben/stellenportal
Welcome Center Rostock	MV	LK Rostock	2017	ongoing	https://www. welcome-region-rostock.de/
Heimathelden	NI	Emsland, Emden, Wittmund, Au- rich, Leer, Grafschaft Bentheim	2017	ongoing	https://www.emsachse.de/ heimathelden
Wendlandleben, Willkom- men im Wendland	NI	Lüchow-Dannenberg	2017	ongoing	www.wendlandleben.de, http: //willkommen-im-wendland.de/

Table 2.B.5: List of return initiatives (*continued*)

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Heimvorteil	NW	Olpe, Siegen-Wittgenstein, Hochsauerlandkreis, Soest, Märkischer Kreis	2015	ongoing	https://heimvorteil-hsk.de/
Heimat Vom Zurückkommen Bleiben	Eifel: NW and RP Ankommen, und	Euskirchen, Ahrweiler, Bernkastel Wittlich, Eifelkreis Bitburg Prüm, Städteregion Aachen, Rhein-Sieg-Kreis, Vulkaneifel, Düren, Cochem-Zell, Mayen-Koblenz, Trier-Saarburg	2017	ongoing	https://heimateifel.de/
Sachse komm zurück	SN	Dresden, Görlitz, Bautzen, Meißen, Sächsische Schweiz-Osterzgebirge	2004	ongoing	https://www.sachsekommzurueck.de/servlet/portal?knoten_id=9320&sprache=deu&ref_detail=RootServlet&ref_sprache=deu
Chemnitz zieht an	SN	Chemnitz	2008	ongoing	https://www.chemnitz-zieht-an.de/index.php/start

Table 2.B.5: List of return initiatives (*continued*)

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Ab in die Wachstumsregion Dresden	SN	Meißen, Bautzen, Dresden	2014	ongoing	https://www.wachstumsregion-dresden.de/
Die Heimkehrerbörse	SN	Sächsische Schweiz-Osterzgebirge	2014	ongoing	https://www.heimkehrerboerse.info/
Regionalmanagement Erzgebirge	SN	Erzgebirgskreis, Mittelsachsen	2001	ongoing	https://www.wfe-erzgebirge.de/regionalmarketing-entwicklung
Das Vogtland sind wir	SN	Vogtlandkreis	2015	2015	
Nestbau-Zentrale Mittelsachsen	SN	Mittelsachsen	2015	ongoing	https://www.nestbau-mittelsachsen.de/
Servicestelle Heimat	SN	Sächsische Schweiz	2014	ongoing	https://fachkraefte-oberlausitz.de/projekte/servicestelle-heimat/
Bleiben-Ansiedeln-Zurückkehren	SN	Sächsische Schweiz	2014	ongoing	https://baz-initiative.de/arbeiten-und-wohnen-saechsische-schweiz.html

Table 2.B.5: List of return initiatives (*continued*)

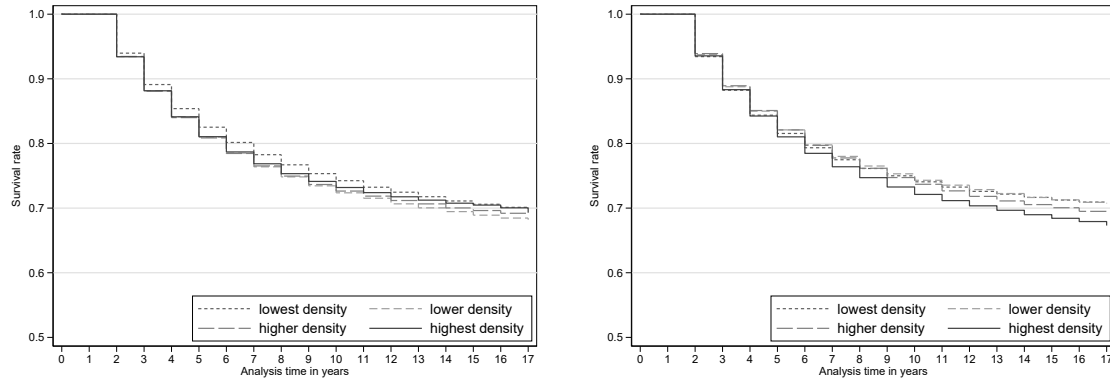
Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Welcome Center Erzgebirge	SN	Erzgebirgskreis	2016	ongoing	https://www.welcome-erzgebirge.de/
Raumpionierstation Oberlausitz	SN	Görlitz, Bautzen	2015	ongoing	https://www.raumpioniere-oberlausitz.de/
revenio...zurückkommen lohnt!	ST	Harz	2006	ongoing	http://www.revenio.de/
Zuhause im Harz	ST	Harz	2013	ongoing	https://www.zuhause-im-harz.de/
Zurück in die Heimat	ST	Wittenberg	2017	ongoing	https://www.zurueck-in-die-heimat.de/
Abi-Rückkehrer	ST	Anhalt-Bitterfeld	2016	ongoing	https://www.abi-rueckkehrer.de/
Welcome Center Kyffhäuserkreis	TH	Kyffhäuserkreis	2015	ongoing	https://www.kyffhaeuser.de/landkreis-politik/welcome-center/
Karriereheimat	TH	Wartburgkreis, Hildburghausen, Schmalkalden-Meiningen	2016	ongoing	https://karriereheimat.de/

Table 2.B.5: List of return initiatives (*continued*)

Name	Federal State [†]	Counties (NUTS 3-regions)	Start	End (Status: Nov 2017)	URL
Regionalmanagement Nordthüringen	TH	Kyffhäuserkreis, Nordhausen, Unstrut-Hainich-Kreis	2017	ongoing	https://www.perspektive-nordthueringen.de/regionalmanagement

[†] RP: Rhineland-Palatinate, NW: North Rhine-Westphalia, BY: Bavaria, BB: Brandenburg, SN: Saxony, MW: Mecklenburg-Western Pomerania, ST: Saxony-Anhalt, TH: Thuringia, NI: Lower Saxony
Source: Stiller and Ohlhoff (2021).

2.C Additional estimation results for return migration



(a) By density at origin of initial migration (b) By density at the destination of initial migration

Figure 2.C.1: Frequency of return migration by labor market density

Notes: The figure illustrates Kaplan-Maier estimates of return migration as defined in Section 3. In both figures, we differentiate between four types of local labor markets that differ with regard to density. The latter is measured by the number of workers subject to social security within 50 km of the geometric center of a municipality. The number of employees has been computed based on municipality averages in the period 1999–2017. Weighted by the number of workers subject to social security in the observation period in Germany, the first, second and third quartile of local labor market density in Germany are 53.86 employees per km², 85.23 employees per km² and 144.89 employees per km². These values are used as thresholds to define the different types of local labor markets.

Source: IEB, own calculations.

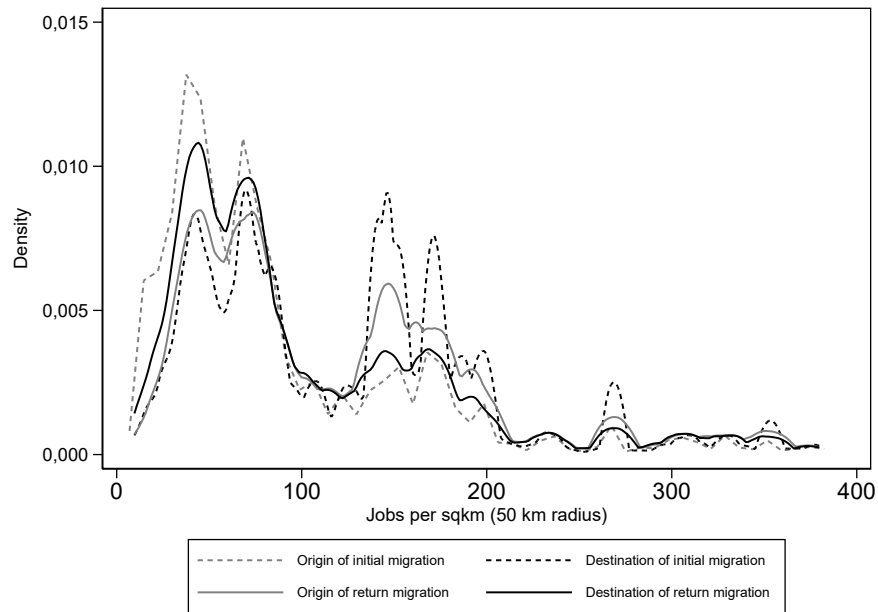


Figure 2.C.2: labor market density at the origin and destination of initial and return migration

Notes: The figure indicates for all potential return migrants in our sample (405,320 workers) the labor market density (jobs within 50 km) at the origin and destination of initial migration. For all workers, which are detected as return migrants (92,639 workers), it, furthermore, shows the labor market density at the origin and destination of return migration. The local number of jobs within 50 km has been computed based on municipality averages in the period 1999-2017 and refers to employment subject to social security. The employment density of the largest German cities, Berlin, Hamburg and Munich, amounts to 172 emp.\ km², 142 emp.\ km² and 152 emp.\ km² within a 50 km radius, respectively. Corresponding values of other big cities in Germany are: Frankfurt a. M.: 199 emp.\ km², Cologne: 269 emp.\ km², Dusseldorf: 353 emp.\ km². Weighted by the number of all workers subject to social security in the observation period, the first, second and third quartile of local labor market density in Germany are 53.86 jobs per km², 85.22 jobs per km² and 144.89 jobs per km².

Source: IEB, own calculations.

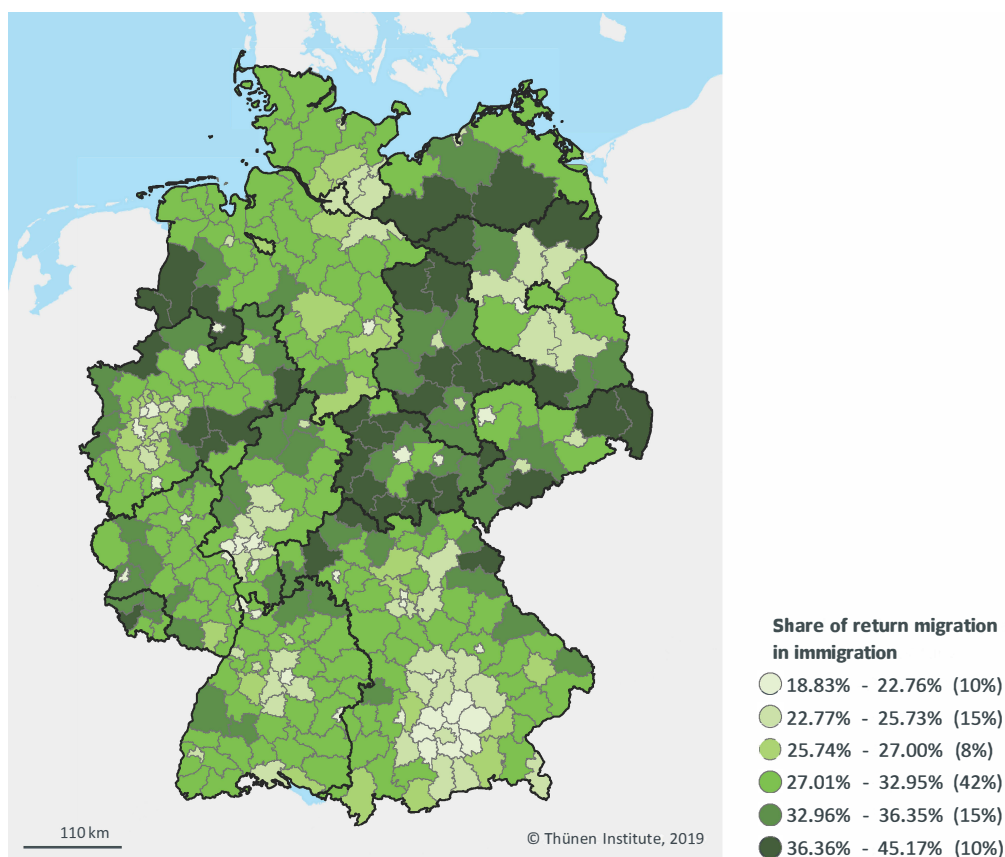


Figure 2.C.3: Share of return migration in labor force immigration per region, 2014–2017

Notes: The map refers to workers who moved from one year to another between the 360 German county regions in the period 2014–2017. Return migrants are identified by comparing the destination region with all previous residential regions of the worker since 1999 or the individual labor market entry. Information prior to 1999 and labor market entry are not considered due to data availability limitations. Thus, the reported share constitutes a lower bound. In the legend, the share of regions per class in all 360 county regions is given in parentheses. The threshold between the third and fourth class (27 percent) corresponds to the national average share of return migration in the total migration volume.

Source: Meister et al. (2020, Karte 1) based on IEB.

Table 2.C.1: Selection between discrete and continuous survival model

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration		Wage prior to initial migration		
	All	No	Yes	Low	Medium	High
Number of failures, i.e., return migration events (nf)	92,639	31,389	61,250	15,822	31,471	13,957
Number of intervals, i.e., years (r)	16	16	15	15	15	15
Number of individuals (n)	405,320	135,851	269,469	65,843	136,216	67,328
Number of worker-year observations	2,532,971	950,705	1,582,266	393,160	799,860	388,719
Proportion of ties $pt = (nf - r)/n$	0.2285	0.2309	0.2272	0.2401	0.2309	0.2071

Notes: Relocations are reported in the data set on an annual basis. For this reason, there are multiple exits (return migration events) that are reported at the same time information (year). There is a rule of thumb on whether to use discrete or continuous survival model depending on the proportion of ties (pt). If it is less than 0.20, one should apply a continuous model. If pt is larger than 0.25, one should use a discrete model. Both types of models can be used between 0.20 and 0.25 (Chalita et al., 2002).

Source: IEB, own calculations.

Table 2.C.2: Association between control variables and likelihood of return migration, full sample

Personal characteristics		
Age, reference: 30-34 years	ref.	
15-24 years	1.456***	(0.036)
25-29 years	1.165***	(0.017)
≥35 years	0.841***	(0.016)
Female	0.941***	(0.010)
Mother	0.946***	(0.019)
Foreign nationality	0.759***	(0.021)
High school degree (<i>Abitur</i>)	0.913***	(0.011)
labor market biographies		
Tenure (in months)	0.996***	(0.000)
Experience (in months)	1.003***	(0.000)
Employment before vocational training (in months)		
outside labor market of residence during voc. training	0.974***	(0.001)
in labor market of residence during voc. training	1.008***	(0.000)
Years till initial migration since end of vocational training	0.975***	(0.004)
Onward migration after initial migration	0.583***	(0.007)
labor market status in previous year		
Months employed	ref.	
Months minor employed	0.946***	(0.002)
Months unemployed	1.010***	(0.002)
Months no labor market participation	1.021***	(0.002)
Months employed public sector	1.000	(0.002)
Daily gross wage ^a	0.899***	(0.011)

Table 2.C.2: Association between control variables and likelihood of return migration (*continued*)

labor market status between end of vocational training and initial migration^b		
Months employed	ref.	
Months minor employed	1.058***	(0.005)
Months unemployed	1.039***	(0.004)
Months no labor market participation	1.024***	(0.002)
Months employed public sector	0.995	(0.004)
Characteristics of the local labor market of residence during vocational training^c		
Median daily gross wage (occup. specific)	1.495***	(0.100)
Unemployment rate (occup. specific)	1.047**	(0.023)
Sectoral specialization (emp. share of individual VET sector)	0.955***	(0.009)
Occupational specialization (emp. share of individual VET occ.)	1.047***	(0.014)
Net migration rate (in 1,000)	1.002	(0.002)
Employment growth due to newly founded firms ^d	0.006*	(0.017)
Characteristics of the local labor market of current residence^c		
Median daily gross wage (occup. specific)	0.573***	(0.042)
Unemployment rate (occup. specific)	1.025	(0.023)
Sectoral specialisation (emp. share of individual VET sector)	1.025***	(0.010)
Occupational specialisation (emp. share of individual VET occ.)	1.013	(0.013)
Net migration rate (in 1,000)	0.995***	(0.001)
Observations: 2,532,971; Individuals: 405,320; Pseudo R2: 0.051		

Table 2.C.2: Association between control variables and likelihood of return migration (*continued*)

^a The individual wage is considered in logarithmic form and relative to the occupation-region specific wage level in the current region of residence, so that the individual wages refer to the relative position in the wage distribution (see discussion by De la Roca, 2017). Individual wage differentials due to different region-occupation specific wage levels are captured by the regional occupation-specific wage information.

^b Averages over the years between the end of vocational training and initial migration.

^c Regional wage level, unemployment rate and specialisation are considered in logarithmic terms and relative to the rest of Germany (cf. Mitze, 2019).

^d Employment growth is based on information from the Establishment History Panel (BHP) by the IAB. In order to approximate local demand shocks caused by new firms, we identify all new firms at the level of the considered overlapping local labor markets and compute the region specific number of new jobs created by new establishments classified as new establishment start-up (medium/large) or spin-off of part of an existing establishment relative to total regional employment.

Notes: Odd ratios (exponentiated coefficients) are reported that have been estimated based on Equations (1), (2) and (5) and refer to the likelihood of return migration. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, own calculations.

