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How does the Covid-19 pandemic affect regional labor markets and why do large cities suffer most?

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Abstract

We estimate the spatially heterogeneous effects of the coronavirus disease 2019 pandemic on labor market dynamics in Germany until December 2021. While initially slightly stronger in rural regions and large agglomerations, adverse effects quickly become more pronounced and persistent in large agglomerations compared to all other region types. We ascribe the larger impact of the pandemic in large agglomerations to two factors. First, a combination of a higher share of skilled workers and jobs suitable for working from home is positively related to an increased inflow rate into unemployment. We argue that local spillover effects from reduced product market demand in large cities caused by changes in behavior such as working from home or online shopping are a possible explanation. Second, some of our results suggest that a lower outflow rate out of unemployment is associated with a higher precrisis unemployment rate in large agglomerations. This might reflect the less favorable composition of unemployment in large cities, which reduces the probability of transitions into employment during crises.

KEYWORDS

agglomerations, Covid-19 pandemic, employment, labor market flows

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1 | INTRODUCTION

Global economic shocks can have heterogeneous regional effects. In analyzing this heterogeneity, the concept of regional resilience, which is defined as a region's ability to resist and recover from shocks, has attracted widespread attention (e.g., Doran & Fingleton, 2018; Martin, 2012; Martin & Sunley, 2014). An extensive literature has provided evidence on the regional disparities concerning the strength and consequences of the Great Recession (e.g., Di Caro, 2017; Fratesi & Rodríguez-Pose, 2016; Groot et al., 2011; Martin et al., 2016). Likewise, the coronavirus disease 2019 (Covid-19) pandemic represents a global crisis with a large potential for regionally heterogeneous effects due to, for example, variation in infection rates or differences in public policy responses and regional economic structure. Within this context, a debate has emerged about whether the pandemic has more detrimental effects on agglomerations (Florida et al., 2021; Nathan & Overman, 2020; Rosenthal et al., 2021). However, empirical evidence concerning regional resilience to the Covid-19 pandemic and a possible differential impact on agglomerations, in particular, remains scarce.

This paper addresses these points by estimating the spatially heterogeneous effects of the Covid-19 pandemic on labor market dynamics in Germany until December 2021. The objective is to assess regional differences in the development of labor market transitions during the pandemic and to identify potential sources of these disparities. We use administrative data on monthly transitions between employment and unemployment by region and economic sector in a two-stage regression approach. In the first stage, we apply a shift-share model that decomposes transitions into a sectoral and a regional component. We then use the estimated region-month effects in a difference-in-differences analysis. This approach allows us to empirically assess regional differences in the initial labor market impact of the pandemic, but also its subsequent development. According to our results, the unfavorable impact on labor market transitions was initially slightly more pronounced in rural regions and large agglomerations. Subsequently, however, most regions quickly started to recover, while the 10 largest agglomerations experienced a less favorable development. So far, the differential development turns out to be persistent. Our approach also allows us to decompose the overall effect on labor market dynamics into separate parts reflecting higher employment-to-unemployment and lower unemployment-to-employment transitions. The larger effect of the pandemic on big cities is mainly due to a stronger increase in transitions into unemployment.

There are several reasons why the effect of the Covid-19 pandemic might vary across regional labor markets. First, the pandemic has led to behavioral changes that seem to differ in their extent across regional labor markets because, among other things, there is important spatial variation in disease severity (e.g., Ascani et al., 2021; Desmet & Wacziarg, 2021; McCann et al., 2022; Rodríguez-Pose & Burlina, 2021). Chetty et al. (2020), for instance, show that high-income individuals in the United States reduced spending, especially in regions with a high Covid-19 incidence and in sectors that involve face-to-face interaction. There is also evidence to suggest that changes with respect to working from home, online shopping, and social interaction caused by the Covid-19 crisis may affect big cities in particular via a (permanent) decline in local demand (Nathan & Overman, 2020). Obviously, social distancing and lockdown measures affect mobility patterns (Couture et al., 2022) and increase working from home (De Fraja et al., 2020). A high percentage of jobs that can be done remotely are concentrated in cities. According to Althoff et al. (2022), regional differences in the decline of spending in the United States, especially for the local service economies, are closely related to regional differences in the percentage of mobile (high-skilled) workers who started working from home. Alipour, Falck, and Schüller (2023) show that increased working from home gave rise to a spatial shift in spending from previously consumption-intensive urban centers toward more residential areas in Germany.

Second, the design of policy measures, both containment measures (Kosfeld et al., 2021) and assistance schemes (Dörr et al., 2022), can give rise to sector-specific shocks.¹ This implies that the economic structure of

¹Naumann et al. (2020) provide a survey of different policies implemented in Germany during the early phase of the pandemic.

regional labor markets becomes an important mediating factor. In fact, this is one of the most prominent factors discussed in the literature on the regional effects of major economic crises (e.g., Martin et al., 2016; Martin & Gardiner, 2019). Available evidence suggests that a region's sectoral structure influences its resistance to shocks as well as the speed and extent of the recovery aftershocks. Grabner and Modica (2022) examine industrial resilience in the United States before and after 2008 and conclude that metropolitan areas are more resilient than other types of areas *inter alia* due to the unrelated variety of their industrial structure. Partridge et al. (2022) stress that, in the context of the current Covid-19 crisis, a high share of manufacturing employment seems to harm local resilience in the United States because of its initially pronounced negative response to the pandemic shock. Moreover, the apparent adverse effect of leisure services on resilience is argued to be unique to the Covid-19 crisis. Kim et al. (2023) also emphasize the importance of industrial structure for a region's resistance to the Covid-19-induced recession: regional specialization in essential industries with low interpersonal interactions (e.g., nonstore retail, financial and professional services) is significantly related to regional economic resistance. In contrast, United States states specialized in nonessential industries with high interpersonal interactions are more vulnerable to the Covid-19 shock.

Third, other structural factors discussed in the literature related to the economic resilience of regions refer to the firm size distribution, the skill level of the local workforce, and the level of unemployment. A qualified workforce might improve the adaptability of regional labor markets in response to shocks (Fusillo et al., 2022; Martin et al., 2016). Palomino et al. (2022) show that skill level is a key mediating factor of the pandemic effect on workers and labor markets in the case of Spanish regions. Lower levels of human capital make regions especially vulnerable to shocks in terms of poverty and unemployment. Firm size might matter if large firms benefit from better access to credit and greater financial reserves than small enterprises (Bartik et al., 2020; Kim & Kim, 2022). Small firms are therefore more likely to respond to unforeseen crises with redundancies. Crisis effects could therefore be relatively strong in regions with a high share of small businesses. Resilience might also be influenced by precrisis labor market conditions. Analyzing local authority districts in Great Britain, Houston (2020) finds that the prepandemic unemployment rate is an important predictor of the increase of the unemployment rate in the first months of the Covid-19 crisis. A region that already showed a comparatively high level of unemployment before the crisis is likely to face more severe adjustment problems.