Table 2.C.3: Average effects of return initiatives on return migration in the medium term based on different specifications of nearest neighbor matching

common			Workers employed prior to initial migration				Number of considered regions	
support imposed	Number of neighbors	Considered variables	All	Low wage	Medium wage	High wage	Treated (out of 65)	Non-treated (out of 336)
yes	1	density, ur, nmr, east	1.208***	1.138	1.245***	1.357**	61	51
yes	1	wage, ur, nmr, east	1.192***	1.138	1.245***	1.188	55	45
yes	1	density, wage, ur, nmr	1.227***	1.143	1.268***	1.295**	53	43
yes	1	density, nmr, east	1.214***	1.134	1.249***	1.375**	60	47
yes	1	density, ur, east	1.185***	1.075	1.241***	1.265*	57	45
yes	1	ur, nmr, east	1.168***	1.103	1.270***	1.129	61	50
yes	2	density, ur, nmr, east	1.170***	1.115	1.227***	1.279**	61	88
yes	2	wage, ur, nmr, east	1.216***	1.139*	1.258***	1.316**	55	86
yes	2	density, wage, ur, nmr	1.206***	1.137	1.252***	1.306**	53	76
yes	2	density, nmr, east	1.185***	1.101	1.232***	1.388***	60	78
yes	2	density, ur, east	1.198***	1.105	1.247***	1.308**	57	85
yes	2	ur, nmr, east	1.196***	1.136	1.259***	1.220*	61	87

Table 2.C.3: Average effects of return initiatives on return migration in the medium term based on different specifications of nearest neighbor matching (*continued*)

common			Workers employed prior to initial migration				Number of considered regions	
support imposed	Number of neighbors	Considered variables	All	Low wage	Medium wage	High wage	Treated (out of 65)	Non-treated (out of 336)
yes	3	density, ur, nmr, east	1.176***	1.107	1.226***	1.327**	61	112
yes	3	wage, ur, nmr, east	1.224***	1.148*	1.270***	1.322**	55	115
yes	3	density, wage, ur, nmr	1.188***	1.125	1.233***	1.307**	53	96
yes	3	density, nmr, east	1.186***	1.101	1.228***	1.431***	60	108
yes	3	density, ur, east	1.207***	1.129	1.239***	1.327**	57	114
yes	3	ur, nmr, east	1.204***	1.128	1.271***	1.246**	61	118
yes	4	density, ur, nmr, east	1.173***	1.11	1.213***	1.347**	61	134
yes	4	wage, ur, nmr, east	1.201***	1.128	1.252***	1.301**	55	134
yes	4	density, wage, ur, nmr	1.190***	1.124	1.242***	1.295**	53	116
yes	4	density, nmr, east	1.184***	1.109	1.219***	1.416***	60	134
yes	4	density, ur, east	1.199***	1.123	1.238***	1.290**	57	138
yes	4	ur, nmr, east	1.217***	1.145*	1.279***	1.262**	61	144

Table 2.C.3: Average effects of return initiatives on return migration in the medium term based on different specifications of nearest neighbor matching (*continued*)

common			Workers employed prior to initial migration				Number of considered regions	
support imposed	Number of neighbors	Considered variables	All	Low wage	Medium wage	High wage	Treated (out of 65)	Non-treated (out of 336)
no	1	density, ur, nmr, east	1.209***	1.160*	1.239***	1.322**	63	52
no	1	wage, ur, nmr, east	1.194***	1.146*	1.234***	1.235	63	49
no	1	density, wage, ur, nmr	1.195***	1.121	1.268***	1.226	63	46
no	1	density, nmr, east	1.161***	1.067	1.225***	1.303**	63	48
no	1	density, ur, east	1.170***	1.078	1.227***	1.272*	63	47
no	1	ur, nmr, east	1.155***	1.104	1.242***	1.135	63	52
no	2	density, ur, nmr, east	1.161***	1.118	1.217***	1.248*	63	89
no	2	wage, ur, nmr, east	1.210***	1.145*	1.241***	1.338**	63	89
no	2	density, wage, ur, nmr	1.182***	1.138*	1.255***	1.200	63	81
no	2	density, nmr, east	1.167***	1.09	1.221***	1.316**	63	78
no	2	density, ur, east	1.182***	1.109	1.232***	1.290**	63	89
no	2	ur, nmr, east	1.170***	1.117	1.225***	1.236*	63	87

Table 2.C.3: Average effects of return initiatives on return migration in the medium term based on different specifications of nearest neighbor matching (*continued*)

common			Workers employed prior to initial migration				Number of considered regions	
support imposed	Number of neighbors	Considered variables	All	Low wage	Medium wage	High wage	Treated (out of 65)	Non-treated (out of 336)
no	3	density, ur, nmr, east	1.166***	1.111	1.215***	1.295**	63	112
no	3	wage, ur, nmr, east	1.220***	1.158**	1.252***	1.349**	63	118
no	3	density, wage, ur, nmr	1.169***	1.124	1.241***	1.198	63	100
no	3	density, nmr, east	1.171***	1.095	1.219***	1.339**	63	108
no	3	density, ur, east	1.184***	1.116	1.222***	1.317**	63	116
no	3	ur, nmr, east	1.182***	1.116	1.237***	1.264**	63	118
no	4	density, ur, nmr, east	1.165***	1.117	1.202***	1.317**	63	134
no	4	wage, ur, nmr, east	1.184***	1.126	1.220***	1.321**	63	139
no	4	density, wage, ur, nmr	1.187	1.105***	1.136*	1.247***	63	336
no	4	density, nmr, east	1.171***	1.106	1.212***	1.327**	63	134
no	4	density, ur, east	1.181***	1.12	1.221***	1.285**	63	139
no	4	ur, nmr, east	1.196***	1.134*	1.246***	1.282**	63	144

Table 2.C.3: Average effects of return initiatives on return migration in the medium term based on different specifications of nearest neighbor matching (*continued*)

common			Workers employed prior to initial migration			Number of considered regions		
support imposed	Number of neighbors	Considered variables	All	Low wage	Medium wage	High wage	Treated (out of 65)	Non-treated (out of 336)

Notes: Odd ratios (exponentiated coefficients) are reported that have been estimated based on Equations (1) , (2) and (5) and refer to the likelihood of return migration of medium-skilled workers. ***, ** and * indicate significance at the 1%, 5% and 10% levels and refer to robust standard errors which are clustered at the level of NUTS 3-regions. For considered control variables and fixed effects refer to the notes of Table 3 in the main part of the article. The specifications vary with regard to the control group which is based on k -nearest neighbor matching at the regional level. For our matching procedure we consider levels and past trends of the following characteristics: unemployment rate (ur), net migration rate (nmr), regional wage level (wage), employment density (density), and an indicator variable for East/West Germany (east). Unemployment rate, net migration rate, and regional wage level all refer to medium skilled workers with completed vocational training. For a detailed description of our matching procedure, see section 3.3 in our article. The two regions treated in 2001 are dropped in each specification since we cannot compute the change of all regional characteristics over the preceding three years due to data availability limitations.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.4: Average effects of return initiatives on return migration in the short and medium term conditional on separate time trends

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration			Wage prior to initial migration	
	All	No	Yes	Low	Medium	High
<i>with separate linear time trends for treated / non-treated regions in addition</i>						
Implementation phase	1,037 (0,025)	0,995 (0,047)	1,063** (0,027)	0,929 (0,051)	1,093** (0,046)	1,144** (0,073)
Medium term phase	1,153*** (0,043)	1,059 (0,063)	1,226*** (0,049)	1,107 (0,080)	1,265*** (0,070)	1,416*** (0,169)
<i>with region specific linear time trends in addition</i>						
Implementation phase	1,027 (0,026)	1,003 (0,055)	1,037 (0,031)	0,874* (0,060)	1,092* (0,050)	1,121 (0,091)
Medium term phase	1,132** (0,055)	1,052 (0,088)	1,162* (0,089)	1,012 (0,108)	1,257*** (0,109)	1,395* (0,249)
Observations	2,532,971	950,705	1,582,266	393,160	799,860	388,719
Individuals	405,320	135,851	269,469	65,843	136,216	67,328

Notes: Odd ratios (exponentiated coefficients) are reported that refer to extensions of our base-line model presented in Table 3 in our article. First, we add separate linear time trends for treated / non-treated regions. Second, we include region specific linear time trends. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.5: Average effects of return initiatives on return migration in the short and medium term (exclude workers treated in 2001 and 2016 or 2017, respectively)

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration		Wage prior to initial migration		
	All	No	Yes	Low	Medium	High
<i>Excluding workers from regions treated in 2001</i>						
Implementation phase	1.027 (0.025)	0.989 (0.044)	1.052** (0.027)	0.945 (0.049)	1.083** (0.043)	1.056 (0.071)
Medium term phase	1.136*** (0.038)	1.056 (0.046)	1.200*** (0.049)	1.144* (0.082)	1.234*** (0.060)	1.249** (0.137)
<i>Excluding workers from regions treated in 2016 or 2017</i>						
Implementation phase	1.009 (0.032)	0.957 (0.052)	1.047 (0.036)	0.915 (0.057)	1.053 (0.067)	1.087 (0.071)
Medium term phase	1.125*** (0.040)	1.038 (0.048)	1.198*** (0.051)	1.119 (0.083)	1.220*** (0.064)	1.226* (0.134)

Notes: Odd ratios (exponentiated coefficients) are reported that refer to specifications, where we estimate the same model like in Table 3 in the article, but without workers from regions that were treated at the very beginning or at the very end of the observation period. These workers only partially contribute to the identification of the treatment effects in the short and medium term. In the top panel, we exclude 2 of the 65 treated regions and in the bottom panel we exclude 31 of the 65 treated regions (see Figure 3 in the article). Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.6: Average effects of return initiatives on return migration in the short and medium term by school-leaving degree

	(1)	(2)
	High school diploma	
	No	Yes
Implementation phase	1.032 (0.027)	1.022 (0.069)
Medium term phase	1.127*** (0.040)	1.270*** (0.109)
Observations	2,058,190	472,699
Individuals	329,153	75,980
Pseudo R2	0.0512	0.0553

Notes: Odd ratios (exponentiated coefficients) are reported that refer to specifications, where we estimate the same model like in Table 3 in the article, but we distinguish workers by the highest level of schooling and consider those with high school diplomas (Abitur) and those with lower levels. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels. Table 2.B.1 provides information on the distribution of the two skill groups between the samples considered in the main analysis.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.7: Average effects of return initiatives on return migration if return migration is defined at the level of NUTS 3-regions

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration		Wage prior to initial migration		
	All	No	Yes	Low	Medium	High
Implementation phase	1.009 (0.027)	0.985 (0.050)	1.022 (0.030)	0.903 (0.057)	1.082* (0.050)	0.990 (0.073)
Medium term phase	1.138*** (0.043)	1.061 (0.052)	1.194*** (0.056)	1.097 (0.094)	1.237*** (0.071)	1.232* (0.135)
Observations	2,677,128	1,002,058	1,675,070	416,983	846,421	410,259
Individuals	412,494	137,888	274,606	67,488	138,749	68,144
Pseudo R2	0.0508	0.0703	0.0428	.0453	.0472	.0487

Notes: Odd ratios (exponentiated coefficients) are reported that refer to specifications, where we estimate the same model like in Table 3 in the article, but return migration is defined as moving back to the NUTS 3-region of residence during vocational training. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

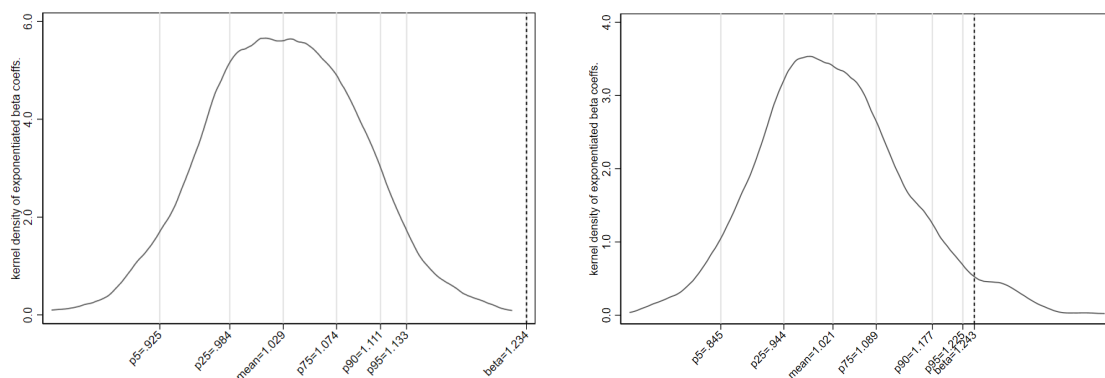
Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.8: Average effects of return initiatives on return migration in the short and medium term (staggered implementation)

Only regions treated in...	Implementation phase	95% confidence interval	Medium term phase	95% confidence interval
<i>Workers employed prior to initial migration with medium wage</i>				
2004	1.695	[0.942 - 3.049]	1.944	[0.970 - 3.899]
2006	1.102	[0.947 - 1.281]	0.873	[0.771 - 0.988]
2007	0.924	[0.694 - 1.231]	1.188	[0.940 - 1.502]
2008	1.208	[0.957 - 1.526]	1.348	[1.145 - 1.587]
2012	1.149	[0.836 - 1.580]	1.186	[0.949 - 1.483]
2013	1.138	[0.908 - 1.428]	1.309	[1.181 - 1.451]
2015	0.956	[0.786 - 1.164]	1.234	[0.925 - 1.646]
2016	0.938	[0.829 - 1.061]	.	[. - .]
2017	1.176	[1.058 - 1.309]	.	[. - .]
Average	1.124	[0.880 - 1.441]	1.265	[0.974 - 1.644]
<i>Workers employed prior to initial migration with high wage</i>				
2004	1.315	[0.272 - 6.351]	1.235	[0.333 - 4.585]
2006	1.877	[1.461 - 2.412]	2.704	[2.174 - 3.363]
2007	0.757	[0.576 - 0.993]	0.798	[0.521 - 1.224]
2008	0.992	[0.669 - 1.470]	1.225	[0.724 - 2.070]
2012	1.033	[0.707 - 1.511]	1.546	[1.267 - 1.887]
2013	0.783	[0.680 - 0.901]	1.000	[0.641 - 1.561]
2015	1.183	[1.040 - 1.346]	.	[. - .]
2016	0.771	[0.388 - 1.529]	.	[. - .]
2017	1.079	[0.788 - 1.479]	.	[. - .]
Average	1.044	[0.659 - 1.654]	1.310	[0.778 - 2.205]

Notes: Odd ratios (exponentiated coefficients) are reported. To address the staggered implementation of the return initiatives, we estimate our baseline model (see Table 3 in the article) separately for nine groups of treated regions that are defined based on the year of treatment (see Figure 3 in the article). No effects are estimated for regions treated in 2001 because we do not observe the pre-treatment phase. We do not obtain an estimate for the medium term effect if we consider workers with high wages and regions treated in 2015 because the implementation phase is defined a year longer for this group as for the medium wage group (see discussion in the article). In each iteration, the treatment group is restricted to those workers that lived during vocational training in the regions in which a return initiative was established in the considered year. The control group always comprises those workers who, during vocational training, lived in one of the 336 regions without a return initiative. This ensures that workers from early treated regions are not part of the control group of later treated regions. At the bottom of the table, we report the geometric mean of the individual estimated treatment effects and the bounds of the confidence intervals, respectively. Confidence intervals are calculated using robust standard errors, which are clustered at the level of NUTS 3-regions of residence during vocational training.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.



(a) Workers in the middle of the wage distribution (b) Workers at the top of the wage distribution

Figure 2.C.4: Estimates of the medium term effect of return initiatives on return migration if treatment is assigned randomly to regions (placebo test)

Notes: Each figure illustrates the distribution of the odds ratios (exponentiated coefficients) obtained by 1,000 estimations of our baseline model (see Table 3 in the article) with a treatment that is assigned randomly to NUTS 3-regions. When assigning the treatment randomly, we always keep the number of treated regions in East and West Germany per year constant (as with the original data) and, furthermore, ensure that large cities (*kreisfreie Städte*) are not among the treated regions. Regions that actually were treated might be chosen as well. The figures refer to the estimated treatment effect in the medium term phase. The black dashed lines indicate the estimates that we obtain based on the true treatment (cf., Columns (5) and (6) in Table 3 in our article).

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.9: Average effects of return initiatives on return migration and onward migration in the short and medium term

	(1)			(2)			(3)		
				Wage prior to initial migration					
	All			Medium			High		
	No migration	Return migration	Onward migration	No migration	Return migration	Onward migration	No migration	Return migration	Onward migration
Implementation phase	ref	1.039 (0.026)	1.005 (0.013)	ref	1.099** (0.046)	1.011 (0.013)	ref	1.149** (0.080)	1.016 (0.015)
Medium term phase	ref	1.154*** (0.044)	1.019 (0.024)	ref	1.250*** (0.064)	1.028 (0.021)	ref	1.420*** (0.180)	1.044** (0.022)
Observations	2,180,810			704,121			343,061		
Individuals	405,320			136,353			66,063		
Pseudo R2	0.4834			0.45484			0.46886		

Notes: The reported results are relative risk ratios and refer to a multiple-exit model where the treatment is specified according to Equation (5). We differentiate the outcome between three alternatives: staying at the destination of initial migration (baseline category), moving back to the local labor market of residence during vocational training, and onward migration to a third local labor market. We test whether the likelihood to return to the former region of residence and the likelihood to move to a third region (relative to remaining in the destination of initial migration) differ if a return initiative exists in their former region of residence. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, **, and * indicate significance at the 1%, 5%, and 10% levels. All models include the same control variables and fixed effects as our baseline model (see Table 3 in our article). In addition, the models include separate linear time trends for treated / non-treated regions like the specifications in the upper panel of Table 2.C.4 because onward migration appears to follow different time trends. The number of worker-year observations is smaller than in our baseline models because a worker is considered only until the first move after initial migration which can be either return or onward migration in these specifications.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Table 2.C.10: Average effects of return initiatives with / without certain characteristics on return migration in the short and medium term

	(1) More remote	(2) Consultation services	(3) Local employers	(4) Vacancies	(5) Housing	(6) Newsletter
<i>Workers employed prior to initial migration with medium wage[†]</i>						
Implementation phase × I(type=No)	1.093* (0.053)	1.047 (0.065)	1.028 (0.069)	1.086 (0.133)	1.144 (0.182)	1.114** (0.052)
Medium term phase × I(type=No)	1.212*** (0.080)	1.405*** (0.121)	1.199*** (0.067)	1.342*** (0.101)	1.379*** (0.141)	1.209*** (0.066)
Implementation phase × I(type=Yes)	1.059 (0.077)	1.092* (0.054)	1.131** (0.059)	1.082* (0.047)	1.078* (0.046)	1.017 (0.084)
Medium term phase × I(type=Yes)	1.263*** (0.073)	1.219*** (0.066)	1.249** (0.126)	1.209*** (0.065)	1.218*** (0.065)	1.301*** (0.128)
Observations	799,860	798,413	798,413	798,413	798,413	798,413
Individuals	136,216	135,931	135,931	135,931	135,931	135,931
Pseudo R2	0.048	0.048	0.048	0.048	0.048	0.048
t-test [‡] (p-value)	0.627	0.162	0.720	0.239	0.282	0.511
<i>Workers employed prior to initial migration with high wage[†]</i>						
Implementation phase × I(type=No)	1.071 (0.084)	1.253 (0.172)	0.923 (0.105)	0.819* (0.094)	0.802* (0.103)	1.032 (0.108)
Medium term phase × I(type=No)	1.388** (0.188)	0.856 (0.265)	1.108 (0.151)	0.979 (0.301)	0.770 (0.265)	1.250* (0.147)
Implementation phase × I(type=Yes)	1.044 (0.131)	1.019 (0.080)	1.136 (0.092)	1.084 (0.077)	1.083 (0.076)	1.104 (0.085)
Medium term phase × I(type=Yes)	1.039 (0.181)	1.263** (0.138)	1.467*** (0.185)	1.289** (0.136)	1.302** (0.138)	1.117 (0.290)
Observations	388,719	387,987	387,987	387,987	387,987	387,987
Individuals	67,328	67,190	67,190	67,190	67,190	67,190
Pseudo R2	0.047	0.047	0.047	0.047	0.047	0.047
t-test [‡] (p-value)	0.188	0.233	0.119	0.392	0.143	0.687

[†] Average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

[‡] t-test that shows whether the effects in the median time phase are the same between type=No and type=Yes.

Notes: Odd ratios (exponentiated coefficients) are reported that refer to specifications, where we estimate the same model like in Table 3 in our article, but with interaction effects of the treatment variable and an indicator variable referring to a certain feature of the return initiative. In each specification, we also consider separate reference categories (pre-treatment phases) for the two types of return initiatives distinguished per column. We calculate the average distance of the municipalities per NUTS 3-region to the nearest large city with at least 100,000 inhabitants weighted by the number of workers per municipality. A region is considered more (less) remote if the average distance between the municipalities of the region and the nearest large city is more (less) than 63 km which is the 75th percentile. ‘Consultation services’ indicates whether the return initiative provides personal counseling of people interested in returning. ‘Local employers’ indicates whether the return initiative provides information on local companies on their website. ‘Vacancies’ indicates whether the return initiative provides specific job offers on their website. ‘Housing’ indicates whether the return initiative provides information on the housing market and general information about life in the region. ‘Newsletter’ indicates whether the return initiative provides a newsletter. Robust standard errors are given in parentheses, which are clustered at the level of NUTS 3-regions of residence during vocational training. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, own data collection and own calculations based on Stiller and Ohlhoff (2021).

2.D Impact of return initiatives on location choice

Motivation

In all our analyses so far, we identified the impact of return initiatives on labor migration by comparing the temporal evolution of the probability of return migration to treated and to non-treated regions and, thus, focused on the initiatives' impact on return migration. However, the initiatives offer their services not exclusively to former residents, but also to other workers with a general interest in possibly moving to the region. Therefore, the question arises whether the initiatives also attract workers who did not live in the considered region previously. This is the subject of this section.

Empirical strategy

To study the impact of return initiatives on location choice in a broader sense, the empirical model needs to address that the return initiatives were set up in different regions and years, and we now examine location choice more generally rather than focusing on migration to a specific region (the former region of residence) per worker as we do for return migration. Therefore, we need to analyze whether different regions have been chosen more frequently as a region of residence at different points in time due to the establishment of a return initiative.

To do so, we estimate a conditional logit model (McFadden, 1974) and analyze in which region workers live in a certain year.³⁰ Specifically, we follow Steele et al. (2016) and assume that the probability that worker i resides in year t in region r is given by:

$$Prob(y_{it} = r | \eta_{it}) = \frac{\exp(\eta_{rit})}{\sum_{s=1}^{R_{it}} \exp(\eta_{sit})}, \quad r = 1, \dots, R_{it} \quad (2.6)$$

³⁰A description of the conditional logit model is provided by Greene (2019), for instance.

where y_{it} is a random variable indicating the observed individual's region of residence in year t , R_{it} is the number of all possible regions an individual can choose in each year (in our case 401 NUTS 3-regions), η_{rit} denotes a linear predictor which is a function of region-specific characteristics that may vary between individuals and/or time and η_{it} is the corresponding vector of linear predictors for worker-year observation it .

In what follows, we differentiate between two cases. First, we investigate whether regions with a return initiative attract vocational training graduates by analyzing the location choices of the latter from the end of training until they leave the local labor market in which they lived as an apprentice, with some never migrating (at least until the end of the period of observation). Thereafter, we focus on the location choice of mobile workers, i.e. those workers who moved to another region at some point after graduation, and study whether they are more likely to move to a treated region after their initial migration upon graduation. This latter analysis allows us to directly compare the impact of return initiatives on workers who lived in a treated region during vocation training and might return, i.e. on return migration, with their effect on other mobile workers who lived in a non-treated region as an apprentice and also already moved elsewhere.

When analyzing the initial migration after graduation, we assume for η_{rit} :

$$\eta_{rit} = \alpha_r + \beta_1 I(y_{i,t-1} = r) + RI_{rt} \quad (2.7)$$

where α_r is a region-specific constant which we interpret as an indicator of the overall attractiveness of region r . $I(y_{i,t-1} = r)$ is an indicator function referring to the residential region in the previous year. The associated parameter β_1 is expected to be large and positive, since most workers are immobile between two subsequent

years, which is why the region of residence in $t - 1$ in many cases explains where a worker lives in t (cf. Steele et al., 2016). In the second specification, where we examine subsequent migration after the initial move upon graduation, we augment Equation (2.7) by the term $\beta_2 I(y_i^{vact} = r)$. Indicator function $I(y_i^{vact} = r)$ identifies the individual residential region during vocational training (y_i^{vact}) to take into account that workers might choose their former region of residence rather than another region if they move again after having left their region of residence during training.³¹ RI_{rt} refers to the implementation of a return initiative in region r distinguishing between the implementation phase and the medium term phase like in the main analysis (compare Equation (5) in our article):

$$RI_{rt} = \gamma^{imp} I(t_0(r) \leq t \leq t_0(r) + \epsilon) + \gamma^{med} I(t > t_0(r) + \epsilon). \quad (2.8)$$

γ^{imp} and γ^{med} indicate whether workers are more likely to live in a region in the short and medium term after a return initiative has been established there.

³¹Notice that $I(y_{i,t-1} = r)$ and $I(y_i^{vact} = r)$ cannot be equal to one simultaneously in our augmented set-up, since we focus on the location choice of workers, who left the residential region of vocational training and do not consider years after a worker returned to this former region of residence as in our main analysis (see data description in our article).

We consider the treatment RI_{rt} separately for workers who do not already live in the respective treated region and for those who do, when we study location choice until the first move upon graduation. This allows us to separate the impact of initiatives on moving to a treated region ($\gamma_1^{imp}, \gamma_1^{med}$) and the impact on staying in a treated region ($\gamma_2^{imp}, \gamma_2^{med}$). η_{rit} is then given by:

$$\begin{aligned}
\eta_{rit} = & \alpha_r + \beta_1 I(y_{i,t-1} = r) \\
& + \gamma_1^{imp} I(t_0(r) \leq t \leq t_0(r) + \epsilon) I(y_{i,t-1} \neq r) \\
& + \gamma_1^{med} I(t > t_0(r) + \epsilon) I(y_{i,t-1} \neq r) \\
& + \gamma_2^{imp} I(t_0(r) \leq t \leq t_0(r) + \epsilon) I(y_{i,t-1} = r) \\
& + \gamma_2^{med} I(t > t_0(r) + \epsilon) I(y_{i,t-1} = r).
\end{aligned} \tag{2.9}$$

If we focus on mobile workers, those who already left the local labor market of residence during training, we consider the treatment separately for workers who originally lived in the considered region in which a return initiative is established and for workers who did *not* live in the treated region during vocational training to allow for heterogeneous effects on return migration of former residents and on the immigration of all other workers such that η_{rit} is given by:

$$\begin{aligned}
\eta_{rit} = & \alpha_r + \beta_1 I(y_{i,t-1} = r) + \beta_2 I(y_i^{vocc} = r) \\
& + \gamma_1^{imp} I(t_0(r) \leq t \leq t_0(r) + \epsilon) I(y_i^{vocc} \neq r) \\
& + \gamma_1^{med} I(t > t_0(r) + \epsilon) I(y_i^{vocc} \neq r) \\
& + \gamma_2^{imp} I(t_0(r) \leq t \leq t_0(r) + \epsilon) I(y_i^{vocc} = r) \\
& + \gamma_2^{med} I(t > t_0(r) + \epsilon) I(y_i^{vocc} = r).
\end{aligned} \tag{2.10}$$

In Equation 2.10, γ_1^{imp} and γ_1^{med} refer to the impact of return initiatives on location choice of workers who did not live in the considered region during vocational training in which a return initiative is established, while γ_2^{imp} and γ_2^{med} capture the effect on potential return migrants who lived in the treated region during vocational training but elsewhere in $t - 1$.

Data

For our analysis of location choice after the completion of vocational training, we use a 25% random sample of all apprentices who graduated in Germany in the period 1999–2013 and study the location choices of these individuals at the level of the 401 German NUTS 3 regions in subsequent years after graduation. After applying similar sample restrictions as outlined in Section 2.A, we end up with information on 207,210 workers. For these workers, we construct an annual worker panel with information on the individual residential location, amongst other characteristics, which captures all years from the end of vocational training until (i) a worker leaves the local labor market of residence during vocational training by moving to another part of Germany, (ii) a worker is not represented in the IEB for two or more consecutive years (e.g. because the person has temporarily left the German labor market)³² or (iii) the end of the observation period (year 2017) is reached. To estimate the conditional logit model, we ideally would need to expand our worker-year panel by a factor of 401, i.e. the number of regions, such that the data set comprises all alternatives for worker i at year t . However, our annual worker panel already captures 1,734,755 observations, which means that the number of observations in the expanded data set would be almost 700,000,000 which makes estimation infeasible. Therefore, we reduce the expanded data set by drawing a random sample from all 401 alternatives and estimate the model on

³²In exceptional cases, we also allow a longer interruption and impute the missing data, e.g. if a woman has given birth to a child and lives in the same region before and after her disappearance from the IEB (cf. Section 2.A).

a subset of alternatives (see Train, 2009 and Steele et al., 2016 for an in-depth discussion of this procedure which builds on the independence of irrelevant alternatives assumption (IIA) of the conditional logit model). Specifically, we select the observed residential region of worker i in year t and add four randomly selected alternatives. The final number of observations then is 8,673,775 worker-region-year combinations.

To study mobility after the initial migration upon graduation which was associated with leaving the training region, we use the same year-worker panel as in the main part of the article: former vocational training graduates from all over Germany that moved to another local labor market after graduation, and also study their location choices at the level of the 401 German NUTS 3 regions in the years after initial migration. Again, we randomly sample from all 401 alternatives and estimate the model on a subset of five alternatives per worker and year, always including the observed residential region of worker i in year t . To further reduce the data set, we focus on the first five worker-year observations in our data set per person. We believe that this reduction is not harmful as mobility rates decrease significantly in the course of individual working lives.³³ We end up with 6,894,020 observations.

Results

Table 2.D.1 shows the results of the model presented in Equation (2.6) with η_{rit} defined in Equation (2.9) for the entire sample of graduates, who are still living in the local labor market of residence during vocational training in $t - 1$, and by the employment status and the wage level in the first year after graduation. The very large effect of the indicator for the residential region in the previous year shows that spatial immobility is much more likely than migration out of the local labor market in which a person lives (cf., e.g., Steele et al., 2016).

³³See Figure 1 in our article with respect to the return migration rates.

The odds ratios that capture the effect of return initiatives on location choice of workers who do *not* live in a treated region so far (γ_1^{imp} and γ_1^{med}) are not statistically different from one at conventional levels of significance. This indicates that a return initiative is not increasing the immigration of vocational training graduates from other regions. However, we partly find significant effects of the return initiatives on graduates who live in the treated regions (γ_2^{imp} and γ_2^{med}). In particular, graduates who are employed in the first year after graduation and receive a medium wage appear to be more likely to stay in the local labor market if a return initiative exists. One possible explanation is that some graduates use the information provided by the return initiatives to inform themselves about the local labor market and potential future employers in the region, among other things, and are more likely to decide to stay in the region based on this information, on average.

Table 2.D.1: Effects of return initiatives on region choice after graduation

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed first year after graduation [†]			Wage first year after graduation [‡]	
	All	No	Yes	Low	Medium	High
Residential region in previous year	9136.813*** (336.505)	7707.088*** (771.392)	9417.504*** (373.570)	9699.731*** (870.214)	9299.983*** (504.411)	9413.818*** (734.116)
Return initiative exists × Treated region is <i>not</i> residential region in previous year						
Implementation phase (γ_1^{imp})	1.035 (0.039)	0.890 (0.094)	1.055 (0.043)	1.037 (0.082)	1.030 (0.062)	1.092 (0.099)
Medium-time phase (γ_1^{med})	0.970 (0.048)	0.876 (0.876)	0.981 (0.981)	1.027 (1.027)	0.964 (0.964)	0.953 (0.953)
Return initiative exists × Treated region is residential region in previous year						
Implementation phase (γ_2^{imp})	2.460*** (0.718)	1.922 (1.378)	2.564*** (0.819)	1.279 (0.652)	3.561*** (2.069)	2.174 (1.273)
Medium-time phase (γ_2^{med})	1.602*** (0.331)	1.229 (0.598)	1.681*** (0.385)	0.864 (0.296)	2.494*** (0.873)	3.374* (2.450)
Number of observations	8,673,775	1,042,660	7,631,115	1,640,215	3,990,310	2,000,590
Number of cases (workers×years)	1,734,755	208,532	1,526,223	328,043	798,062	400,118
Total number of alternatives / regions	401	401	401	401	401	401
Considered alternatives / regions per worker	5	5	5	5	5	5

[†] Indicator for full-time employment in the first year after the completion of vocational training.

[‡] Daily wage in full-time employment in the first year after the completion of vocational training. We use the same threshold values as in our paper where we distinguish potential return migrants according to the average daily wage in full-time employment between the end of vocational training and the first migration.

Notes: Results for location choice model (McFadden, 1974). Odd ratios (exponentiated coefficients) are reported that have been estimated based on Equations (2.6) and (2.9) and a sample of vocational training graduates that haven't moved since graduation so far. Robust standard errors are given in parentheses and are clustered at the worker level. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

Providing results for those vocational training graduates who have moved away from the training region in the years after graduation, Table 2.D.2 shows the results of the model presented in Equation (2.6) with η_{rit} defined in Equation (2.10) for the different samples that we consider in our article. Among all six samples considered, the most important predictor of location choice in the current year is again the residential region of the previous year. Additionally, there is a higher probability that workers choose to reside in the region where they lived during their vocational training (hence, they return) than in a third region. The odds ratios that capture the effect of return initiatives on location choice of the considered workers who did not live in the treated region during vocational training (γ_1^{imp} and γ_1^{med}) are not statistically different from one at conventional levels of significance, except for the low-wage subgroup in Column (4) in the medium term

phase. Altogether, this suggests that regions are not more likely to be chosen after the establishment of a return initiative by workers from other regions and that return initiatives do not influence the location choice of most considered workers.

Table 2.D.2: Effects of return initiatives on region choice after graduates initially move

	(1)	(2)	(3)	(4)	(5)	(6)
		Employed prior to initial migration [†]		Wage prior to initial migration [‡]		
	All	No	Yes	Low	Medium	High
Residential region in previous year	3656.104*** (0.000)	3268.720*** (0.000)	3939.457*** (0.000)	3821.843*** (0.000)	4281.329*** (0.000)	3774.419*** (0.000)
Residential region during voc. training	186.190*** (0.000)	159.474*** (0.000)	206.007*** (0.000)	200.710*** (0.000)	229.296*** (0.000)	171.198*** (0.000)
Return initiative exists × Treated region is <i>not</i> residential region during voc. training						
Implementation phase (γ_1^{imp})	1.011 (0.740)	1.051 (0.339)	1.002 (0.958)	1.012 (0.884)	1.010 (0.873)	0.984 (0.855)
Medium-time phase (γ_1^{med})	1.013 (0.734)	1.064 (0.291)	1.061 (0.264)	1.233** (0.031)	1.017 (0.813)	1.015 (0.904)
Return initiative exists × Treated region is residential region during voc. training						
Implementation phase (γ_2^{imp})	1.348** (0.023)	1.274 (0.305)	1.428** (0.023)	1.657* (0.064)	1.416 (0.152)	1.097 (0.767)
Medium-time phase (γ_2^{med})	1.357*** (0.003)	0.961 (0.816)	1.731*** (0.000)	1.507* (0.065)	1.691*** (0.003)	2.644*** (0.004)
t-test ($H_0: \gamma_1^{med} = \gamma_2^{med}$)	.011	.502	.000	.051	.008	.014
Number of observations	6,894,020	2,332,830	4,561,190	1,124,360	2,296,615	1,140,215
Number of cases (workers×years)	1,378,804	466,566	912,238	224,872	459,323	228,043
Total number of alternatives / regions	401	401	401	401	401	401
Considered alternatives / regions per worker	5	5	5	5	5	5

[†] Indicator for full-time employment between the end of vocational training and initial migration.

[‡] Average daily wage in full-time employment between the end of vocational training and initial migration. Thresholds are the first and third quartile.

Notes: Results for location choice model (McFadden, 1974). Odd ratios (exponentiated coefficients) are reported that have been estimated based on Equations (2.6) and (2.10) and a sample of vocational training graduates who have moved away from the training region. Robust standard errors are given in parentheses and are clustered at the worker level. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Source: IEB, Stiller and Ohlhoff (2021), own calculations.

However, we obtain significant effects similar to our main analysis where we focus on return migration if we consider the impact of return initiatives on the location choice of those workers who lived in the treated region during vocational training and emigrated after graduation captured by γ_2^{imp} and γ_2^{med} . While we again find that workers who were not employed in the training region prior to initial migration are not more likely to return, we do obtain significant effects for workers who stayed longer and here in particular for those with medium and high wages (cf. Table 3 in section 4.2 in our article). Overall, it seems that return

initiatives appeal more to workers who have already lived in the region previously than to workers who have not. We also test the null hypothesis that the medium term effects of the return initiatives for workers who lived in the region during vocational training (γ_2^{med}) and for workers who did not (γ_1^{med}) are the same. For both groups, the medium and the high wage group, as well as for the pooled samples in Columns (1) and (3), we can reject the null hypothesis at the 5 percent level.

2.E Association between return initiatives and regional net migration rate and growth rate of gross value added

Motivation

In this section, we summarize additional regression results where we examine return initiatives' impact on regional characteristics rather than on the individual likelihood of return migration as in the main part of our study. Specifically, we consider the regional net migration rate (focusing on medium-skilled workers like in the main part of our study) and a region's growth rate of gross value added as dependent variables.