Fourth, analyses often consider the role of agglomeration in regional resilience. The findings on previous crises point to a beneficial impact of agglomeration on regional recovery (Capello et al., 2015; Di Caro & Fratesi, 2018; Xiao et al., 2018). Density is associated with a higher quality of firms and workers because of sorting, which, in turn, may result in a higher resilience of urban labor markets. Moreover, agglomeration economies might help to overcome crises because face-to-face contact in dense regions remains a critical means of gaining new information and creating high returns to skill and innovation (Glaeser, 2022). However, the Covid-19 crisis may differ from previous shocks such as the economic crisis in 2008/2009 in this respect. There is a debate on whether the pandemic reduces the strength of agglomeration economies that rely on proximity and spatial interaction (Althoff et al., 2022; Brueckner et al., 2023). Containment measures such as social distancing and working from home, which reduce face-to-face contact, might reduce learning opportunities that cities provide.² Because human interaction and activity are more concentrated in dense areas, the responses to the pandemic such as avoidance of proximity, which Florida et al. (2021) describe as social scarring, might be more pronounced in cities. Moreover, it is primarily the jobs of high-skilled workers that can be done remotely, which means that cities with their high share of knowledge-intensive jobs may experience a particularly strong decline in knowledge spillovers. As a result, agglomeration economies might not shield dense urban areas from adverse economic effects of the current crisis (Partridge et al., 2022). Liu and Sue (2022) provide the first evidence in support of this hypothesis. Their findings suggest that occupations with a high working-from-home potential experienced the strongest decline of the urban

²Glaeser (2022) discusses first evidence on the weakness of online learning as opposed to face-to-face knowledge exchange. He argues that matching benefits in large urban labor markets may also decline because employers find it harder to onboard new workers online.

wage premium during the pandemic, which seems to be, at least partially, a result of reduced interactions (with co-workers, customers, clients, and other professionals).

Do large cities suffer more strongly from adverse labor market effects induced by the Covid-19 crisis? Only a few studies examine regional differences in the labor market effects of the crisis, most of them focusing on the initial shock and the effects of policy measures. Juranek et al. (2021) investigate the impact of nonpharmaceutical interventions on regional labor markets in Scandinavian countries. Their results indicate that all regions were severely hit by the crisis. Dall Schmidt and Mitze (2021) examine the local labor market effects of a regionally differentiated reopening of public services in Denmark. According to their results, regions benefit from an earlier opening that led to a significant reduction in excess unemployment caused by the pandemic. Carvalho et al. (2022) use information from electronic payments and mobility data to provide evidence on regionally differentiated changes in behavior and economic consequences for Portuguese regions during the early phase of the crisis. They show that most sectors experience a stronger downturn in the main cities as compared to other regions in Portugal.

Our results suggest that the impact of the pandemic on large agglomerations in Germany can be ascribed to two factors. First, a combination of a higher share of skilled workers and jobs suitable for working from home is positively related to an increased inflow rate into unemployment. This might be due to local spillover effects from reduced product market demand. Big cities are characterized by a high share of jobs that are suitable for remote work as well as an above-average percentage of high-skilled workers. This combination of factors likely correlates with changes in behavior such as increased working from home or online shopping, which might go hand in hand with a permanent loss of demand for goods and services provided, especially in big cities, and corresponding job losses. Second, some results suggest that a lower outflow rate out of unemployment might be associated with a higher precrisis unemployment rate in large agglomerations. We interpret this as reflecting that during economic crises, it becomes more difficult in particular for low-skilled unemployed, who are overrepresented in big cities, to find a new job.

The remainder of the paper proceeds as follows: Section 2 describes specific features of the Covid-19 pandemic in Germany and discusses the different data sources and our measure of labor market transitions. The empirical methodology is the subject of Section 3, while we present the results and evidence on potential mechanisms that might underlie these results in Section 4. Section 5 concludes.

2 | COVID-19 PANDEMIC: GERMAN CONTEXT AND DATA

2.1 | Covid-19 pandemic in Germany

The first case of a Covid-19 infection in Germany was confirmed on January 27, 2020 in the Bavarian town of Starnberg near Munich.³ From the end of February onwards, the number of infections started to increase rapidly, in particular in some local hotspots (Nauman et al., 2020). German locations close to the major Austrian ski resort Ischgl, the municipality of Heinsberg (located in the Carnival-celebrating Rhineland region) and Mulhouse (cross-border movement of German and French workers) constitute “super-spreader locations” for the transmission of infections within Germany at the beginning of the pandemic. The early spread of Covid-19 was thus far from homogeneous—the two southernmost states, Bavaria and Baden-Württemberg, were among the most affected in Spring 2020. However, even within these states, there was a lot of variation (Felbermayer et al., 2020).

Spatial patterns of infection rates also vary significantly over time. Whereas in the initial period of the pandemic big cities were often more affected (Kosfeld et al., 2021), this changed during the second and third pandemic waves. However, systematic differences between the population-based Covid-19 infection rates of urban and rural areas

³See Roberts et al. (2021) and Bosen & Thurau, (2021), <https://www.dw.com/en/covid-how-germany-battles-the-pandemic-a-chronology/a-58026877> (retrieved 24.03.2023).

cannot be detected (see Figure A4 in the Supporting Information: Material).⁴ As Rodríguez-Pose and Burlina (2021) put it, density may have influenced the timing of early outbreaks, but other factors become important over time. These include the age structure of the population, its level of education, policy measures, and actions. Moreover, despite homogeneous rules concerning testing for Covid-19 infections across German regions (Kosfeld et al., 2021), regional testing intensity varied remarkably. In the later waves of the pandemic, the highest infection rates were recorded in East Germany⁵, but even this did not prove to be a consistent pattern. Low vaccination rates in East German regions might be one potential factor behind this pattern. Altogether, the population share of vaccinated persons is relatively low in Germany compared to other Western European countries (Ebbinghaus et al., 2022).

In Germany, there was initially a strong political consensus that policy measures in response to the pandemic should be identical across regions, at least at the level of federal states. Thus, the first measures were introduced almost uniformly in all federal states by the middle of March 2020 (Kosfeld et al., 2021). This applies to containment measures as well as policies that are aimed at supporting adversely affected firms. Differences in the timing of implementation across federal states amounted to only 1 week. One important policy to address the pandemic impact on the labor market in Germany was short-time work. It is a country-wide policy that was widely used already during previous economic crises. The German Federal Employment Agency (FEA) covers the labor costs of short-time workers. For the hours lost, the employees receive at least 60% of their net pay. Almost 18% of the employees received short-time work benefits during the first lockdown period in Germany. Marginal employees, freelancers, and other self-employed are not entitled to short-time work allowance. However, the self-employed received lump-sum payments (Corona-Soforthilfe), tax reductions, and deferrals of social security and tax payments (Ebbinghaus et al., 2022).