Data

We merge the information on return initiatives at NUTS 3-level provided by Stiller and Ohlhoff (2021) with regional net migration rates, which we calculate on the basis of all medium-skilled workers in the IEB (see Section 3.2 in the article), and with information on a regions' annual gross value added growth rate. The underlying data on gross value added at NUTS 3-level is regularly calculated and published by the Working Group on National Accounting by the German States

(Arbeitskreis Volkswirtschaftliche Gesamtrechnung der Länder). We deflate the data using the Federal Statistical Office's consumer price index.

Empirical strategy

When estimating the impact of return initiatives on the regional net migration rate and regional gross value added growth, we take into account the staggered treatment and apply the Sant'Anna and Zhao (2020) doubly robust DiD estimator with multiple periods proposed by Callaway and Sant'Anna (2021) and integrated in Stata as `csdid` jointly with Fernando Rios-Avila. As control groups, we only use never-treated regions which were similar to the treated regions prior to the treatment, on average. Specifically, we use the same synthetic control group of regions like in our analysis of individual return migration (Section 4.3 in our paper) which is based on matching and entropy balancing as described in Section 3.3 in our article, when we consider the regional net migration rate as the dependent variable. For our analysis of the impact of a return initiative on a region's growth rate of gross value added, we generate an additional control group. We apply matching and entropy balancing as outlined in Section 3.3. in the article based on levels and trends (prior to the treatment) of the regional gross value added growth rate and the net migration rate as well as the level of labor productivity (average gross value added per hour worked) and an indicator for East/West Germany. Since we impose common support in matching, two out of 63 treated regions are excluded if we consider the net migration rate as the dependent variable. If gross value added growth is concerned, nine out of 63 treated regions are excluded.

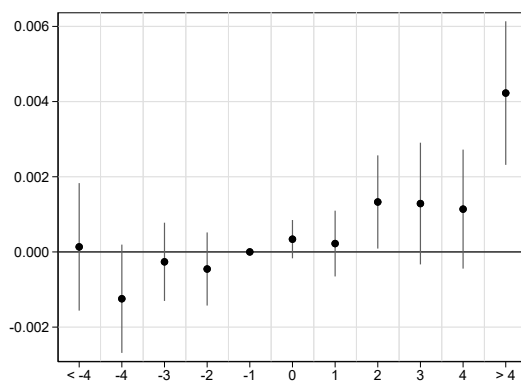
Results

Figure 2.E.1 summarizes the result of our regressions.³⁴ As regards the net migration rate in panel (a), we find no significant differences in the trend prior to the treatment for the control and the treatment groups.

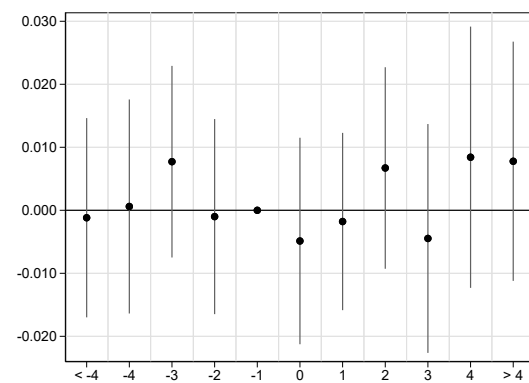
Similar to our individual analyses on return migration (Figure 4 in the article), a few years after the introduction of a return initiative, the net migration rate tends to increase slightly and remains at a higher level. Due to the large confidence intervals, however, the potential increase cannot be quantified precisely. It lies in the range between 0 and around 2 additional net immigrants per one thousand workers living in the region. The average effect more than four years after the introduction of the return initiative is around four additional net immigrants per 1000 workers according to the estimation results.

Measured in terms of the growth rate of gross value added, however, the return initiatives have no significant influence on regional development (see panel (b)). The difference between the growth rates of the treatment and control groups does not noticeably change with the establishment of the initiatives.

³⁴We gratefully thank Fernando Rios-Avila for describing how to generate panel event plots containing average effects for selected time periods (< 4 and > 4 in our case) after running `csdid` in Stata here: <https://www.statalist.org/forums/forum/general-stata-discussion/general/1622165-diff-in-diff-drddid-and-csdid/page7>.



(a) Net migration rate



(b) Growth rate of gross value added

Figure 2.E.1: Regional net migration rate and gross value added growth prior to and after the establishment of a return initiative

Notes: The figure illustrates the results of the staggered DiD setup proposed by Callaway and Sant'Anna (2021) where 0 on the horizontal axis denotes the year in which a return initiative is implemented. 95% confidence intervals are based on wild bootstrap standard errors. The net migration rate refers to medium-skilled labor and is measured in terms of net immigration between June 30 in year $t - 1$ and June 30 in t per worker living in a region on June 30 in $t - 1$. The growth rate of gross value added refers to the change between the years $t - 1$ and t and is measured in percent.

Source: IEB, Arbeitskreis Volkswirtschaftliche Gesamtrechnung der Länder, Stiller and Ohlhoff (2021), own calculations.

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Chapter 3

The urban-rural divide and the support of the far-right

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Abstract This paper examines the urban-rural divide in right-fringe voting support, using unique municipality-level data from Germany for the period 2001-2019. Our results show that there is an urban-rural divide in Germany. On average, right-fringe parties receive a 0.3 percentage points (or 4.6%) lower vote share in cities with more than 20,000 inhabitants. In addition, we find that spatial sorting of high-skilled individuals, foreigners, and differences in age and income levels individually and jointly can explain the urban-rural divide statistically. The nature of the urban-rural divide differs significantly between East and West Germany and changes with the emergence of the *Alternative für Deutschland* (AfD).

3.1 Introduction

Right-wing populism has been on the rise in most Western democracies. The growing support for right-fringe parties and candidates has been fueled by various factors such as financial crises, industrial decline, globalization and trade exposure, immigration, and cultural and identity issues (see Guriev and Papaioannou, 2022, for a comprehensive overview). The literature on the economic causes of populism consistently reveals a distinct spatial pattern, where populists gain strongholds in regions struggling to cope with structural change. Rodríguez-Pose (2018) calls this phenomenon “the revenge of the places that don’t matter”.

Accordingly, there seems to be a strong urban-rural divide in the support of populist parties, in particular at the right-fringe of the political spectrum. In fact, the narrative that left-behind places have spurred the resurgence of populist voting has led to the coinage of the phrase “geography of discontent” (Dijkstra et al., 2020). Populist parties capitalize on the divide in economic success by positioning themselves as representing “ordinary people” against the “cosmopolitan elites” (Guriev, 2018). This perceived divide between urban “elites” and non-urban “ordinary” citizens corresponds to an urban-rural divide in populist support observable in election data.

This paper assesses the anatomy of the urban-rural divide in the support of far-right parties and investigates its drivers. The maps in Figure 3.1.1 describe how right-fringe party support is spatially distributed within Germany, based on election results of the federal election in 2017. Panel 3.1.1a shows the vote share obtained by right-fringe parties, including the AfD, in each municipality. Far-right voting support shows a clear pattern between East and West Germany. It is particularly high (dark blue colors) in East Germany, except for Berlin and some other

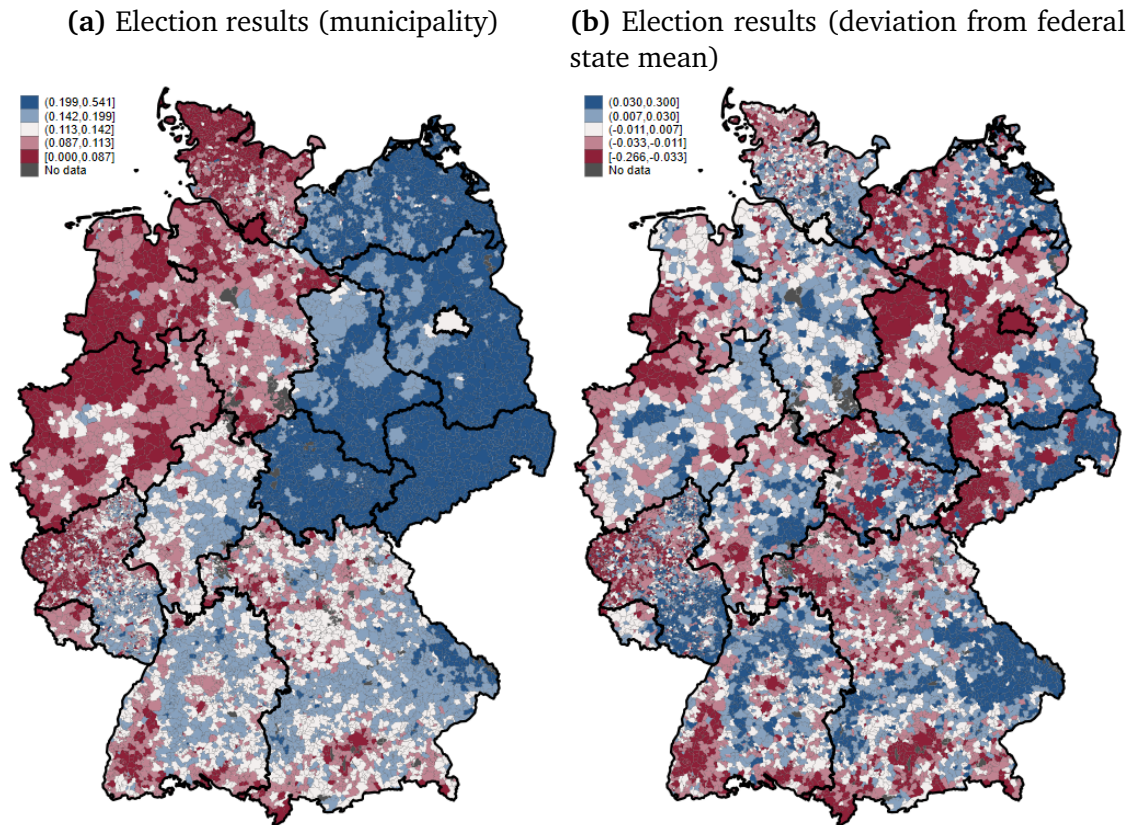


Figure 3.1.1: Vote share of right-fringe parties (federal election 2017)

Notes: Panel (a) on the left-hand site shows the election results of right-fringe parties including the AfD for the federal election in 2017. For a definition of right-fringe parties, see Section 3.3.1. Panel (b) shows the deviation of the election result of a municipality from the mean value of the respective federal state. City-states are combined with their neighboring states: Hamburg with Schleswig-Holstein, Bremen and Bremerhaven with Lower Saxony, and Berlin with Brandenburg.

larger cities (e.g. Halle (Saale), Jena, Leipzig, and Potsdam). Panel 3.1.1b accounts for state-level differences and shows the deviation of the election result of a municipality from the mean value of the respective federal state.¹ The figure indicates that in East and West Germany the support of the right-fringe is lower in urban agglomerations. We see clusters in red (low right-fringe shares) for larger cities and their neighboring municipalities within states (e.g. Leipzig and Dresden in Saxony). The maps show that Germany has both an East-West and an urban-rural divide with regard to far-right support.

¹City-states are combined with their neighboring states: Hamburg with Schleswig-Holstein, Bremen and Bremerhaven with Lower Saxony, and Berlin with Brandenburg.

The empirical analysis proceeds in consecutive steps. We first document the urban-rural divide in Germany. On average, right-fringe parties receive a 0.3 percentage points (or 4.6%) lower vote share in cities with more than 20,000 inhabitants.² This gap is much larger and more persistent in East Germany. In the East, the gap amounts to 15% of the mean vote share compared to West Germany, where it amounts to 1% of the mean vote share. In West Germany, the urban-rural divide vanishes with the advent of the AfD but is significant for the early period of our analysis from 2001 to 2010, when the AfD was not yet on the ballots.

Our goal is to better understand the drivers of differences in voting behavior between urban and rural municipalities. A large literature on urban economics has documented the sorting of individuals into cities of different sizes and types, (see Diamond and Gaubert, 2022, for a recent overview). Since urban and peripheral regions thus differ in the composition of their residents, we examine whether – and in how far – the urban-rural voting patterns are driven by the differing composition of their population. In particular, we examine differences in skill levels, the share of foreign workers, age structure, and in wage distribution. Our main interest is in the relative importance of these different dimensions of “urbanity” for the observed differences in right-fringe support.

We find that our channels individually and jointly can explain the urban-rural gap in right-fringe voting support. In particular, once we condition on the share of foreign workers and different wage percentiles, the urban-rural gap in right-fringe vote shares disappears. That is, if cities and the periphery had the same share of foreign workers (and the same share of non-EU workers among foreign workers) or the same wage profiles, right-fringe support would be the same in urban and

²We tested different population thresholds and measures of “urbanity”, and found a threshold of 20,000 inhabitants per municipality to be decisive for the urban-rural divide within Germany. However, in our subsequent empirical analyses, we also check the robustness of our results to using different threshold levels and other definitions of “urbanity”.

rural municipalities. Moreover, conditioning on the skill and age composition of the population turns the urban-rural gap positive: if cities had the same age and skill composition as the periphery, they would actually have higher right-fringe vote shares. Hence, sorting of individuals by different characteristics explains the observed urban-rural gaps in populist support. Accounting for the sorting observed, other city characteristics have the potential to even increase populist support.

We also uncover substantial East-West differences in the relative importance of the sorting channels when it comes to explaining the urban-rural divide. For West Germany, we find an urban-rural gap in the early period 2001-2010, which can be explained by skill composition, foreign worker shares, and wages. For East Germany, the urban-rural gap is persistent over time. In the early period, it survives the inclusion of all our channel variables, while in the late period (2011-2019), it can mainly be explained by skills.

The remainder is organized as follows: Section 3.2 provides a brief overview of the regional differences in right-fringe support and discusses how the paper adds to the literature. Section 3.3 describes the data and the empirical approach. Section 3.4 presents the results and Section 3.5 concludes.

3.2 Literature review

Our paper contributes to the literature on the spatial aspects of right-wing populism. This literature has revealed pronounced regional differences in the responses of populist support to economic shocks such as trade exposure (Autor et al., 2020) or migration (Steinmayr, 2021). We contribute to this literature in several ways.

First, similar to Scala and Johnson, 2017, Kenny and Luca, 2021 and Rickards-

son, 2021, we study whether the voting patterns for right-fringe parties differ between more urban and more rural places. Beyond documenting the size of the urban-rural gap in populist support, we assess its drivers. Although our analysis is not causal, we exploit the granularity of our data to decompose the overall differences between cities and the periphery into the share related to differences in the skill composition of the population, the foreign population, demography and the wage distribution, see below.

Moreover, we follow Dippel et al., 2021 who discuss East-West differences in right-populist support for Germany. We explore how urban-rural voting patterns of right-fringe parties differ between East and West Germany and over time. As described above, we find that the urban-rural gap is much larger and more persistent in the East than in West Germany. With the emergence of the AfD, the gap vanishes in the West but not in the East.

Furthermore, we describe how spatial sorting along different dimensions, i.e. our “channels”, affects the urban-rural gap. We see that East-West differences in the urban-rural gap partly relate to our channels having differential impacts in Western and Eastern German cities.

Firstly, we look into sorting by skill and education levels. High-skilled individuals tend to self-select into urban agglomerations, which might lead to differences in voting patterns. From an individual perspective, more educated voters tend to vote more conservative (Marshall, 2016), although in many countries, the association between education and voting conservative has weakened or even reversed over time (Gethin et al., 2021). Regionally, higher education levels have consistently been found to decrease support for *radical and populist* right-wing parties (Cavaille and Marshall, 2019). High-skilled individuals do not only sort into cities because of income incentives, they also appreciate the diversity and variety of

the urban lifestyle. We thus expect sorting by skill to be a relevant driver of the urban-rural divide in populist support.

Secondly, we examine the relative importance of the sorting of foreigners for explaining the urban-rural divide. Due to differing labor demand and network effects, the population share of foreigners tends to be higher in cities than in rural municipalities. Since foreigners cannot vote in national or state elections, they do not affect election results directly – but indirectly, as political parties may adjust their stance on immigration to the size of the foreign population, and the salience of the foreign population may affect political preferences of the native population (Colussi et al., 2021). A large literature has studied the effect of immigration on far-right voting. Dustmann et al. (2018) for example study the effect of immigration on far-right voting in Danish municipalities. They show that immigration increases voting support for the extreme right, but not in the 5% largest cities, which they interpret in light of contact theory. While far-right support tends to be lower the higher the share of foreigners living in a region, further immigration may increase right-fringe support (e.g. Edo et al., 2019; Halla et al., 2017), depending on the type of migration and the mode of contact with the native population (Steinmayr, 2021). To account for those differential effects, we will account for both, the share of the foreign workforce and the prevalence of non-EU foreigners, who might affect attitudes towards immigration differently (Hainmueller and Hopkins, 2014).

Thirdly, spatial sorting has an impact on the age distribution. We explore whether age differences between cities and the periphery may explain the urban-rural divide in populist support. On the one hand, older individuals may vote differently than younger ones, but the age effect need not be linear. Geys et al., 2022 for example find that right-fringe support is highest relative to left-wing sup-

port among very young and old voters, and lowest for the middle-aged. On the other hand, minors do not vote, so the share of minors affects voting only through its effect on parents or childless individuals. Since the age composition of small and large cities differ, as we document below, age composition may affect the urban-rural voting patterns we observe.

Eventually, we assess the relative importance of city-rural differences in the wage distribution. Income affects voters' preferences for public goods and redistribution and hence, their party preferences. We will analyze the effect of municipalities' median income in the spirit of the median voter model. Aggeborn and Persson (2017) argue that low-income voters have a stronger demand for basic public services at the expense of spending on refugee support systems or foreign aid. We will also look at one measure of income inequality (the ratio of the 75th to 40th percentile of the wage distribution). Some studies suggest that higher inequality increases voting for right-fringe parties (e.g. Han, 2016; Pastor and Veronesi, 2021). Since larger cities tend to have both higher median wages and greater wage inequality, we expect the wage distribution to affect the urban-rural difference in far-right voting.³

3.3 Data and empirical strategy

3.3.1 Regional election data

To assess right-fringe populist support, we rely on administrative data on the outcomes of all federal elections (*Bundestagswahlen*) and state elections (*Landtagswahlen*) in Germany from 2001 to 2019, obtained from the Federal Statistical

³All four channels measure different aspects of spatial sorting. Thus naturally, the sorting variables are not orthogonal to each other. For instance, skill composition and wages are naturally correlated. Our aim is not to assess the impact of one variable independent of all others, but to learn about their relative importance.

Office of Germany and from the statistical offices of the German states. We observe the votes of all parties that ever ran for election on the municipality level, i.e. the smallest administrative unit in Germany as spatial unit of observation. To classify parties as right-fringe, we follow Dippel et al. (2021) and calculate the aggregate vote share those parties receive. Dippel et al. (2021) rely on the German Offices for the Protection of the Constitution, both on the federal and the state level, to classify parties as right-fringe. Following this logic, the *Alternative für Deutschland* (AfD) is the most prominent right-fringe party observed in the later period of our analysis. In the earlier period, prominent examples are the National Democratic Party of Germany (NPD - Nationaldemokratische Partei Deutschlands), the Republicans (REP - Die Republikaner) and the German People's Union (DVU - Deutsche Volksunion) which merged with the NPD in 2011.⁴

Parties on the right fringe of the political spectrum adhere to nationalist ideologies, often express skepticism about the democratic system and constitutional guarantees of universal rights, and often engage in polemics against migrants and foreigners (Falck et al., 2014). The AfD was founded in 2013 as an anti-Euro party, but has developed a distinct anti-immigration stance ever since. Its ties to nationalist ideology classify at least some factions of the AfD as right-extremist in line with Dippel et al. (2021). Our main dependent variable is the share of aggregate right-fringe votes in total votes by municipality. While the average vote share of all right-fringe parties was 2% in the pre-AfD period, it was 13% in the later periods from 2013 on which underlines the great importance of the party. In the subsequent analysis, we use these parties' combined vote share as our central dependent variable and refer to them as right-fringe parties. The vote share is defined as votes for right-fringe parties divided by all valid votes.⁵

⁴More information on the German election system and a list of all the parties considered can be found in Appendix 3.A.1 and Table 3.A.1.

⁵In the following, we use the words right-fringe and far-right parties as synonymous.

We harmonize election dates into four election periods that cover one federal election and one state election each. Thus, we can track each municipality for eight different elections around the federal election dates 2005, 2009, 2013, and 2017.⁶ An advantage of our long panel is that we can differentiate between election periods with and without the AfD, which was founded in 2013. Urban-rural voting patterns could have changed with the emergence of the AfD. Thus, we will study how the results change over time. We account for territorial reforms, such that our final dataset is a balanced panel of municipalities, which corresponds to the territorial structure of Germany in 2019. Table 3.A.3 in the appendix shows the summary statistics for the election data.

3.3.2 Urban and rural regions

To analyze the urban-rural gap in right-fringe populist support, we first have to categorize the approximately 10,700 German municipalities into urban and rural.⁷ We follow the Federal Office for Building and Regional Planning (2024), which classifies German municipalities along different dimensions. With respect to population size, the classification distinguishes between three types of cities – small, medium, and large – and rural municipalities. An alternative classification (see, Friedrich et al. (2021)) also takes into account whether a municipality fulfills urban functions, e.g. providing schools or administrative services for a broader region (*Zentrale Orte*). We have examined both classifications and contrasted empirical results with alternative measures based on population density. Essentially, all measures of “urbanity” provide a similar picture: differences in right-fringe support increase with population size, density, and functional specialization, but

⁶Table 3.A.2 shows the types of election per year since 2001.

⁷In 2019, the number of municipalities was 11,006. We are able to observe the election results for 10,767 municipalities.

the main divide is between rural municipalities and cities by any measure.⁸

Given the spatial structure of Germany with its state-level heterogeneity, our analysis focuses on a city definition by size, and we define urban municipalities as having at least 20,000 inhabitants.⁹ We use the population from 2019 to categorize municipalities, so that the categorization is constant over time. This leaves us with 700 urban and 10,067 rural municipalities. On average, an urban municipality has 70,311 inhabitants and a rural municipality has 3,322 inhabitants. In total, 82,656,147 people live in Germany, 49,217,462 or 59.5% in urban areas and 40.5% (33,438,685) in rural areas according to our definition.¹⁰

Figure 3.3.1 shows the distribution of urban and rural municipalities in Germany. Red indicates urban and blue rural municipalities. Historically, urban centers have been widely scattered throughout Germany. There is a strong cluster of urban municipalities in the western state of North Rhine-Westphalia.

⁸Section 3.4.2 examines in detail the robustness of our urban-rural indicator with respect to the chosen population threshold and alternative concepts for “urbanity”.

⁹This largely corresponds to medium and large cities. Small cities already show lower right-fringe support than rural municipalities, specifically if they fulfill urban functions, e.g. host larger schools or provide administrative services. However, not all German states contain sufficiently many small cities to further differentiate between rural municipalities and small cities. Similarly, large cities are regionally clustered. Since our empirical analysis includes state fixed effects, we differentiate between rural and urban municipalities only, split by the threshold of 20,000 inhabitants.

¹⁰In the following, we use the terms cities and urban regions as synonymous. We also use the terms rural and peripheral interchangeably.

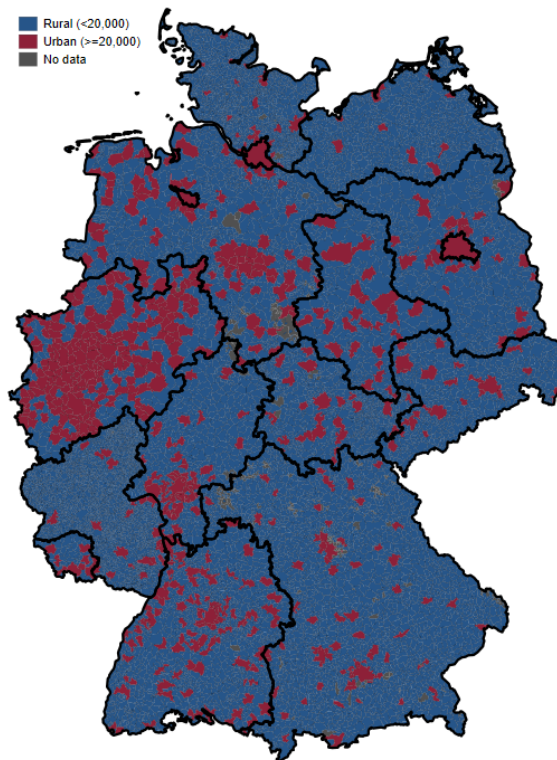


Figure 3.3.1: Urban and rural municipalities in Germany

Notes: The map shows the categorization of German municipalities into rural (blue) and urban (red). The rural category is defined as municipalities with $<20,000$ inhabitants ($N=10,067$) and the urban category are municipalities with $\geq 20,000$ inhabitants ($N=700$). Categories are based on the population level as of 2019.

3.3.3 Municipality characteristics

We merge our election data with municipality-level information from different data sources. This information is used to control for between-municipality variation in populist support within each category, and to explore channels explaining the city-rural divide.

First, we use data from the platform “*Indikatoren und Karten zur Raum- und Stadtentwicklung*” (INKAR). The database contains a large number of indicators from the ongoing spatial observation of the Federal Office for Building and Regional Planning (2024). Information on regional characteristics is available at the municipality level and for long time series. Second, we use the Integrated Em-

ployment Biographies (IEB) of the Institute for Employment Research (IAB). The IEB maintained by the Institute for Employment Research (IAB) provides a comprehensive resource for analyzing labor market outcomes down to the individual level. The IEB combines administrative data from various sources, such as social security records and unemployment insurance notifications, to construct detailed employment histories for individuals. These biographies capture essential information such as gender, nationality, qualification levels, occupations, and industry affiliations. In the IEB, we observe the universe of individual employees subject to social security contributions and registered unemployed individuals. In total, the IEB covers about 90% of the workforce in Germany.¹¹ From 1999 onward, the IEB provides individual-level information not only for the place of work, but also for the place of residence. We aggregate individual characteristics by the municipality of residence and by year.¹²

The INKAR and IEB datasets are merged with the election dataset via a unique municipality key (“*Allgemeiner Gemeindeschlüssel (AGS)*”) and by year (in which the election took place). Together, we have a municipality-level panel with 83,672 observations. This means that we can match 10,459 municipalities over four election periods with two elections per period. We use these sources to construct measures of the channels described above, that is, variables that we think are potential drivers of observed urban-rural voting differences. We also control for additional variables that could be linked with voting outcomes.

Our first potential channel is a municipality’s skill composition. To measure regional skill composition, we use the workers’ qualification level. We differentiate between low, medium and highly qualified workers. Workers with low qualification do not have vocational training or a university degree. Workers with medium

¹¹For a more detailed description and features of the IEB see Frodermann et al. (2021).

¹²We use yearly information at the reporting date June 30.

qualification have completed vocational training. Highly qualified workers have a degree from a technical college or university.

Our second channel is the share of foreigners. Since there is no information on the nationality of the entire population at the municipality level, we use the information on workers' nationality in the IEB data. Our first indicator is the total share of foreigners in the working population. Moreover, election outcomes could be influenced not only by the overall share of foreigners but also through the composition of different nationalities. Therefore, we also consider the share of non-EU foreigners in the foreign working population.¹³

As our third channel, we consider a municipality's age structure. We use the share of children (0-17 years) in the total population and the adult population divided into four groups: 18-29 years, 30-49 years, 50-64 years and 65 years and older.

The last channel we explore is the municipalities' wage structure. We use workers' daily median wage to as an indicator of the wage of decisive voter groups. Further, we use the wage gap between the 75th and 40th wage percentiles as an inequality measure. The wage gap within a municipality is calculated as: $\text{wage gap}_{p(75),p(40)} = (wage_{p(75)} - wage_{p(40)}) / wage_{p(40)}$.

We also include additional covariates to account for within-city-group heterogeneities such as voter participation, gender compositions, the employment rate and the population change over the past five years. A description of the variables is presented in Section 3.A.2 in the appendix. Table 3.A.4 in the appendix presents summary statistics for all regional variables used for the period of analysis 2001-2019.

¹³We use the EU-28 countries including the United Kingdom over the complete observation period.

3.3.4 Descriptives

Before delving into regression results on the urban-rural voting gap, we provide some descriptives both on the voting gap and the variables that we use as potential channels to ‘explain’ this gap. Table 3.3.1 shows the differences in rural minus urban mean outcomes, separately for West and East Germany and the two time periods (early (2001-2010) and late (2011-2019)).¹⁴ Panel A shows the urban-rural voting gap. We see that the gap is positive for East and West Germany and for both periods. The average voting gap in West Germany in the early period is 0.34 percentage points (pp). This means that the average vote share for right-fringe parties in rural municipalities is 0.34 pp higher than in urban regions. The gap decreases for West Germany in the late period to 0.20 pp. In East Germany, the gap is larger in both periods and increases from 1.14 pp in the early period to 1.89 pp.

Panel B shows differences in qualification. In the early period in West Germany, the average share of low-skilled workers was 2.25 pp lower in rural than in urban regions. This difference increased with time. In East Germany, the rural-urban difference in low-skilled workers is small (-0.39 pp) in the early period and increases substantially to almost two percentage points in the late period. The share of high-skilled workers is also higher in urban than in rural regions. This is true for West and East Germany and for the early and late periods. We also find that the differences increase over time.

Panel C presents the variables on the foreign workforce. As expected, the share of foreigners is higher in cities than in rural regions. Furthermore, the differences increase from the early to the late period in both parts of Germany. The internal

¹⁴Table 3.B.1 in the appendix shows the means of the channel variables for urban and rural regions.

share of non-EU foreigners is also larger in cities than in rural areas. The difference increases over time in West Germany and decreases in East Germany.

The age groups shows mixed results (panel D). The share of children is higher in rural areas, but the differences decrease over time. Young adults (18-29 years) are more likely to live in cities, and the difference increases over time, especially in East Germany. For the 50-64 year old, we find a larger share in urban areas in the early period, but lower shares in urban areas in the late period. There are more people of retirement age (65 and older) in urban regions, and the difference is larger in the East.

Finally, in panel E, we find that the median wage level is higher in cities and that this difference is larger in the East than in the West. The $p(75)/p(40)$ wage gap (our inequality measure) is also larger in cities, and the gap increases over time in East Germany.

In summary, we find sorting of low-skilled *and* high-skilled individuals into larger cities, and that sorting has increased over time. We also find sorting of foreigners into larger cities. Wages are larger but more unequal in cities. In the next section, we explore how these sorting patterns contribute to the urban-rural voting gap that we observe.

Table 3.3.1: Mean differences of sorting variables within city categories

	West-early (1)	West-late (2)	East-early (3)	East-late (4)
A) Election results				
Right-extremist and AfD	0.34	0.20	1.14	1.86
B) Qualification channel				
Low-skilled workers	-2.25	-2.93	-0.39	-1.98
Medium-skilled	6.25	8.11	4.55	6.45
High-skilled workers	-4.02	-5.18	-4.16	-4.46
C) Foreigner channel				
Foreign workers	-5.52	-6.15	-1.00	-2.10
Non-EU foreign workers	-16.69	-17.99	-34.79	-28.15
D) Demography channel				
0-17 years	1.69	0.24	1.22	0.57
18-29 years	-1.19	-1.38	-1.13	-2.83
30-49 years	0.70	-0.20	2.39	1.13
50-64 years	-0.36	1.97	-0.07	4.15
65 and older	-0.84	-0.63	-2.40	-3.02
E) Wage channel				
Median wage	-4.18	-3.71	-7.30	-7.17
Wage gap _{p(75),p(40)}	-5.97	-5.87	-3.57	-5.75

Notes: Mean differences between rural and urban municipalities for West Germany and East Germany. The means are calculated for the early election period (2001-2010) and the late period (2011-2019) per municipality. Each municipality is weighted equally. The differences are calculated as $\text{mean}_{\text{rural}} - \text{mean}_{\text{urban}}$. Table 3.B.2 in the appendix shows the means for the respective groups. The rural category is defined as municipalities with <20,000 inhabitants and the urban category is defined as municipalities with $\geq 20,000$ inhabitants in 2019.

3.3.5 Empirical strategy

We are interested in whether urban and rural municipalities vote differently, that is, in the gap in mean right-fringe election results between rural and urban regions. We estimate this gap with the following baseline model:

$$Y_{rt} = \beta_0 + \beta_1 U_r + \sum_{i=1}^I \beta_i X_{irt} + \tau_{p(t)} \times \sigma_e + \gamma_{s(r)} + \epsilon_{rt}. \quad (3.1)$$

The dependent variable Y_{rt} is the vote share of right-fringe parties in munici-

pality r and year t . U_r is an indicator variable that is equal to 1 for urban municipalities and 0 otherwise. The parameter β_1 measures the urban-rural voting gap. Each election period p covers two observations for each municipality, one federal election and one state election. To control for differences between election types and their dynamics, we include election period times election type fixed effects $\tau_{p(t)} \times \sigma_e$.¹⁵ We also include fixed effects for federal states γ_s to account for regional differences in both the party and the territorial structure.¹⁶ Since several other regional and time-varying determinants may influence the support of right-fringe parties, we add I municipality-level control variables X_{irt} to increase the precision of our model.¹⁷ As usual, β_0 represents the constant and ϵ_{rt} is an error term clustered at the level of 361 district regions (*Kreisregionen*).¹⁸

To test in how far our sorting variables, i.e. skill composition, foreign population, demography, and wages, can explain the urban-rural divide in right-fringe support, we follow the empirical approach of Elder et al. (2010). They show that a pooled regression with an indicator variable that indicates rural and urban regions provides a good approach to separate between-group mean differences into explained and unexplained parts. To test in how far the urban-rural gap is explained by our channels, we add the J_C variables for each channel C :

$$Y_{rt} = \lambda_0 + \lambda_1 U_r + \sum_{j=1}^{J_C} \lambda_j C_{jrt} + \sum_{i=1}^I \lambda_i X_{irt} + \tau_{p(t)} \times \sigma_e + \gamma_{s(r)} + \epsilon_{rt}. \quad (3.2)$$

Although the effects in Equation (3.2) cannot be interpreted causally, λ_1 represents the “unexplained” part of the urban-rural gap and λ_j represents the part

¹⁵See Section 3.3.1 for an explanation of the panel structure.

¹⁶In Section 3.A.1, we briefly explain the German election system. Section 3.4.2 and Section 3.B.1 in the appendix provide further information on the model specifications.

¹⁷The covariates are described in Section 3.A.2 in the appendix.

¹⁸District regions merge city-districts to surrounding counties. While city districts and counties are administrative regions, district regions approximate local labor markets that are comparable nationwide. Alternative standard errors are discussed in Section 3.B.1.

which is “explained” by channel j . Furthermore, comparing the estimated λ_1 from Equation (3.2) to β_1 from Equation (3.1) allows to inferring on the statistical relevance of each channel in “explaining” the urban-rural voting gap.

Importantly, the observed channels are not orthogonal. Thus, in addition to adding each channel separately, we eventually include all four channels simultaneously to compare their relative importance.

In another step, we split the sample into rural and urban municipalities and estimate the models separately since the channels could have different effects within rural or urban regions. This approach is similar to a fully interacted model in which we interact all variables with our urban indicator. A sample split is comparable to an Oaxaca-Blinder decomposition in that it decomposes the effects of the covariates for the rural and urban subsamples (Blinder, 1973; Oaxaca, 1973).

3.4 Results

3.4.1 Urban-Rural Divide Over Time and Space

We start by describing the results of regressing the right-fringe populism vote share on our urban indicator in Table 3.4.1. Unless noted otherwise, the dependent variable is the aggregate vote share of all right-fringe parties, including the AfD, c.f. Table 3.A.1 However, since the AfD was established relatively late and first ran in the 2013 elections, we will differentiate our results by the first two election periods (2001–2010), where the AfD was not on the ballot and the last two (2011–2019), where it was.¹⁹ We also show the results of separate regressions for West and East Germany. All regressions include our baseline controls as

¹⁹The AfD was founded in 2013 which is not perfectly congruent with the period 2011-2019. Table 3.B.6 in the appendix shows the results where we treat the years 2013-2019 only as late period. The results are robust and stable compared to the results for 2011-2019. For this reason, we maintain the balanced panel structure for 2011-2019 for the ensuing analysis.

well as state fixed effects.

Columns (1)–(3) of Table 3.4.1 show that for Germany as a whole, right-fringe support is significantly lower in urban than in rural municipalities. This holds for the full sample and for both time periods (the early period without and the late period with the AfD). On average, the vote share obtained by right-fringe parties is about 0.3 percentage points (pp) lower in cities. This amounts to 4.5% of the right-fringe vote share over the entire period.