In addition to direct support measures such as the lump-sum payments to which very small enterprises with up to 10 employees were eligible, other important assistance schemes of the German government to stabilize and stimulate the economy included liquidity loans under public guarantee schemes for small- and medium-sized enterprises and granted tax payment deferrals and lower tax prepayments for all firm types (Dörr et al., 2022). Moreover, regular value-added tax (VAT) rates were reduced between July and December 2020 from 19% to 16% and the VAT rate on necessities, such as food and books, was reduced from 7% to 5%.

Quite predominantly, the requirements of entitlement of the aforementioned assistance schemes were uniformly designed in all regions. In contrast, taking advantage of the Federal states' assistance schemes varied significantly between sectors depending on the size of sector-specific shocks.

2.2 | Pandemic-induced changes in labor market transitions

We use administrative data from the FEA on the number of transitions from employment into unemployment and vice versa. The data are available on a monthly basis and cover the period from January 2017 until December 2021. Crucially for our analysis, the number of transitions can be differentiated by region and sector.

At the sectoral level, we use 88 two-digit sectors according to the 2008 edition of the German Classification of Economic Activities. At the regional level, we employ the 141 functional labor market regions by Kosfeld and Werner (2012). These entities combine administrative units at the county level based on commuting patterns. Furthermore, we use a classification to assign individual labor market regions into three categories based on their degree of urbanization: rural regions, urbanized regions, and agglomerations.⁶ We further split the third category

⁴See also https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/InteraktiveAnwendungen/corona-dashboard/corona-dashboard_einstieg.html (retrieved March 24, 2023).

⁵See also <https://ourworldindata.org/vaccination> (retrieved 24.03.2023).

⁶The classification uses the population share living in large and medium size cities, population density, and population density excluding large- and medium-sized cities (see https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/regionen/siedlungsstrukturelle-arbeitsmarktregionstypen/Arbeitsmarktregionen_Typen.html). See the Supporting Information: Material for more details.

into large and small agglomerations as some studies indicate that the largest cities suffered from an above-average impact of the pandemic. Some authors discuss whether changes in behavior induced by the health crisis might even constitute the beginning of the end for big cities. Thus, in particular for large cities, we might expect important and possibly persistent effects of the pandemic (e.g., Florida et al., 2020, Nathan & Overman, 2020). We consider the 10 largest agglomerations as measured by the number of workers. These regions account for an important share of total economic activity in Germany and for approximately 30% of total employment.⁷

To evaluate how the pandemic has affected labor market transitions between employment and unemployment, we define a measure of excess net inflows into unemployment, which compares the net flow into unemployment for a given region-sector cell in a specific month with the corresponding flow observed 2 years earlier. This measure is constructed in three steps. First, we compute the net flow into unemployment for each region-sector cell and month, which is defined as the difference between the number of transitions from employment into unemployment and the opposite flow from unemployment into employment. Second, we construct the 2-year difference of this quantity by subtracting the corresponding net flow into unemployment that is observed 2 years earlier (see Lemieux et al., 2020 for a similar approach).⁸ Third, we standardize the resulting difference by dividing it with the number of employees in the corresponding region-sector cell from June 2019, which eases comparisons between region-sector cells.

In the absence of trends or labor market shocks, the 2-year difference in the net inflow rates into unemployment would be expected to be close to zero. A negative labor market shock, which increases job loss and makes transitions from unemployment into employment less likely, would lead to an increase in the net inflow rate compared to the situation 2 years earlier. To better track the development of labor market transitions, we use the cumulative sum of the relevant monthly rates starting in January 2019. The advantage of a cumulative measure is that it allows an easy comparison of the current state of a regional labor market with the prepandemic situation. Our measures therefore enable us to directly evaluate two aspects of resilience: resistance to the initial shock and recovery, that is, return to precrisis levels (see Martin & Sunley, 2014 for a discussion of different types of resilience). We refer to this quantity as the excess net inflow rate into unemployment.⁹ Another advantage of our approach is the use of high-frequency (monthly) data that are available at an appropriate spatial level. In addition, we can analyze the effects of the crisis in a more differentiated way than many other studies because we consider the inflow as well as the outflow side of regional unemployment.

Figure 1 shows the excess net inflow rate for Germany and for each of the four region types from January 2019 onwards.¹⁰ Three features are noticeable. First, the pandemic led to a drastic increase in the net inflow rate between March and May 2020. For Germany, it more than doubled from a value of below 6 in March 2020 to over 14 in May 2020, which implies that the cumulative number of net transitions into unemployment increased by around 9 per 1000 employees (relative to 2 years earlier). Evaluated at the total number of employees in June 2019, this implies an increase of 307,000 net transitions. The differences between the region types were initially small, with rural areas experiencing a slightly larger increase than agglomerated or urbanized regions.

Second, the excess net inflow rate started decreasing in Germany from July 2020 onwards, and by December 2021, the measure was slightly smaller than at the start of the pandemic. At the national level, it took approximately

⁷We define large agglomerations as those regions with the largest population in the year 2019: Berlin, Bochum, Düsseldorf, Essen, Frankfurt, Hamburg, Hannover, Köln, München, and Stuttgart. Ten out of 33 agglomerations belong to the group defined as large agglomerations in our study. In total, large agglomerations represent 7% of all labor market regions, but account for approximately 30% of total employment in 2019. 21% of employees work in small agglomerations, 30% in urban regions, and 16% in rural regions. Figure A1 in the Supporting Information: Material provides a map of the functional labor market regions and different region types.

⁸This approach implies that observations from 2020 and 2021 are compared to different reference periods (2018 and 2019, respectively). In principle, differences in the results for these years could therefore be caused by the change in the reference period. However, we show that using a constant reference period (the average of the years 2016–2018) produces similar results. Table A3 in the Supporting Information: Material summarizes the results corresponding to Table 1 in the paper.

⁹For brevity, we sometimes drop the term excess.

¹⁰Figure A2 in the Supporting Information: Material shows corresponding measures for excess inflow rate and outflow rate.