Interestingly, with the emergence of the AfD, the urban-rural divide narrows. In the early period (column 2), right-fringe support was $(0.332/2.928 \times 100 =)11.34\%$ lower in urban than in rural municipalities. With the AfD on the ballots (column 3), overall support of the right fringe increased, while the urban-rural divide decreased to $(0.294/10.143 \times 100 =)2.90\%$. Apparently, the AfD was more successful in attracting urban voters than other right-fringe parties.

This dynamic is particularly pronounced in West Germany (columns 4-6). While in the early period (column 5), the urban-rural divide amounted to 5.95% of the right-fringe vote, in the late period with the AfD (column 6), right-fringe parties received even *more* support in cities than in the periphery, although the difference is statistically insignificant. In contrast, in East Germany, the urban-rural gap in populist support persists throughout the whole period, although it decreases in relative terms. In the early period, right-fringe parties gained $(1.561/5.223 \times 100 =)29.90\%$ less of the votes in urban than in rural regions. In the later period, the gap amounted to $(2.063/19.386 \times 100 =)10.64\%$.

Thus, overall, while right-fringe support is higher in East Germany, the urban-rural divide is more pronounced there as well. Subsequently, we will dive deeper into how different channels may contribute to the marked differences in the spatial divide in populist support between East and West Germany.

Table 3.4.1: Urban-rural differences in voting outcomes by region and period

	(1)	Germany (2)	(3)	(4)	West (5)	(6)	(7)	East (8)	(9)
	Full	Early	Late	Full	Early	Late	Full	Early	Late
Urban	-0.298*** (0.088)	-0.332*** (0.058)	-0.294** (0.117)	0.043 (0.073)	-0.135*** (0.048)	0.110 (0.103)	-1.860*** (0.316)	-1.561*** (0.214)	-2.063*** (0.448)
Constant	2.060 (1.731)	8.991*** (1.946)	4.887** (2.283)	1.964 (1.701)	4.374*** (0.830)	4.467* (2.551)	23.052*** (3.278)	22.950*** (3.174)	28.152*** (5.323)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86136	43068	43068	66896	33448	33448	19240	9620	9620
Mean outcome	6.536	2.928	10.143	4.877	2.269	7.485	12.304	5.223	19.386
Adjusted R^2	0.709	0.409	0.733	0.724	0.251	0.664	0.817	0.328	0.711

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parenthesis are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. Early indicates the first two election periods including the federal elections in 2005 and 2009. Late indicates the third and fourth election period including the federal elections in 2013 and 2017.

3.4.2 Robustness of the baseline results

In this section, we examine the robustness of our main results. First, in Section 3.B.2 we explain how we include regional fixed effects on the state level since we have the problem that city-states have only one or two municipalities. In Table 3.B.3 we show that the results are robust to the way in which we include state fixed effects in the model.

Second, Table 3.B.4 shows the results with and without the baseline controls. We see that for Germany as well as for West and East Germany, our controls increase the adjusted R^2 while the results of our urban indicator are stable across all sub-samples.

In our main analysis in Table 3.4.1, we set the population threshold for considering a municipality to be urban to 20,000 inhabitants. In so doing, we follow the categorization of the Federal Office for Building and Regional Planning (2024). However, the threshold of 20,000 inhabitants is somewhat arbitrary. For this reason, we first test whether our results are driven by large cities. Table 3.B.5 in the

appendix shows the results for Germany and for East and West Germany when we exclude municipalities with more than 100,000 inhabitants from the sample.²⁰ We find that we still do not have a significant urban effect for West Germany. For Germany overall and for East Germany, the results are slightly lower, but comparable in magnitude and precision to our baseline results.

In a second step, we re-estimate the coefficient for the urban-rural indicator for different population thresholds and present the results in Figure 3.4.1. The results show that the coefficients are all comparable in size. The confidence intervals of all four categories overlap. The point estimate for 20,000 inhabitants is the largest which is significantly different from zero on the 95%-level.²¹ The results indicate that our results are robust to alternative definitions of the urban status.

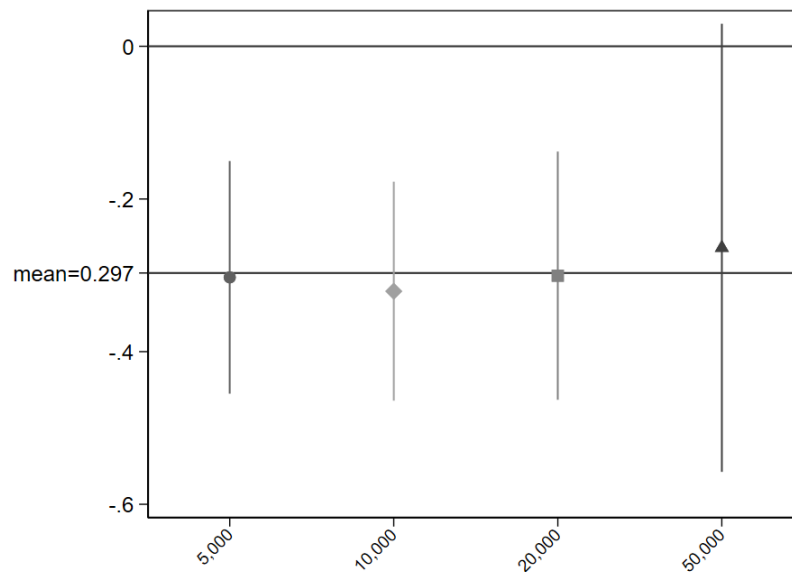


Figure 3.4.1: Urban-rural indicator for different population thresholds

Notes: The figure shows the coefficients and 95% confidence intervals (clustered on the district region level) for different population thresholds for the urban-rural indicator (Equation (3.1) without controls X_{rt}). The x-axis indicates the number of inhabitants that has to be exceeded for a municipality to be considered as an urban municipality. The mean on the y-axis indicates the average over the four coefficients and is -0.297.

²⁰Again, we use the population information from 2019.

²¹For an even larger threshold, the estimated effect is larger but more imprecisely measured.

Another concern is the existence of spatial autocorrelation. This means that the level of urbanization of one municipality is not independent of the level of urbanization of neighboring municipalities. For this reason, we use the *degree of urbanization* index (DEGURBA), a concept defined by the European Union (2021), as an alternative urban-rural measure. The *degree of urbanization* classifies municipalities as cities, towns and suburbs, or rural areas. The classification is based on a combination of geographical contiguity and population density, measured by minimum population thresholds applied to one-square-kilometer population grid cells. The advantage of the concept is that the definition of a municipality as urban also takes into account the population in neighboring municipalities. Figure 3.4.2 plots both indicators for Germany. Panel (a) shows the urban indicator we use, panel (b) the *degree of urbanization*. It is clear that the number of urban municipalities is higher in panel (b). It can also be seen that the agglomerations in panel (a) now include surrounding municipalities (e.g. Berlin or Munich).

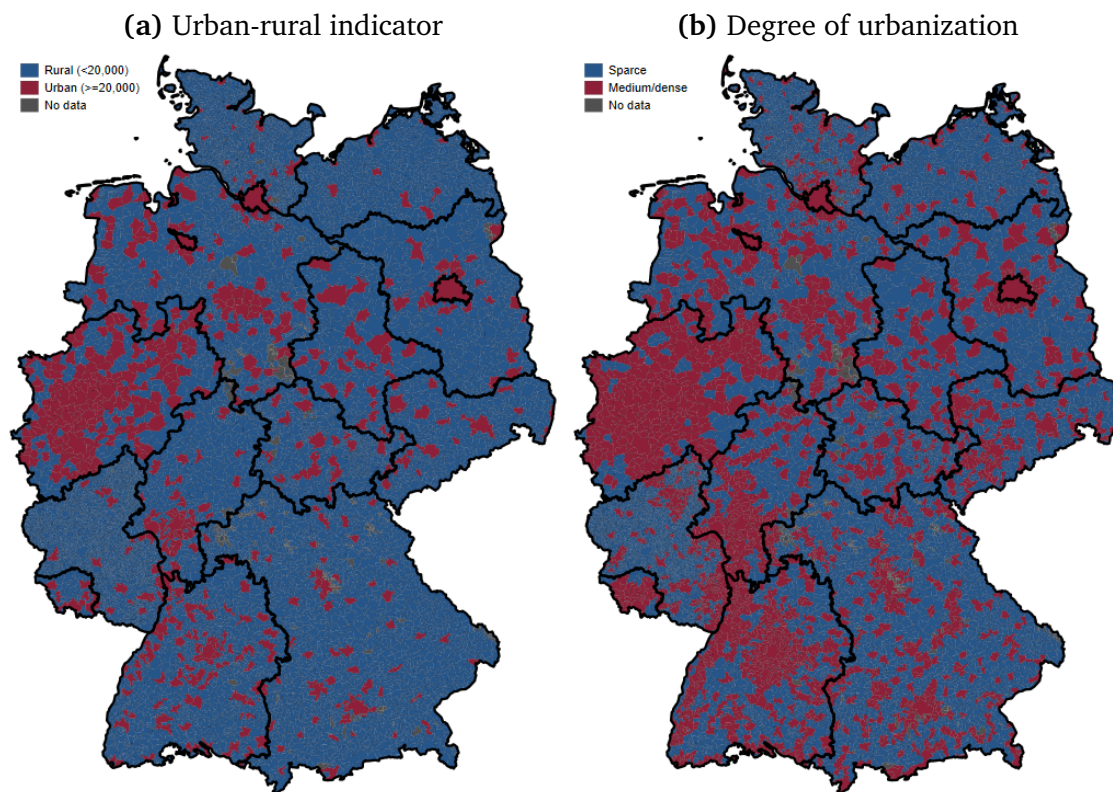


Figure 3.4.2: Urban-rural indicator for different geographical contiguity

Notes: Panel (a) on the left-hand side indicates the urban-rural indicator used in the analysis. The rural category is defined as municipalities with $<20,000$ inhabitants ($N=10,067$) and the urban category are municipalities with $\geq 20,000$ inhabitants ($N=700$). Categories based on the population level in 2019. Panel (b) on the right-hand side shows the *degree of urbanization* (DE-GURBA) defined by the European Union (2021).

Table 3.4.2 shows our estimates of the urban-rural gap using both concepts. Columns (1)–(3) show the results for our baseline urban indicator, columns (4)–(6) the results for the *degree of urbanization*. It can be seen that the effects are comparable in size and precision. The results suggest that the urban-rural gap is not affected by spatial autocorrelation.

Table 3.4.2: The urban coefficient (different specifications)

	Urban-indicator			DEGURBA		
	(1) Germany	(2) West	(3) East	(4) Germany	(5) West	(6) East
Urban	-0.298*** (0.088)	0.043 (0.073)	-1.860*** (0.316)			
Medium/dense region				-0.321*** (0.072)	-0.022 (0.068)	-1.471*** (0.190)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86136	66896	19240	86136	66896	19240
Mean outcome	6.536	4.877	12.304	6.536	4.877	12.304
Adjusted R^2	0.709	0.724	0.817	0.709	0.724	0.818

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019 in the columns (1)-(3). In columns (4)-(6), medium and dense regions are defined as cities, towns and suburbs in contrast as rural areas by the *degree of urbanization* (DEGURBA) (European Union, 2021).

3.4.3 Channels behind the urban-rural differences

We now assess the channels behind the urban-rural differences in right-fringe support. As a benchmark, we first report results for Germany as a whole in Table 3.4.3. For each of our potential channels, we show how the coefficient for our urban indicator changes once we condition on the corresponding sorting variables (see Equation (3.2)).

Table 3.4.3: Influence of each channel on the urban-coefficient

	(1) Germany	(2) Qualification	(3) Foreigners	(4) Demography	(5) Wages	(6) All
Urban	-0.298*** (0.088)	0.203** (0.091)	0.030 (0.096)	0.533*** (0.106)	-0.132 (0.081)	0.832*** (0.116)
Low-skilled workers		-0.008 (0.021)				0.064*** (0.017)
High-skilled workers		-0.118*** (0.013)				-0.128*** (0.017)
Foreign workers			-0.077*** (0.017)			0.025 (0.016)
Non-EU foreign workers			0.002* (0.001)			0.003*** (0.001)
0-17 years				0.239*** (0.031)		0.190*** (0.028)
18-29 years				-0.358*** (0.050)		-0.416*** (0.053)
50-64 years				0.123*** (0.021)		0.126*** (0.020)
65 and older				0.033* (0.018)		0.012 (0.018)
Median wage					-0.012 (0.008)	0.007 (0.008)
Wage gap $p(75), p(40)$					-0.023*** (0.006)	-0.004 (0.005)
Constant	2.060 (1.731)	-1.840 (2.037)	1.920 (1.691)	3.606 (2.982)	1.933 (1.883)	-0.814 (2.926)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86136	86135	86136	86136	86089	86089
Mean outcome	6.536	6.536	6.536	6.536	6.534	6.534
Adjusted R^2	0.709	0.714	0.710	0.733	0.711	0.739

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. The share of medium-skilled workers is the reference category in the qualification channel. The share of 30-49 year old people is the reference in the demography channel.

Column (1) of Table 3.4.3 repeats the baseline results from Table 3.4.1 column (1) as reference. Column (2) adds the shares of high-skilled and low-skilled workers to our baseline regression. Medium-skilled workers are the omitted category. Voting support for right-fringe parties is significantly lower in municipalities where the share of high-skilled residents is high. This is in line with Greve et al. (2023), who also find that high-skilled employment is negatively related to voting for right-wing populist parties in Germany. The coefficient of the low-skilled is not significantly different from zero. As shown above, highly skilled individuals tend to sort into cities. In fact, conditional on the skill composition, our urban coefficient turns positive. This suggests that if the skill composition were the same in urban and rural municipalities, right-fringe support would be higher in cities than in the periphery. As expected, sorting of high-skilled voters turns out to be an important driver of political polarization in space.

The second channel, i.e. the share and composition of the foreign working population, is explored in column (3) of Table 3.4.3. On the one hand, right-fringe support decreases with the share of foreigners living in a municipality. This is in line with Allport (1954), who argues that contact between different groups leads to a decrease in prejudice and conflict. The share of non-EU foreigners, on the other hand, increases right-fringe support, consistent with the hypothesis that cultural distance between groups may increase political polarization. As we have seen above, both the share of foreign workers and the share of non-EU foreigners in all foreign workers are larger in cities. It turns out that the negative effect of the foreigner share dominates. Thus, sorting of foreigners into larger cities can fully explain the urban-rural divide in right-fringe support.

Column (4) looks at the effect of demography on the urban-rural gap. Apparently, the age composition can also explain the observed urban-rural pattern,

at least in a statistical way. If rural and urban municipalities had the same age composition, cities would have higher support for right-fringe parties. The effects are slightly different for the different age groups. Households in cities have fewer children (0-17 year olds) and the number of children increases right-fringe vote shares, so controlling for children can explain part of the gap. Young voters are more strongly represented (see Table 3.3.1) in cities and less supportive of right-fringe parties, which also explains part of the gap. Older voters increase the right-fringe vote share. These findings are in line with Geys et al. (2022) for Norway, who find that with increasing age more individuals shift to the right of the political spectrum. The effects of older age groups on the urban-rural divide are somewhat mixed: people over 65 are over-represented in cities, this group is positively related to right-fringe support. For the 50-64 age group, the effects are not unequivocal, as sorting of this age group into cities has changed over time (see Section 3.3.4 above).

In column (5) we look at our last channel. We condition on the median wage and the 75th/40th percentile ratio as a measure of inequality. Column (5) shows that conditional on the wage channel variables, the urban-rural gap decreases in magnitude and becomes insignificant. Interestingly, the median wage does not significantly influence the shares of right-fringe votes. Higher wage inequality reduces right-fringe support, which seems to run counter to conventional wisdom. However, note that wage inequality is correlated with the composition of the skill. In fact, below, we show that the effect of inequality becomes insignificant once we also condition on skills.

Finally, in column (6), we include all sorting variables simultaneously. As expected, all channels jointly explain the urban-rural gap. In fact, as with some of the individual channels, it is now “over-explained”. If – for all the sorting variables ob-

served – the composition of the residential population was the same in urban and in rural municipalities, cities would have higher right-fringe vote shares. When we include all sorting variables in the model, some coefficients change in size and statistical precision. First, the qualification channel appears even more important once we condition on the other channels. The effect on the share of low-skilled workers becomes positive and significant, and the effect for high-skilled workers becomes even more negative. Second, the foreign worker share turns insignificant, which seems to indicate that it is correlated with the other sorting variables. For the age groups, results are mostly independent of the other channels, which mirrors findings by Geys et al. (2022). They show that the support for right-wing parties of older people is orthogonal to other characteristics such as income, retirement status, or political interest. Lastly, conditional on all other channel variables, the coefficient of the 75th/40th wage gap is small and insignificant. An explanation could be that the effect of inequality is dominated by skill-sorting.

In a nutshell, the urban-rural gap can be fully explained by the sorting variables, either separately by the different channels, or jointly. Right-fringe support is consistently high where the share of low-skilled individuals is high and the share of high-skilled individuals is low, i.e., in the periphery. Moreover, right-fringe support increases with the share of children and the share of 50-64 year olds but decreases with the share of 18-29 year olds. Conditional on all other variables, sorting of foreigners and wage differentials have no major influence.

In Table 3.4.4 we split the full sample into urban and rural. With the two separate models, we allow the channels to work differently in rural and urban municipalities. Column (1) repeats the results from Table 3.4.3 for Germany while column (2) shows results for the rural subsample and column (3) for the urban subsample.

The direction of the effects of the qualification channel is the same in rural and urban regions. The coefficients for low-skilled workers are almost the same for rural and urban regions and the higher precision of the effect in rural regions should be driven by the higher number of observations in the subsample. The foreigner channel has a positive effect in the rural and urban subsamples while the effect of the foreigner share is larger in urban municipalities, the reverse is true for the internal non-EU foreigner share.

For the demography channel, interestingly, the effect of the 50-64 year old on far right voting is positive in rural municipalities but negative in urban ones. As we have seen in Table 3.B.1, there are slightly more 50-64 year old in rural regions. This group seems to have a differential impact on political preferences in cities as compared to the periphery.

For the wage channel, we find that the median wage has no significant effect on far-right vote shares in rural municipalities, but a negative effect in urban ones.