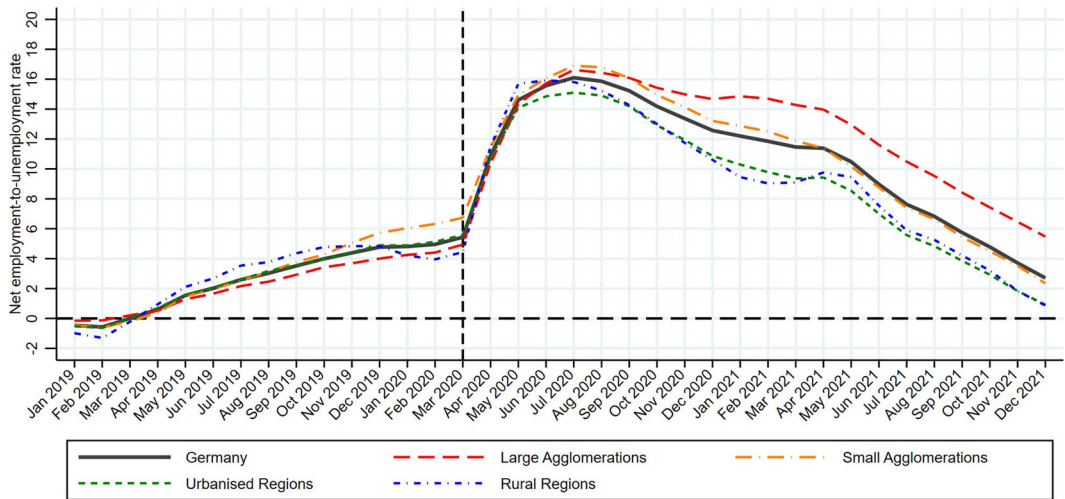


FIGURE 1 Development of cumulative excess net transition rate from employment to unemployment. Unit of observation is region–type–month. The vertical dashed line separates the prepandemic and the postpandemic periods. The excess net transition rates compare the net inflows into unemployment of a specific month with the corresponding measure 2 years earlier. Figure 1 shows the cumulative sum of the excess net transition rates starting January 2019. *Source:* Employment and unemployment statistics of the Federal Employment Agency.

14 months to compensate for the increase in the net inflow rate during the first 4 months of the pandemic. During this period, differences in the development between the four region types became considerably larger. While the recovery was faster in rural and urbanized regions, it took longer in agglomerations and especially in large agglomerations, which—on average—recorded higher cumulated measures every month since July 2020 than other region types. In December 2021, the cumulative measure of large agglomerations continued to exceed the prepandemic level and was still more than twice as high than in urbanized and rural regions.

Third, the prepandemic development shows that the net inflow rate into unemployment increased relative to the period 2 years earlier, indicating that the German labor market was already weakening in 2019. This development can be seen for all four region types, but while the trend is almost identical between both types of agglomerations and urbanized regions, the development in rural regions appears to be subject to seasonal fluctuations. Taking these patterns into account as part of the empirical analysis will be crucial for identifying the effect of the pandemic on labor market dynamics.

However, Figure 1 provides no evidence for any anticipation effects on the labor market. What can be seen during the period leading up to the pandemic is a gradual worsening of labor market conditions (compared to the period 2 years earlier), as evidenced by an increase in the excess net rate of employment-to-unemployment transitions. From March to April 2020, there is a sharp increase in the excess net rate, which represents a break rather than a continuation of the previous development. We take this as evidence that while the labor market developed less favorably during the year before the start of the pandemic, there was no anticipation effect.¹¹

¹¹The absence of any anticipation effects on the labor market is also confirmed by the development of labor market expectations as indicated by the Institute of Employment Research's (IAB) labor market barometer (see <https://iab.de/en/daten/iab-labour-market-barometer/>) and changes in mobility (see Schlosser et al., 2020 and <https://www.covid-19-mobility.org/reports/first-report-general-mobility/>).

2.3 | Potential sources of regional differences in labor market transitions

To investigate whether changes in mobility during the pandemic result in regional disparities in labor market transitions, we use daily mobility flows that are derived from mobile phone data collected by the provider Telefónica and aggregated by Teralytics. The data includes the number of movements of mobile phone users within and between counties (a more detailed description of the mobility data is provided in the Supporting Information: Material). To account for behavioral changes triggered by infection rates, we use data from the “Corona-Datenplattform” (<https://www.corona-datenplattform.de/>) to compute the average number of infections per 100,000 inhabitants per month for each labor market region (see also Figure A4 in the Supporting Information: Material).

Different studies emphasize the role of working from home for regional differences in the labor market effects of the pandemic. Following Alipour, Falck, and Schüller (2023), we calculate a measure of potential working-from-home use that is based on the occupation structure of regional employment in the year 2019 combined with survey information on the feasibility of remote work by occupation. Information on regional employment by occupation comes from the employment statistics of the FEA.

Finally, we include different structural characteristics of regional labor markets that are discussed in the literature to influence the size of the pandemic shock and the speed of recovery. We use information from the employment statistics of the FEA to measure the regional establishment size and qualification structure. The establishment size structure is given by the regional share of employment in the following categories: very small (1–9 workers), small (10–49 workers), medium-sized (50–249 workers), and large establishments (more than 249 workers). For the qualification structure, we distinguish between four skill groups that reflect differences in job requirements: assistant workers (up to 1 year of vocational training), skilled workers (at least 2 years of vocational training), specialists (advanced vocational training or bachelor degree), and experts (at least 4 years university education). Furthermore, we use the average regional unemployment rate in 2019 as a measure of initial labor market conditions. This data is taken from the unemployment statistics of the FEA. Descriptive statistics on all variables used in the analysis can be found in Table A1 in the Supporting Information: Material.

3 | EMPIRICAL METHODOLOGY

The aim of the empirical analysis is to assess regional differences in the development of labor market transitions during the pandemic and to describe potential mechanisms behind these disparities. For this purpose, we adopt a two-stage approach comparable to Combes et al. (2008) and Roca and Puga (2017).¹² In the first stage, we address the possibility that regionally different labor market developments may be affected by differences in regional sector structures. To do so, we estimate a shift-share regression model (Patterson, 1991), which allows us to decompose our measures of labor market dynamics into separate regional and sectoral components. In the second stage, we use the estimated region-month components in an event-study difference-in-differences model.

3.1 | First stage: Decomposition

The first stage of the empirical analysis involves estimating a shift-share regression model using the transition rates by region, sector, and month as the dependent variable:

¹²However, while they estimate a wage equation and regress individual wages on worker characteristics, worker fixed effects, and other controls to determine region-time fixed effects, our first stage makes use of more aggregated sector information and a shift-share model on the first stage.

$$y_{jit} = \eta_{it} + \sum_g \chi_{g(i)jt} \mathbb{1}(i \in g) + \varphi_{ij} + u_{jit}. \quad (1)$$

The excess net inflow rate, y_{jit} , in region i , sector j , and month t is decomposed into three components. First, a region-by-month component, η_{it} , that reflects differences in monthly labor market dynamics between regions. Second, a sector-by-month-by-region-type component, $\chi_{g(i)jt}$, that controls for sectoral shocks at the region-type level.¹³ Third, a region-sector-specific constant, φ_{ij} . u_{jit} represents a random error term. We apply the same approach to decompose the excess inflow and outflow rates. To account for differences in size and resulting heteroscedasticity, we estimate a weighted regression using the number of employees in a region-sector cell in June 2019 as weights.

In the first stage, we control for sector-specific shocks that might differ in size between region types and we account for differences in the sector structure of regions. Thus, a systematic variation in the region-by-month component η_{it} between region types cannot be explained by sector-specific shocks or a specialization of specific region types with respect to sectors that have been hit above or below average by the Covid-19 crisis.

3.2 | Second stage: Difference-in-differences analysis

In the second stage, we specify an event-study model for which we define the time period up to and including March 2020 as the prepandemic period¹⁴ to assess the differences in the development of labor market dynamics during the pandemic between the region types.¹⁵ To account for the trends in the transition measures that are discernible in Figure 1 during the prepandemic period (and the seasonal patterns in the case of rural regions), we perform a detrending procedure to generate adjusted region-month effects, $\tilde{\eta}_{it}$, that we use as the dependent variable in the second-stage regression (see the Supporting Information: Material for a description of the procedure). The identifying assumption of the event-study model is that the expected development of regional labor market flows would have followed the prepandemic trend if the pandemic had not taken place. The difference-in-differences model is given by

$$\tilde{\eta}_{it} = \xi_i + \zeta_t + \sum_{g \neq 2} \sum_{s=1}^S \psi_s^g \mathbb{1}(t = s) \mathbb{1}(i \in g) + w_{it}. \quad (2)$$

The parameters ξ_i and ζ_t represent region and month fixed effects, respectively. w_{it} denotes the error term. The parameters of interest are ψ_s^g , which capture how the region-month component of the labor market transition measures differs between region types g (urbanized regions being the reference category) in any month s .¹⁶ For the prepandemic period, we expect the estimated coefficients of ψ_s^g to be close to zero, which would indicate that the labor market transitions developed similarly in all region types. By contrast, differences in the estimated coefficients

¹³Additional analyses in which we disregard the variation of sector-specific transitions between region types indicate that this results in biased estimates of the region-type effects ψ_s^g in the second stage (see Equation 2).

¹⁴While infections with severe acute respiratory syndrome coronavirus-2 were already detected in January 2020 in Germany, the first lockdown was imposed on March 22, 2020. As the administrative statistics on monthly transitions for March 2020 cover the period from February 16, 2020 until March, 15 2020, genuine lockdown effects should not be visible in the March 2020 data.

¹⁵All region types are potentially affected by the Covid-19 pandemic, thus it is not possible to construct a control group of unaffected regions (Cerqua & Letta, 2022). The purpose of this analysis, however, is to evaluate regional differences in the effects of the pandemic. The coefficient estimates therefore provide information about the average impact on a specific region type relative to the impact on the reference region type.

¹⁶Although we include region fixed effects in the second stage difference-in-difference analysis it is possible to identify systematic differences in the effects of the crisis between region types because the region fixed effects only control for the average differences in the region-month effects across region types in the period from January 2019 until December 2021. However, the region types significantly differ from these average disparities over time. This is captured by significant region type-month interaction terms ψ_s^g at the second stage.

during the pandemic period would indicate that labor markets were differently affected by the pandemic. We cluster standard errors at the region level.

To provide more evidence on the factors that give rise to regionally heterogeneous effects of the pandemic, we extend the model given by Equation 2 and include different time-varying (x_{it}) and time-invariant regional characteristics (z_i). The latter enter as interaction terms with month fixed effects and, thus, their effects are allowed to vary over time. The selection of potential factors is informed by the literature survey in Section 1. We consider the structural characteristics of regions (establishment size structure, qualification structure, home office potential, prepandemic unemployment rate) and two factors that capture behavioral changes (regional infection rates, mobility changes).¹⁷ In our full model (Equation 3), the effects of the latter variables may also vary over time.

$$\tilde{\eta}_{it} = \xi_i + \zeta_t + \sum_{g=2}^S \sum_{s=1}^S \psi_s^g I(t=s) I(i \in g) + \sum_{s=1}^S \gamma_s x_{it} I(t=s) + \sum_{s=1}^S \delta_s z_i I(t=s) + w_{it}. \quad (3)$$

The estimated coefficients from Equation (3) provide information on two issues. First, we analyze how these factors affect differences between region types, that is, how ψ_s^g changes if we add different explanatory factors. In particular, the model enables us to evaluate whether the included factors contribute to the above-average impact of the crisis on large agglomerations. Second, we examine how different factors influence the size of the crisis effect on regional labor markets (γ_s, δ_s).

4 | RESULTS

4.1 | Baseline second-stage results and the role of sector-specific shocks

Figure 2 shows the coefficient estimates of ψ_s^g from Equation (2), which illustrate the differential development of the excess net inflow rate in the three region types that has been purged of monthly sectoral effects. After accounting for region-specific trends and seasonal fluctuations, the net inflow rates are very similar up to March 2020. However, deviations from the prepandemic development can be seen from April 2020 onwards.¹⁸ The initial shock to labor markets was slightly more pronounced in rural regions, but also in large agglomerations: between March and May 2020, the change in the net inflow rate is about 1.5 units larger in the latter than in the reference category (urbanized regions). For a large agglomeration of average size (around 1.1 million workers), this implies that the change in cumulative net inflows from employment into unemployment was higher by around 1600 additional transitions compared to the corresponding change in average urbanized regions. However, the development of rural regions and large agglomerations started diverging from June 2020 onwards. While there is no statistically significant difference between rural and urbanized regions, large agglomerations experienced a continuous build-up of net inflows into unemployment. This development was especially pronounced during the second lockdown in autumn and winter 2020, before plateauing at a level of 7.4 in the summer of 2021, that is, more than 14,000 additional net transitions into unemployment in a large agglomeration of average size (compared to the corresponding change in the reference category).

¹⁷Mobility changes and infection rates might also be understood as outcome variables because they might change in response to a variation in economic activity as reflected by our dependent variable. The corresponding regression results should therefore not be interpreted as causal effects but rather as correlations. This is in contrast to the precrisis structural characteristics of the regions which refer to the year 2019.

¹⁸With clustered standard errors the confidence intervals in the prepandemic period become very small. Their computation is based on the variance-covariance matrix of the model's residuals to account for a potential correlation of the error terms within region clusters over time. However, residuals for the prepandemic period should represent (approximately) white noise with no pronounced correlation over time due to the region-specific trend adjustment which is fit using prepandemic data only.