Table 3.4.4: Channels within urban and rural regions

	(1) Germany	(2) Rural regions	(3) Urban regions
Urban	0.831*** (0.116)		
Qualification channel			
Low-skilled workers	0.065*** (0.016)	0.061*** (0.017)	0.052 (0.041)
High-skilled workers	-0.128*** (0.017)	-0.140*** (0.020)	-0.010 (0.029)
Foreigner channel			
Foreign workers	0.024 (0.016)	0.018 (0.017)	0.061*** (0.023)
Non-EU foreign workers	0.003*** (0.001)	0.002** (0.001)	0.009 (0.006)
Demography channel			
0-17 years	0.191*** (0.028)	0.200*** (0.028)	0.133* (0.080)
18-29 years	-0.415*** (0.053)	-0.427*** (0.057)	-0.339*** (0.072)
50-64 years	0.127*** (0.020)	0.135*** (0.020)	-0.235*** (0.077)
65 and older	0.012 (0.018)	0.014 (0.018)	0.097* (0.050)
Wage channel			
Median wage	0.007 (0.008)	0.010 (0.009)	-0.040*** (0.014)
Wage gap p(75-40)	-0.004 (0.005)	-0.002 (0.005)	-0.009 (0.012)
PeriodXElection FEs	Yes	Yes	Yes
State FEs	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	86092	80492	5600
Mean outcome	6.534	6.600	5.580
Adjusted R^2	0.739	0.738	0.810

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. The share of medium-skilled workers is the reference category in the qualification channel. The share of 30-49 year old people is the reference in the demography channel.

3.4.4 East-West-Differences in Mechanisms Over Time

We have already seen that the urban-rural patterns of right-fringe voting differ between East and West Germany. In this section, we repeat the analysis of our different channels for both parts of Germany. Table 3.4.5 shows results from the specification in Table 3.4.3 with channel variables included simultaneously, differentiated by West (column (1)) and East Germany (column (4)). In addition, we split both subsamples into the early (2001-2010) and late (2011-2019) periods.

Regarding the entire period from 2001-2019, we find that once we include all channel variables in the model, the urban-rural gap for West Germany turns positive (column (1)). However, this positive coefficient results entirely from the late period (column (3)). Here, the urban-rural gap conditional on the channels is positive. In contrast, the effect in the early period is slightly negative and not precisely estimated (column (2)). For East Germany, we find that the urban-rural gap is negative for the full sample but not statistically significant. When we decompose the effect by period, we find that the gap in the early period is negative and significant (column (5)), while for the late period, the effect turns positive (column (6)). Thus, we find that in both the West and the East the conditional gap turns positive in the late period in which the AfD is on the ballot. This could be due to either a change in the composition of urban versus rural municipalities, or to changed voting behavior conditional on the composition of the population. We now turn to the differential effect of the channel variables differentiated by East and West over time.

For the qualification structure, we see that the effect for high-skilled workers is always negative and significant which is again in line with Greve et al. (2023). Interestingly, the effects for the low-skilled workers are different in West and East Germany. It seems that in West Germany, the share of low-skilled workers in-

creases the election success of far-right parties, similar to Kessler and Freeman (2005). They find that among other factors the bulk of support for extreme right parties comes from less-educated males in Western European countries. In East Germany, the share of workers in the middle of the qualification structure seems to increase the right-fringe vote share. Broadly interpreted, this could be in line with the hypothesis of Betz (1993), who argues that it is primarily the working class (which in Germany tends to be people with medium-level professional qualifications) who support right-fringe parties.²² In sum, since high- and low-skilled sort into larger cities, skill sorting unequivocally contributes to the urban-rural voting gap in the East, since there are more of both groups in cities and both seem to reduce the support for far-right parties. In the West, however, the effects of high- and low-skilled go in opposite directions: that of the high-skilled works towards a larger urban-rural gap, while that of the low-skilled tends to reduce it. The effects of the different qualification levels on far-right support seem to be relatively stable over time. However, we have seen in Section 3.3.4 that sorting of high- and low-skilled into cities has increased over time. Potentially, this could explain why the conditional urban-rural gap turns positive if the effect of the high-skilled (who tend to vote less right-wing) outweighs that of the low-skilled (who tend to vote more right-wing).

The results for the share of foreign workers differ less between the periods than between West and East Germany. A higher share of foreign workers increases the vote share of right-fringe parties in West Germany (column (1)). The opposite holds for East Germany (column (4)). Here, a higher share of foreign workers reduces the vote share of right-fringe parties. A reason for the different directions could be the different initial share of foreigners between West and East Germany

²²We are aware that the working class is not only made up of workers with intermediate professional qualifications. However, in the absence of other information, we believe that this is the best approximation we can offer.

(see Table 3.B.1). In West Germany, the average share of foreigners is much larger than in the East. Higher shares of foreigners could be perceived negatively by voters because of the potential for competition for jobs, housing, preschool places, etc. In East Germany, the average foreigner share is much lower; an increase in the share of foreigners could lead to more contact between foreigners and natives, which could reduce prejudice (Allport, 1954). Interestingly, this casts new light on the narrative that East Germans vote for the far right despite the much lower foreigner share.

As before, we also look at the internal non-EU foreigner share to study the effect of the ethnic composition of foreign workers in a municipality. We find that the non-EU foreign share also has different effects in East and West Germany. A higher share of non-EU foreign workers increases the right-fringe vote share in West Germany while in East Germany, the relationship is negative. The negative effect in Eastern Germany might be due to the fact that the foreign workforce there is dominated by workers from the successor states of the former Soviet Union and other former socialist countries, which may be considered more similar to the local population (Buch et al., 2021). In sum, since both groups of foreigners reduce the far-right vote share and there are more of them in cities, foreigners contribute to the urban-rural gap in the East. By contrast, there are likewise more foreigners in cities in the West, but they tend to increase right-wing support, so the sorting of foreigners into cities reduces the urban-rural voting gap in West Germany.

For West Germany, we find that the age groups of 0-17, 18-29 and over 65 all have a negative effect on far-right vote shares. This holds for both time periods (except for the 18-29 year old whose effect is insignificant in the early period). Of these age groups, cities have more young (18-29) and older people (over 65) and fewer children. Thus, while the young and old contribute to the urban-rural gap

(there are more of them in cities and they tend to vote less right-wing), the share of children reduces the gap, since there are more of them in rural areas and they reduce the far-right vote share. In East Germany, the pattern is more nuanced: in the early period, children as well as people over 50 lead to lower far-right vote shares. In the late period, there seem to be remarkable changes: the effects of children and the 50-64 year old turn positive, while that of the 65+ group turns insignificant and that of the 18-29 turns negative and significant. Since cities have fewer children, they tend to contribute to the urban-rural gap in the late, but not the early period. Cities also have more young people, which contributes to the voting gap, since they tend to vote less right-wing. There are more people of retirement age in urban municipalities, which contributes to the voting gap in the early period. The share of 50-64 year old is pretty balanced between urban and rural places in East Germany in the early period. In the late period, it is larger in cities, so this age group also contributes to the urban-rural voting gap.

Lastly, we find different effects of median wages for West and East Germany. Within both parts, the effects are relatively stable across periods. Surprisingly, higher median wages increase right-fringe support in West Germany which seems to be in contrast to findings in the literature that higher incomes lead to lower support of far-right parties (e.g. Aggeborn and Persson, 2017). It should be noted, however, that the wage effect is conditional on the skill composition. Since median wages are higher in cities, taken at face value, this finding implies that wages would contribute positively to the urban-rural voting gap in the East (higher wages in the city lead to lower far-right vote shares) but negatively in the West (higher wages in cities lead to higher far-right vote shares). The regional wage 70-40 gap behaves similarly in West and East Germany and the effects seem to be driven by the subsamples for the late periods. Larger wage gaps are related to higher right-fringe support, which supports similar findings by Han (2016). In East Germany,

however, this effect is only marginally significant in the late period. Since larger cities have higher wage gaps, this effect would tend to reduce the urban-rural voting gap.

Table 3.4.5: Relative importance of the channels in East and West Germany

	(1) West-full	(2) West-early	(3) West-late	(4) East-full	(5) East-early	(6) East-late
Urban	0.158** (0.072)	-0.009 (0.054)	0.349*** (0.101)	-0.296 (0.212)	-1.030*** (0.173)	0.840** (0.332)
A) Qualification channel						
Low-skilled workers	0.024** (0.010)	0.032*** (0.008)	0.039*** (0.015)	-0.099** (0.044)	-0.133*** (0.032)	-0.198*** (0.070)
High-skilled workers	-0.128*** (0.019)	-0.082*** (0.010)	-0.145*** (0.022)	-0.125*** (0.041)	-0.060** (0.025)	-0.162*** (0.055)
B) Foreigner channel						
Foreign workers	0.031** (0.012)	-0.006 (0.011)	0.020 (0.015)	-0.091* (0.053)	-0.056 (0.086)	-0.034 (0.059)
Non-EU foreign workers	0.003*** (0.001)	0.002*** (0.001)	0.005*** (0.002)	-0.005*** (0.001)	-0.003*** (0.001)	-0.006** (0.002)
C) Demography channel						
0-17 years	-0.079*** (0.023)	-0.041*** (0.013)	-0.139*** (0.044)	-0.057 (0.056)	-0.251*** (0.063)	0.147* (0.074)
18-29 years	-0.045*** (0.014)	-0.002 (0.010)	-0.095*** (0.026)	-0.179*** (0.045)	0.031 (0.038)	-0.199*** (0.069)
50-64 years	-0.015 (0.015)	0.006 (0.007)	-0.049* (0.027)	-0.013 (0.039)	-0.121*** (0.030)	0.224*** (0.068)
65 and older	-0.065*** (0.015)	-0.042*** (0.009)	-0.102*** (0.025)	-0.062* (0.035)	-0.142*** (0.028)	0.037 (0.047)
D) Wages channel						
Median wage	0.026*** (0.006)	0.016*** (0.004)	0.027*** (0.008)	-0.053* (0.029)	-0.033** (0.016)	-0.097*** (0.035)
Wage gap $p(75), p(40)$	0.011*** (0.004)	0.003 (0.002)	0.017*** (0.005)	0.014 (0.015)	-0.005 (0.007)	0.046* (0.024)
Constant	-0.322 (1.769)	1.263 (0.858)	3.915 (3.246)	28.626*** (4.004)	31.870*** (4.489)	23.594*** (4.958)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66881	33440	33441	19208	9604	9604
Mean outcome	4.877	2.269	7.486	12.303	5.223	19.383
Adjusted R^2	0.734	0.285	0.677	0.823	0.360	0.732

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parenthesis are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. West-full and East-full include all four election periods. West-early and East-early include the first two election periods (2001-2010). The share of medium-skilled workers is the reference category in the qualification channel. The share of 30-49 year old people is the reference in the demography channel.

In sum, our channel variables do explain the urban-rural voting gap (in a statistical sense) in the late period. Once we condition on these variables, we find

that the voting gap turns positive, that is, if urban and rural municipalities had the same composition of the population and wages, the urban ones would have higher far-right vote shares. In the early period, the voting gap disappears in West Germany and remains significantly negative in the East, conditional on our channel variables. This would seem to suggest some differences in either the sorting of households or voting behavior over time.

3.5 Conclusion

In this paper, we use municipality-level data for German elections from 2001-2019 to study the anatomy of the urban-rural divide in the support of far-right parties. We find that, conditional on controls, time and state fixed effects, right-fringe parties receive 0.3 percentage points (or 4.6%) lower vote shares in municipalities with more than 20,000 inhabitants. We also study how this gap changes over space and time. Interestingly, it is much more pronounced and persistent in East Germany than in West Germany.

To understand the drivers of this divide, we analyzed how this gap is affected by different regional characteristics, which we refer to as our influencing channels. Following the literature, we analyze the importance of qualification, foreigners, age structure, and wages. We find that our channels individually and jointly can explain the urban-rural populism gap. In particular, once we condition on the share of foreign workers and different wage percentiles, the urban-rural gap in right-fringe vote shares disappears. That is, if cities and the periphery had the same share of foreign workers (and the same share of non-EU workers among foreign workers) or the same wage profiles, right-fringe parties in urban and rural municipalities would be expected to have the same electoral support. Moreover, conditioning on the skill and age composition of the population turns the urban-

rural gap positive: if cities had the same age and skill composition as the periphery, they would actually have higher right-fringe vote shares. Hence, sorting of individuals by different characteristics explains the observed urban-rural gaps in the election results of the far-right.

We also uncover substantial East-West differences in the relative importance of the different drivers of the urban-rural divide. For West Germany, we find an urban-rural gap in the early period 2001-2010, which can be explained by skill composition, foreign worker shares, and wages. For East Germany, the urban-rural gap is persistent over time. In the early period, it survives the inclusion of all our channel variables, while in the late period (2011-2019), it can mainly be explained by skills. This suggests that either skill sorting or differential voting behavior by skill level has become more important in East Germany over time.

Although we do not propose a causal explanation for urban-rural voting gaps, our analysis helps us understand spatial patterns in right-fringe voting results. We hope that future theoretical and empirical papers will expand on this knowledge by studying the microfoundations of particular mechanisms and will provide causal evidence on the spatial and temporal patterns of urban-rural voting differences.

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Appendix 3

3.A Further information

3.A.1 The German election system and considered parties

Germany is a federal republic, consisting of sixteen states (*Bundesländer*). Each state has its own legislature and government. Like the national parliament, state parliaments are elected on the principle of proportionality. Governments are elected by parliaments.

National elections (*Bundestagswahlen*) are held every four years. State elections (*Landtagswahlen*) regularly occur every four to five years in each of Germany's 16 federal states, although the exact timing may vary. We observe election outcomes for all elections on the municipality level, and harmonize dates to consistent election periods for both national and federal elections. Elections may contain a first-past-the-post element to determine individual candidates, but the share of seats a political party achieves in parliament proportionally depends on its share of party votes, and we exclusively focus on this specific vote share.

In national elections, Germany employs a 5%-threshold, meaning parties must receive at least 5% of the party-vote nationwide (or win at least three direct constituencies) to enter the Bundestag. Similar thresholds apply in many state elections. Since we are not interested in the distribution of seats after an election, but in the voting decisions of individuals, we consider all party-votes cast and not the final composition of parliament. This is particularly important in the case of right-fringe parties, which are often below the threshold (Art, 2007).

To define right-fringe parties, we follow (Dippel et al., 2021), who count a party as being right-extremist if the party, (some of) its factions or (some of) its

candidates or personnel are observed by the Office of the Protection of the Constitution either on the national (*Bundesamt für Verfassungsschutz*) or the state-level (*Landesamt für Verfassungsschutz*). In the meantime, deviating from (Dippel et al., 2021), this also applies to the AfD (*Bundesamt für Verfassungsschutz*, 2022). Right-fringe parties support neo-Nazi ideologies, are anti-democratic, polemicize against internationalization, and agitate against immigrants and foreigners. All considered parties are listed in Table 3.A.1.

Table 3.A.1: List of considered parties

Die Rechte
Hamburger Liste Ausländerstopp
Deutsche Konservative
Deutsche Partei
Die Republikaner
Bund der Deutschen Demokraten
Demokratische Republikaner Deutschlands
Deutsche Liga für Volk und Heimat
Ab jetzt. . . Demokratie durch Volksabstimmung – Politik für die Menschen
Deutschland
Ja zu Brandenburg
Christliche Bayerische Volkspartei
Bund für Gesamtdeutschland
Deutsche Heimatpartei die Nationalliberalen
Aktionsgemeinschaft unabhängiger Deutscher
Unabhängige Wählergemeinschaft der Vertriebenen und anderer Benachteiligter
5-% Block
Unabhängige Arbeiterpartei
Der Dritte Weg
Die Deutschen
Bürgerbewegung pro Deutschland
Bürgerbewegung pro NRW
Interim Partei Deutschland DAS REICHT!
Demokratische Erneuerung
Alternative fuer Deutschland

Notes: The table lists all parties which are considered as right-fringe parties over the observation period from 2001-2019.

Table 3.A.2: Federal and state elections per year

	National election N	State election N	Total N
2001	0	3398	3398
2002	0	944	944
2003	0	3416	3416
2004	0	1513	1513
2005	10767	1496	12263
2006	0	4342	4342
2007	0	2	2
2008	0	3415	3415
2009	10767	2613	13380
2010	0	395	395
2011	0	4345	4345
2012	0	1548	1548
2013	10767	3414	14181
2014	0	1460	1460
2015	0	3	3
2016	0	4342	4342
2017	10767	2485	13252
2018	0	2477	2477
2019	0	1460	1460
Total	43068	43068	86136

Notes: The table shows the year-election type combinations for municipalities. Each election period include two observations per municipality. One federal and one state election.

3.A.2 Further regional variables

In addition to the channel variables described in Section 3.3.3, we employ municipality-level controls to account for within-city-group heterogeneities. Voter participation measures the number of all valid votes in relation to the population eligible to vote. Regional gender compositions are measured by the female population share and the female labor market participation rate. The employment rate is measured as the number of workers subject to social security contributions at the municipality of residence relative to the total workforce. The share of long-term unemployed workers is measured as the share of workers with an unemployment

duration of more than one year in relation to all unemployed workers. Moreover, we account for commuters from other municipalities working in a region. The variable is measured as the number of commuters in the region over all inhabitants. We also include the municipalities' natural balance per 1,000 inhabitants, i.e. the difference between births and deaths divided by population. In addition, we use the municipalities' tax capacity per capita in euros. We also include the population change in percent over the past five years. Table 3.A.4 in the appendix presents summary statistics for all regional variables used for the period of analysis 2001-2019.

3.A.3 Summary statistics

Table 3.A.3: Summary statistics of dependent variables

	Obs.	Mean	SD	Median	Min	Max
Right-extremist and AfD	86136	6.54	7.10	4.00	0.00	65.45
Right-extremist	86136	2.20	2.36	1.56	0.00	38.19
AfD	37175	10.05	8.09	8.07	0.00	62.71

Notes: All variables are calculated in percent (0-100). The number of votes for the specific parties over the number of all valid votes cast in an election. The definition of right extremist parties and the party names are explained in Section 3.A.1.

Table 3.A.4: Summary statistics of explanatory variables

	Obs.	Mean	SD	Median	Min	Max
Population development past 5 years	86136	-0.86	5.86	-0.95	-67.36	210.28
Natural balance	86136	-2.35	6.62	-1.75	-98.90	150.00
Voter participation	86136	66.18	10.05	66.67	23.58	100.00
Employment rate	86136	75.90	5.96	76.37	0.00	100.00
Long-term unemployed	86136	28.57	13.26	28.26	0.00	100.00
Low-skilled workers	86135	11.78	4.42	11.57	0.00	100.00
High-skilled workers	86135	10.36	5.16	9.54	0.00	66.67
Foreign workers	86136	3.34	3.87	2.04	0.00	100.00
Non-EU foreign workers	86136	41.99	29.69	44.67	0.00	100.00
0-17 years	86136	17.60	3.29	17.52	0.00	41.66
18-29 years	86136	12.35	2.55	12.62	0.00	39.25
50-64 years	86136	21.76	4.26	21.48	0.00	52.78
65 and older	86136	20.16	4.15	19.83	0.00	80.00
Female participation rate	86136	47.71	3.34	47.71	0.00	100.00
Female population share	86136	50.04	1.87	50.19	11.11	84.21
Median wage	86089	91.07	17.40	90.94	14.77	189.33
Wage gap $p(75), p(40)$	86089	45.04	11.92	44.04	0.00	361.36
Commuters in region	86136	67.95	18.38	69.68	0.00	100.00
Tax capacity pc (1,000€)	86136	0.55	3.46	0.47	0.00	408.01

Notes: Natural balance, voter participation, employment rate, long-term unemployed, low-skilled workers, high-skilled workers, foreign workers, non-EU foreign workers, 0-17 years, 18-29 years, 50-64 years, 65 and older, female participation rate, female population share, commuters and wage gap in the region are calculated in percent. The median wage is measured in euros. Tax capacity is measured in 1,000 euros per capita. For a explanation of the variables, see Section 3.3.3.

3.B Additional results

In this section, we show additional technical results. First, we show different means by regional characteristics for rural and urban municipalities. Second, we show how we select our standard errors for the models in the main analysis and how we include state fixed effects. Third, we show further regression results which serve as robustness checks.

Table 3.B.1: Means of channel variables within city categories

	Germany		West Germany		East Germany	
	Rural	Urban	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
Qualification channel						
Low-skilled workers	11.60	14.40	12.90	15.49	7.176	8.361
Medium skilled workers	78.32	71.12	77.48	70.30	81.17	75.67
High-skilled workers	10.08	14.48	9.613	14.21	11.66	15.97
Foreigner channel						
Foreign workers	2.986	8.387	3.653	9.490	0.727	2.274
Non-EU foreign workers	40.68	60.88	42.81	60.14	33.46	64.95
Demography channel						
0-17 years	17.65	16.96	18.45	17.49	14.94	14.05
18-29 years	12.25	13.75	12.57	13.85	11.20	13.18
30-49 years	28.15	27.67	28.15	27.90	28.15	26.39
50-64 years	21.84	20.62	21.15	20.34	24.20	22.16
65 and older	20.10	21.00	19.69	20.42	21.52	24.22
Wage channel						
Median wage	90.65	97.11	96.74	100.7	70.00	77.24
Wage gap $p(75),p(40)$	44.70	49.96	43.29	49.21	49.47	54.13

Notes: Means within the rural and urban categories for Germany, West Germany and East Germany. The means are calculated per municipality. Each municipality is weighted equally. The rural category is defined as municipalities with <20,000 inhabitants and the urban category are municipalities with $\geq 20,000$ inhabitants in 2019.

Table 3.B.2: Mean of channel variables within city categories (subcategories)

	(1) Ger-early		(2) Ger-late		(3) West-early		(4) West-late		(5) East-early		(6) East-late	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
A) Election results												
Right-extremist and AfD	2.973	2.283	10.23	8.876	2.293	1.949	7.500	7.300	5.274	4.133	19.47	17.61
B) Qualification channel												
Low-skilled workers	13.14	15.50	10.05	13.30	14.35	16.59	11.46	14.38	9.064	9.450	5.288	7.271
Medium skilled	78.17	71.96	78.47	70.28	77.50	71.24	77.46	69.36	80.47	75.93	81.86	75.42
High-skilled workers	8.674	12.54	11.48	16.42	8.145	12.17	11.08	16.26	10.46	14.62	12.85	17.31
C) Foreigner channel												
Foreign workers	2.204	7.211	3.767	9.564	2.756	8.271	4.550	10.71	0.338	1.334	1.117	3.214
Non-EU foreign workers	44.08	64.47	37.28	57.28	46.94	63.62	38.69	56.67	34.39	69.22	32.52	60.67
D) Demography channel												
0-17 years	18.71	17.47	16.59	16.45	19.85	18.16	17.05	16.81	14.85	13.63	15.03	14.46
18-29 years	12.80	13.89	11.70	13.60	12.52	13.71	12.61	13.99	13.74	14.87	8.647	11.48
30-49 years	30.51	29.52	25.80	25.82	30.44	29.73	25.87	26.07	30.75	28.36	25.56	24.42
50-64 years	18.88	19.04	24.80	22.20	18.40	18.76	23.89	21.93	20.51	20.59	27.88	23.73
65 and older	19.10	20.08	21.10	21.92	18.79	19.63	20.58	21.21	20.15	22.54	22.89	25.91
E) Wage channel												
Median wage	82.71	89.34	98.58	104.9	88.67	92.85	104.8	108.5	62.54	69.84	77.47	84.64
Wage gap $p(75),p(40)$	43.10	48.07	46.29	51.84	41.20	47.17	45.38	51.24	49.53	53.10	49.40	55.16

Notes: Means within the rural and urban categories for Germany, West Germany and East Germany. The means are calculated for the early election period (2001-2010) and the late period (2011-2019) per municipality. Each municipality is weighted equally. The rural category is defined as municipalities with <20,000 inhabitants and the urban category are municipalities with $\geq 20,000$ inhabitants in 2019.

3.B.1 Selection of standard errors

The literature shows that the level of standard errors has a serious impact on the model inference (see e.g. Cameron and Miller, 2015; MacKinnon et al., 2023). For this reason, we analyze the confidence intervals for our urban indicator for different estimators of the variance-covariance matrix. First, we use the heteroskedasticity-consistent standard errors (Huber et al., 1967; White, 1980). Second, we use cluster-robust standard errors that produce correct standard errors if the observations are correlated. The way in which the regional voting data is processed makes it reasonable to assume that there is correlation within regions and also to some extent between regions. However, it is not obvious what degree of clustering is "true" to the data generation process. As clusters, we define municipalities, district regions and states. District regions (*Kreisregionen*, $N=361$) compensates somewhat for the different territorial layouts of the districts ($N = 401$)

in Germany by combining independent cities with fewer than 100,000 inhabitants with their surrounding districts.²³ This adjustment of the districts is particularly important when comparing eastern and western Germany. Figure 3.B.1 shows the development of the confidence intervals. We see an increase in the confidence intervals from top to bottom. We follow Cameron and Miller (2015) and select the level of the cluster before the confidence intervals "explode". In our case, this is the district region level.

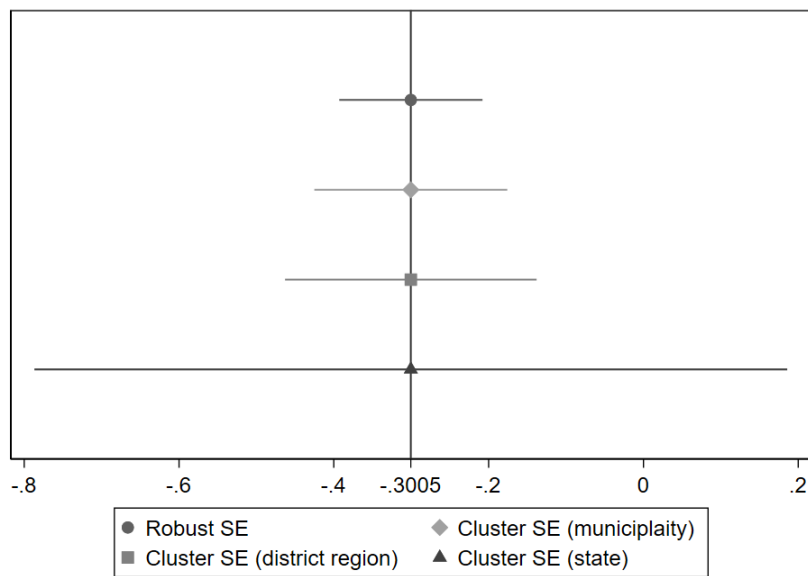


Figure 3.B.1: Confidence intervals for different standard error specifications

Notes: The figure show the 95% confidence intervals for different standard error specifications for the Model described in Equation (3.1) without control variables X_{rt} . Robust: Huber-White variance estimator, Cluster: clustered variance estimator with clusters: municipalities ($N = 10,767$), district regions ($N = 361$), federal states ($N = 12$). We combine the state fixed effects for Hamburg and Schleswig-Holstein, Bremen, Bemerhafen and Lower Saxony and Berlin and Brandenburg.

3.B.2 Aggregation of state fixed effects

When we include state fixed effects in the model, we have the problem that city-states have only one (two) municipality within this category. This is the case

²³To see which districts are merged, see: https://www.bbsr.bund.de/BBSR/DE/forschung/raumb Beobachtung/Raumabgrenzungen/deutschland/kreise/Kreise_Kreisregionen/Kreise.html

for Hamburg, Bremen/Bremerhafen and Berlin. In these cases, we have no variation in the urban-rural indicator which identifies the effect within the state. For this reason, we combine Hamburg and Schleswig-Holstein, Bremen, Bremerhafen and Lower Saxony and Berlin and Brandenburg. Table 3.B.3 shows the results of our baseline model with different fixed effects specifications. Column (1) shows the results without state fixed effects. Column (2) shows the results when we include fixed effects for all 16 states. In comparison to Column (2), Column (3) shows the results with the aggregated state fixed effects. The point estimates in Column (2) and Column (3) are almost equal. This means that the results are not biased by aggregating the city states. Column (4) shows the results without city-states. The results underline that the coefficients are not driven by the aggregation.

Table 3.B.3: Models with different state fixed effects specifications

	(1)	(2)	(3)	(4)
	Without state FE	All states	Combined states	Reduced states
Urban	-1.023*** (0.267)	-0.295*** (0.082)	-0.300*** (0.083)	-0.307*** (0.083)
Constant	2.812*** (0.138)	-0.779*** (0.241)	-0.779*** (0.241)	-0.786*** (0.241)
PeriodXElection FEs	Yes	Yes	Yes	Yes
State FEs	No	Yes	Yes	Yes
Observations	86136	86136	86136	85688
Adjusted R^2	0.475	0.700	0.700	0.700
States		16	12	12

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. The scalar States indicates the number of state fixed effects.

3.B.3 Further robustness checks

Table 3.B.4: Models with and without controls

	(1) Germany	(2) Germany	(3) West	(4) West	(5) East	(6) East
Urban	-0.300*** (0.083)	-0.298*** (0.088)	0.009 (0.074)	0.043 (0.073)	-1.692*** (0.216)	-1.860*** (0.316)
Commuters in region		-0.004*** (0.002)		-0.005*** (0.001)		0.005 (0.004)
Employment rate		0.085*** (0.017)		0.042*** (0.016)		-0.129*** (0.048)
Long-term unemployed		0.014*** (0.004)		0.006* (0.003)		0.022** (0.010)
Population development past 5 years		0.005 (0.006)		-0.003 (0.006)		-0.015 (0.012)
Natural balance		-0.015*** (0.005)		0.000 (0.003)		-0.016 (0.010)
Voter participation		-0.043*** (0.009)		-0.005 (0.005)		-0.003 (0.011)
Female participation rate		-0.115*** (0.016)		-0.084*** (0.013)		-0.016 (0.030)
Female population share		-0.001 (0.015)		-0.000 (0.012)		-0.179*** (0.038)
Tax capacity pc (1,000€)		0.003 (0.003)		0.001 (0.002)		-0.066 (0.223)
Constant	-0.779*** (0.241)	2.060 (1.731)	0.269 (0.186)	1.964 (1.701)	5.276*** (0.511)	23.052*** (3.278)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86136	86136	66896	66896	19240	19240
Adjusted R^2	0.700	0.709	0.718	0.724	0.811	0.817
RMSE	3.894	3.832	2.487	2.459	4.498	4.419

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. The share of medium-skilled workers is the reference category in the qualification channel. The share of 30-49 year old people is the reference in the demography channel.

Table 3.B.5: Results with and without cities with more than 100,000 inhabitants

	Germany		West		East	
	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Reduced	Full	Reduced	Full	Reduced
Urban	-0.298*** (0.088)	-0.233*** (0.087)	0.043 (0.073)	0.057 (0.073)	-1.860*** (0.316)	-1.580*** (0.300)
Constant	2.060 (1.731)	2.056 (1.742)	1.964 (1.701)	1.903 (1.700)	23.052*** (3.278)	23.147*** (3.280)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86136	85488	66896	66336	19240	19152
Mean outcome	6.536	6.547	4.877	4.880	12.304	12.323
Adjusted R^2	0.709	0.709	0.724	0.724	0.817	0.818

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parentheses are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019. Reduced indicates that municipalities with more than 100,000 inhabitants are dropped in the sample. The share of medium-skilled workers is the reference category in the qualification channel. The share of 30-49 year old people is the reference in the demography channel.

Table 3.B.6: Robustness of the late period results (without 2011 and 2012)

	Germany		West		East	
	2011-2019	2013-2019	2011-2019	2013-2019	2011-2019	2013-2019
Urban	-0.294** (0.117)	-0.276** (0.124)	0.110 (0.103)	0.111 (0.113)	-2.063*** (0.448)	-1.984*** (0.397)
Constant	4.887** (2.283)	4.795* (2.457)	4.467* (2.551)	3.852 (2.853)	28.152*** (5.323)	28.662*** (4.693)
PeriodXElection FEs	Yes	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43068	37175	33448	28500	9620	8675
Mean outcome	10.143	11.339	7.485	8.485	19.386	20.715
Adjusted R^2	0.733	0.707	0.664	0.593	0.711	0.691

Notes: Significance levels: * $p = 0.10$ ** $p = 0.05$ *** $p = 0.01$. Standard errors in parenthesis are clustered on the district region level ($N = 361$). Urban is defined as municipalities with at least 20,000 inhabitants in 2019.

Selected Publications

1. Moritz Meister, Jan Cornelius Peters, Anja Rossen, "Welcome back! The impact of 'return initiatives' on return migration to rural regions". *Journal of Economic Geography*, vol. 24, issue 5, pp. 759–784, DOI: <https://doi.org/10.1093/jeg/lbae028>.
2. Meister Moritz, Annekatrin Niebuhr, Jan Cornelius Peters, and Johannes Stiller (2023). "Local attributes and migration balance – evidence for different age and skill groups from a machine learning approach". *Regional Science Policy & Practice*, vol. 15, no. 4, pp. 794–825, DOI: <https://doi.org/10.1111/rsp3.12652>.
3. Buch Tanja, Moritz Meister, and Annekatrin Niebuhr (2021). "Ethnic diversity and segregation in German cities". *Cities*, vol. 115, 103221. DOI: <https://doi.org/10.1016/j.cities.2021.103221>.
4. Meister Moritz and Annekatrin Niebuhr (2021). "Comparing ethnic segregation across cities—measurement issues matter". *Review of Regional Research*, vol. 41, no. 1, pp. 33–54, DOI: <https://doi.org/10.1007/s10037-020-00145-4>.

Eidesstattliche Versicherung

Ich erkläre hiermit, dass ich meine Doktorarbeit “Essays in Empirical Economics” selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Bei-träge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

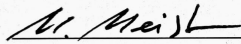
Kiel, 7. March 2025

Moritz Meister

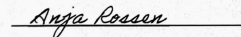
Erklärungen zu Ko-Autorenschaften

Erklärung zur Ko-Autorenschaft im Projekt „Die räumliche Mobilität von Arbeitskräften im Erwerbsverlauf - Analysen für ländliche Räume in Deutschland“

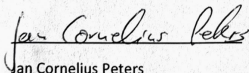
Die Autoren Moritz Meister, Jan Cornelius Peters und Anja Rossen erklären hiermit, dass alle drei einen genuine Betrag im Sinne der „DFG-Leitlinien zur Sicherung guter wissenschaftlicher Praxis“ zu dem in dieser Dissertation vorliegenden Papier „Welcome back! The impact of 'return initiatives' on return migration to rural regions“ geleistet haben. Der Beitrag von Moritz Meister erstreckt sich auf die Aufbereitung von Daten (Konzeption und Umsetzung), ökonometrische Analysen (insb. Verlaufsdatenanalysen), Interpretationen der Auswertungsergebnisse sowie das Verfassen des Manuskripts. Der Beitrag von Anja Rossen umfasst die Aufbereitung von Daten (Konzeption und Umsetzung), ökonometrische Analysen (u. a. matching) sowie das Verfassen des Manuskripts. Der Beitrag von Jan Cornelius Peters umfasst die Entwicklung des Forschungsvorhabens, die theoretische Einordnung in die Literatur, Konzeptionierungen der Datenaufbereitung und der Datenauswertung, die Interpretation der Auswertungsergebnisse sowie das Verfassen des Manuskripts. Die Autoren sind in alphabetischer Reihenfolge genannt, weil alle drei Autoren in enger Zusammenarbeit einen ähnlich großen Beitrag zum Artikel geleistet haben.



Moritz Meister



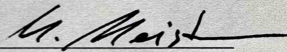
Anja Rossen



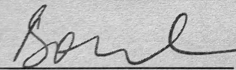
Jan Cornelius Peters

Erklärung zur Ko-Autorenschaft für das Papier „The Urban-Rural Divide in Support of the Far-Right“

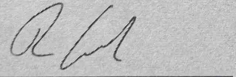
Die Autoren Moritz Meister, Rainald Borck und Robert Gold erklären hiermit, dass alle drei einen genuine Betrag im Sinne der „DFG-Leitlinien zur Sicherung guter wissenschaftlicher Praxis“ zu dem in dieser Dissertation vorliegenden Papier „The Urban-Rural Divide in Support of the Far-Right“, geleistet haben. Der Beitrag von Moritz Meister erstreckt sich auf die theoretische Einordnung in die Literatur, die Aufbereitung der Daten, die Analyse, Auswertung und Interpretation der Auswertungsergebnisse sowie das Verfassen des Manuskripts. Der Beitrag von Rainald Borck umfasst die Entwicklung des Forschungsvorhabens, die theoretische Einordnung in die Literatur, die Interpretation der Ergebnisse sowie das Verfassen des Manuskripts. Der Beitrag von Robert Gold umfasst die Entwicklung des Forschungsvorhabens, die Aufbereitung der Daten, Auswertung und Interpretation der Auswertungsergebnisse, sowie das Verfassen des Manuskripts.



Moritz Meister



Rainald Borck



Robert Gold