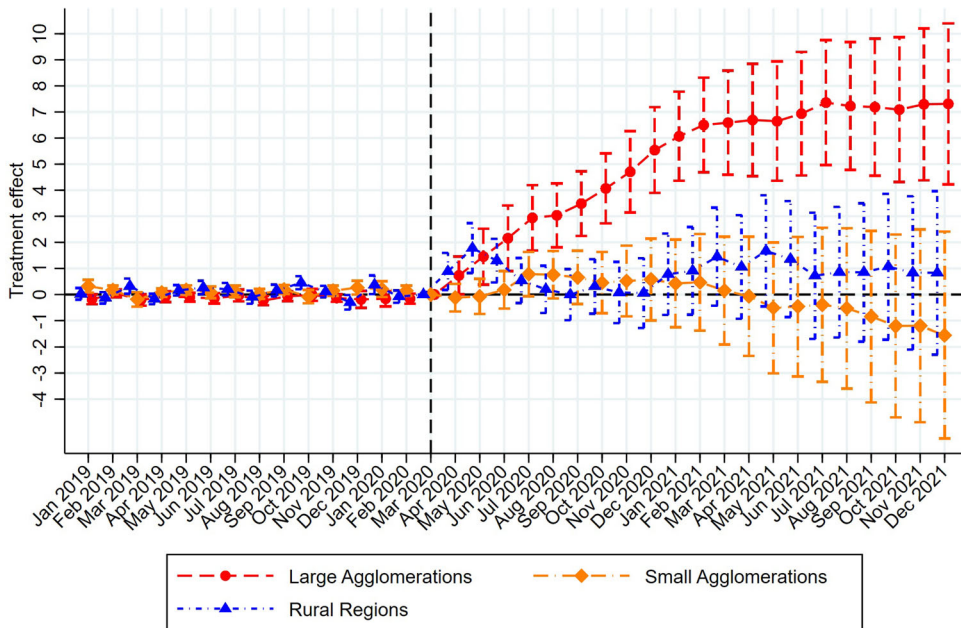


FIGURE 2 Baseline difference-in-differences estimates—excess net inflow rate. Unit of observation is region-month. The plot shows the estimated coefficients of the region group-month interactions in Equation (2) using the excess net inflow rate as the dependent variable. Urbanized regions are the reference category. Vertical lines indicate the 95% confidence interval, which is based on robust standard errors clustered at the region level. Employment and unemployment statistics of the Federal Employment Agency.

In previous studies (e.g., Kim et al., 2023; Partridge et al., 2022), the sector structure has been shown to be an important factor for local resilience during the pandemic. Palomino et al. (2022) identify that it is sectoral differences, for example, specialization in the tourism industry, that mark regions' vulnerability to the economic impact of the pandemic. However, the unfavorable development of large agglomerations here is not due to sector-specific shocks and a specialization of large cities in sectors that have been hit above average because we control for corresponding effects in the first stage (see Section 3.1). Thus, the sector structure of large agglomerations does not explain the above-average effect of the pandemic that we observe for this region type in Germany.

Estimating Equation (2) using the excess inflow rate from employment into unemployment and outflow rate from unemployment into employment allows us to decompose the regional differences in the development of the net rate. The corresponding results are shown in Figure 3A,B. The results provide evidence that the unfavorable development in large agglomerations can be primarily ascribed to increases in the transition rate from employment into unemployment, which points toward comparatively large increases in layoffs in the densest regions during the pandemic. However, a lower outflow rate from unemployment also contributes to the below-average performance of large agglomerations. Small agglomerations and rural regions do not differ significantly from urbanized regions in terms of the inflow rate, while the development of flows into employment is temporarily less favorable.

4.2 | Potential mechanisms behind the average pandemic effect

Having established that the increase in the excess net inflow rate into unemployment was larger and more persistent during the pandemic in large agglomerations, we turn to an evaluation of possible sources for this

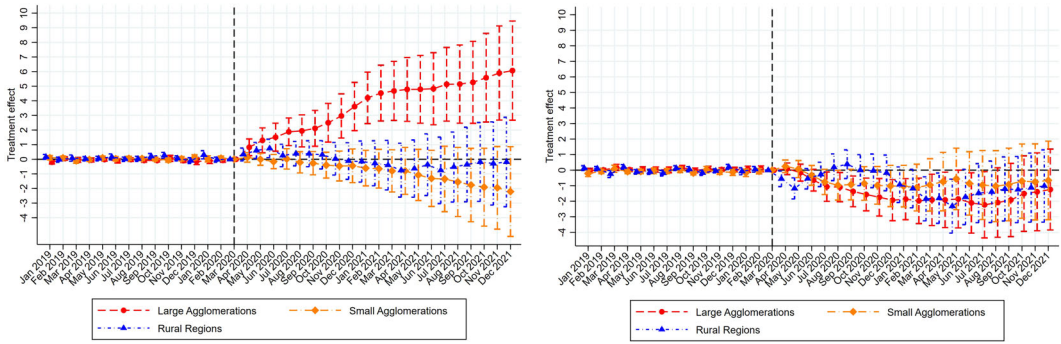


FIGURE 3 Baseline difference-in-differences estimates—decomposing the excess net inflow rate. Inflow rate from employment into unemployment (left). Outflow rate from unemployment into employment (right). Unit of observation is region-month. The plots show the estimated coefficients of the region group-month interactions in Equation (2) using the excess inflow rate (left) and the excess outflow rate (right) as the dependent variable. Urbanized regions are the reference category. Vertical lines indicate the 95% confidence interval, which is based on robust standard errors clustered at the region level. *Source:* Employment and unemployment statistics of the Federal Employment Agency.

differential development. To this end, we re-estimate Equation (3) and include successively larger sets of control variables.

In the first extension, we include two time-varying control variables: the regional Covid-19 infection rate and the change in regional mobility. Spatial differences in infection rates might give rise to regionally different behavioral changes that in turn may influence labor market outcomes. Potential behavioral adjustments to the pandemic also include a reduction in mobility, which in turn reduces the demand for certain goods and services. As business and touristic travel is presumably more relevant in large agglomerations, a reduction in mobility could disproportionately affect labor markets in large cities.

In the second extension, we add a set of time-invariant variables that capture differences in the prepandemic labor market conditions and structural characteristics of regions, which may, according to the literature on regional resilience, influence a region's ability to adjust to economic shocks. These characteristics include the regional unemployment rate, the share of employees in occupations that are suitable for working from home, the qualification, and the establishment size structure of the regions. While the average effect of these time-invariant variables is absorbed in the regional fixed effects, we extend the model by interacting these measures with month dummies. Doing so allows us to account for the possibility that the relevance of these factors may vary across different episodes of the pandemic. In the full model, we also interact the time-varying control variables with month dummies.

The extensions of the baseline model serve the purpose of assessing how the differences in the estimated region group-months effects change when control variables are successively added. To ease the presentation of the results, Table 1 shows the average value of the estimates of ψ_s^g for the prepandemic (January 2019–March 2020) and the pandemic period (April 2020–December 2021). The upper panel shows the results for the net inflow rate, while the middle and the lower panel contain the results for the inflow and the outflow rates, respectively. The first column repeats the results from the baseline model. The second column refers to the results from the specification including time-varying variables (Extension 1), the third column to the results from the specification that further includes the interactions between time-invariant variables and months dummies (Extension 2), and the fourth column to the full model.

TABLE 1 Average difference-in-differences estimates.

	Period			
	Baseline	Extension 1	Extension 2	Full model
<i>Panel A: Excess net inflow rate from unemployment to employment</i>				
Large agglomerations				
Prepandemic	-0.119 (0.081)	-0.016 (0.117)	-0.087 (0.143)	-0.195 (0.266)
Pandemic	5.29*** (0.863)	5.19*** (0.866)	1.37 (1.257)	1.3 (1.156)
Small agglomerations				
Prepandemic	0.117 (0.080)	0.155 (0.087)	0.127 (0.112)	-0.002 (0.171)
Pandemic	-0.093 (0.926)	-0.181 (0.941)	-1.17 (0.874)	-1.28 (0.850)
Rural regions				
Prepandemic	0.0922 (0.098)	0.111 (0.098)	0.163 (0.108)	-0.074 (0.168)
Pandemic	0.835 (0.785)	1.06 (0.796)	0.763 (0.862)	0.54 (0.864)
R ²	0.831	0.832	0.871	0.873
<i>Panel B: Excess inflow rate from employment to unemployment</i>				
Large agglomerations				
Prepandemic	-0.0643 (0.052)	-0.0004 (0.088)	-0.144 (0.119)	0.061 (0.207)
Pandemic	3.79*** (0.920)	3.76*** (0.915)	1.39 (1.146)	1.59 (1.210)
Small agglomerations				
Prepandemic	0.0384 (0.056)	0.0488 (0.063)	-0.0289 (0.078)	0.037 (0.114)
Pandemic	-0.846 (0.708)	-0.914 (0.428)	-1.17 (0.711)	-1.08 (0.738)
Rural regions				
Prepandemic	0.0863 (0.075)	0.0807 (0.074)	0.0564 (0.084)	0.078 (0.123)
Pandemic	-0.0941 (0.758)	-0.017 (0.803)	0.252 (0.830)	0.277 (0.822)
R ²	0.665	0.668	0.762	0.759
<i>Panel C: Excess outflow rate from unemployment to employment</i>				
Large agglomerations				
Prepandemic	0.0548 (0.063)	0.0153 (0.093)	-0.0579 (0.121)	0.256 (0.258)
Pandemic	-1.5** (0.732)	-1.43* (0.723)	0.0183 (1.027)	0.293 (0.958)
Small agglomerations				
Prepandemic	-0.079 (0.069)	-0.106 (0.079)	-0.156 (0.091)	0.0386 (0.146)
Pandemic	-0.753 (0.736)	-0.733 (0.730)	-0.00507 (0.750)	0.201 (0.733)
Rural regions				
Prepandemic	-0.0059 (0.065)	-0.03 (0.067)	-0.106 (0.098)	0.152 (0.139)
Pandemic	-0.929 (0.637)	-1.08 (0.661)	-0.511 (0.751)	-0.263 (0.728)
R ²	0.582	0.586	0.670	0.676
N	5076	5076	5076	5076



TABLE 1 (Continued)

	Period			
	Baseline	Extension 1	Extension 2	Full model
Time variant	No	Yes	Yes	No
Time invariant (interacted with month dummies)	No	No	Yes	Yes
Time variant (interacted with month dummies)	No	No	No	Yes

Notes: The table shows the average estimated effects of the region-type-months interactions in the pre-pandemic and the pandemic period for the excess net inflow, the inflow, and the outflow rate (reference category: urbanized regions). Robust standard errors clustered at the region level are shown within parentheses. Control variables are: infection rate, mobility index (time variant), pre-pandemic home office potential, unemployment rate, skill structure, and establishment size structure (time invariant).

Abbreviation: FEA, Federal Employment Agency.

***, **, * indicate statistical significance at the 0.01, 0.05, and 0.1 level.

Source: Employment and unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

In the baseline model, the average pandemic difference-in-difference estimate for large agglomerations amounts to 5.29 in the case of the excess net inflow rate.¹⁹ Adding infections and mobility leaves the magnitude of the estimate virtually unchanged. Differences in infection rates and mobility therefore do not appear to be the reason for the unfavorable development of labor market dynamics in large cities (relative to other region types). By contrast, controlling for regional pre-pandemic characteristics reduces the average estimated pandemic effect in large agglomerations by about 75% (from 5.29 to 1.37) and the difference between large agglomerations and the reference category becomes statistically insignificant. This suggests that the relatively large net inflow rate in large agglomerations is to a large extent associated with initial structural characteristics. Further introducing time-varying effects of mobility and infections only leads to marginal changes in the estimate of the average pandemic effect. That structural characteristics are overall more important compared to mobility and infections seems to be a general result: including the former also tends to affect the estimates for the other region types more strongly than the inclusion of mobility changes and infection rates.²⁰

Findings for the excess inflow and outflow rates confirm the evidence in Section 4.1, that the effects of the crisis are not symmetric: the average pandemic effect on inflow rates is more than twice as large as the corresponding effect on the outflow rate in the case of large agglomerations. For the transitions into as well as out of unemployment, there are no significant differences between large agglomerations and urbanized regions once we include structural characteristics. The factors that we consider, in sum, thus weaken the recovery of large cities relative to other regions.

In the baseline specification, the difference in the average effect during the pandemic from the reference category is comparatively small and statistically insignificant in the case of small agglomerations and rural regions. Controlling for additional factors also affects the magnitude of these coefficient estimates. Inclusion of infection rates and mobility changes, as well as measures of pre-pandemic regional economic characteristics, further reduces the average pandemic effect on the excess net inflow rate in small agglomerations. As in the case of large agglomerations, these factors seem to exacerbate the effect of the pandemic. This suggests that the causes, which

¹⁹This corresponds to the mean of the estimated coefficients (red dots) in Figure 2.

²⁰We further show that the findings for large agglomerations are not driven by a single region. Table A4 in the Supporting Information: Material provides the average pandemic and pre-pandemic effect for large agglomerations in the baseline and the full model when a single region from that group is excluded from the analysis. The results remain comparable in magnitude to those in Table 1.

appear to hamper economic recovery after the pandemic in large and small agglomerations, are similar but much stronger in large cities. Altogether, however, average effects and their changes are minor and not precisely estimated for small agglomerations and rural regions.

4.3 | Relevance of individual factors

To identify which factors are the main drivers of the reduction in the estimated average pandemic effect, we re-estimate the full model and successively remove individual control variables or pairs of control variables. Based on these reduced models, we compute the estimated pandemic effect in the same way as in Table 1. If the estimated effect deviates from the corresponding effect identified from the full model (column 5 in Table 1), we argue that the omitted factor or pair of factors is relevant for the change in the average pandemic effect observed in Table 1.

Figure 4 shows the difference in the estimated average pandemic effect between different reduced models (displayed on the vertical axis) and the full model in the case of large agglomerations (see Figures A6 and A7 for the corresponding results for small agglomerations and rural regions). Two results stand out. First, excluding the share of workers employed in jobs that are suitable for working from home in combination with the skill level of regional employment (model M2.17) leads to an increase in the excess net inflow rate, which is entirely due to a higher

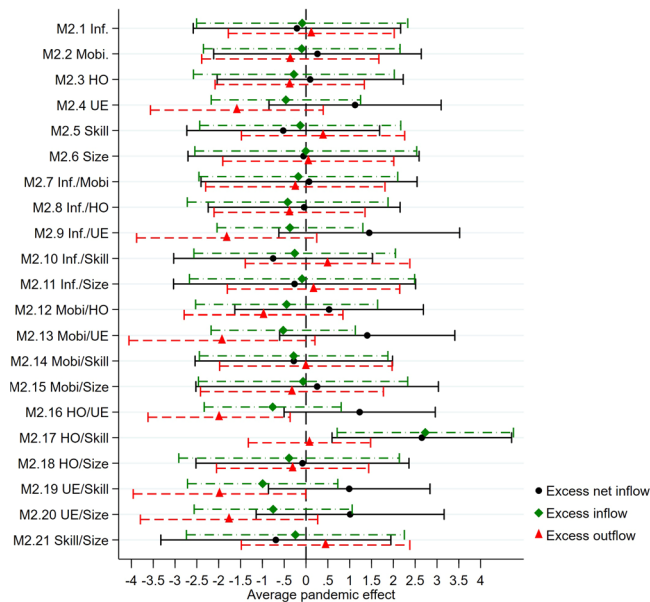


FIGURE 4 Relevance of individual factors and combinations of factors—large agglomerations. The figure shows the deviation of the average coefficient estimate of the region–month dummies in the pandemic period for large agglomerations for different model specifications from the corresponding estimate in the full model. Separate estimates are shown for the excess net inflow, the inflow, and the outflow rate. Each symbol (black dots for the net inflow rate, green diamonds for the inflow rate, and red triangles for the outflow rates) represents the deviation of the estimated average pandemic effect—together with the 95% confidence interval, which is based on robust standard errors clustered at the region level. HO, working-from-home potential; Inf., infection rates; Mobi., mobility changes; Size, establishment size structure; Skill, qualification structure of local workforce; UE, prepandemic unemployment rate. *Source:* Employment and unemployment statistics of the Federal Employment Agency, Teralytics, and Corona-Datenplattform.

inflow rate from employment to unemployment (by contrast, the excess outflow rate stays unchanged). Second, the excess net inflow rate also increases whenever the initial unemployment rate is excluded by itself (model M2.4) or in combination with other variables (model M2.9, M2.13, M2.16, and M2.19). This increase of the excess net inflow rate is smaller than in model M2.17, not precisely estimated and driven by a reduction in outflows from unemployment into employment. We observe significant changes in the excess outflow for models M2.16 and M2.19. However, a comparison of the different models indicates that the variation of coefficient estimates is primarily caused by the exclusion of the unemployment rate (model M2.4), although the difference between the full model and M2.4 is not significant.²¹ We discuss these findings in more detail below.

4.3.1 | Working from home

The results for model M2.17 in Figure 4 show that a region's share of jobs suitable for working from home and the share of high-skilled workers constitute one explanation for the less favorable development of the excess net inflow rate into unemployment in large agglomerations.²² Table A2 shows that working-from-home jobs as well as high-skilled jobs are overrepresented in large agglomerations. We hypothesize that the mechanism responsible for the unfavorable development of large agglomerations is an above-average reduction in consumer demand, which leads to increased transitions into unemployment. In line with Althoff et al. (2022) and Alipour, Falck, Krause, et al. (2022), we interpret the result as pointing to a drop in consumption spending caused by the absence of (high-income) consumers or commuters in city centers due to working from home, which may primarily affect retail sale and restaurants. Other industries in large cities might also be impaired via spillovers as sector-specific shocks may propagate through localized input–output linkages. Reissl et al. (2022) and Inoue et al. (2021), for instance, provide evidence that adverse effects of (local) lockdowns are transmitted through domestic value chains to other parts of the regional economy, which are not directly affected by containment measures. Our results do not imply that workers in working-from-home jobs experienced excess transitions into unemployment, but rather that the absence of commuting into city centers led to a loss of employment in retail sales or hospitality jobs that spreads out to the local economy.²³

4.3.2 | Regional pre-pandemic unemployment and its composition

Higher excess net inflow rates into unemployment in large agglomerations also appear to be due to less favorable economic conditions in the form of higher pre-pandemic unemployment rates (see Table A2). One reason why the higher unemployment rates in large agglomerations might be associated with lower outflow rates into unemployment during the pandemic is the composition of unemployment. As can be seen from Figure A5, the share of unskilled job seekers (i.e., those without vocational training) is larger in large agglomerations than in the other region types. During crises, low-skilled unemployed are particularly likely to face difficulties in finding a new job, which translates into fewer transitions out of unemployment. Evidence for a role of pre-crisis unemployment for regional resilience during the Covid-19 crisis is also provided by Cochrane et al. (2022), who show that the

²¹In fact, we observe a significant difference between the full model and model M2.4 if we use the average of the years 2016–2018 as a constant reference period for the net inflow into unemployment instead of the net inflow that is observed 2 years earlier (see Figure A8 in the Supporting Information: Material and Section 2.2).

²²In contrast, Grabner and Tsvetkova (2022) show that the pre-pandemic share of jobs that can be performed remotely correlates positively with labor market resilience in terms of vacancies during the first Covid-19 wave, especially in smaller US cities. The findings by Palomino et al. (2022) indicate that higher local levels of remote work are accompanied by lower regional vulnerability to poverty and inequality in Spain.

²³We further argue that the fact that the deviation from the full model only occurs when both variables are removed is due to the high correlation between the working-from-home share and the share of high-skilled workers (correlation coefficient is 0.88): if the working-from-home share is dropped by itself, its effect on the excess net inflow rate is picked up by the share of high-skilled workers.

strongest predictor of a postshock increase in unemployment benefits is the unemployment rate 2 years earlier. Moreover, results by Brown and Cowling (2021) also underline the importance of unfavorable precrisis labor market conditions. Their findings, based on the 100 largest towns in Great Britain, suggest that any potential recovery following the Covid-19 crisis will be more difficult to achieve for cities in which economic conditions were already worse before the start of the pandemic.

We only briefly discuss the findings for small agglomerations and rural regions (see Figures A6 and A7 in the Supporting Information: Material). The outcomes for small agglomerations resemble the pattern of large cities (see Figure 4), but all deviations from the full model tend to be smaller and not statistically significant, pointing to weaker effects of the factors that are also relevant for large agglomerations. For rural regions, we can hardly detect important differences from the full model.

4.4 | Dynamic effects of control variables

In this subsection, we assess the impact of the control variables on the transition rates and how this relationship varies at different stages of the pandemic. Figure 5 shows the estimated coefficients of the interactions of the control variables and the month dummies from Equation (3). For all control variables, the estimates tend to be close to zero during the prepandemic period.

Variation in regional infection rates is not related to changes in the inflow and outflow rates for most of the pandemic period. Larger effects are found during the early stages of the pandemic as well as during the summer of 2021, though they are often statistically insignificant. By contrast, changes in mobility tend to have larger effects, in particular during the second wave of the pandemic (December 2020–April 2021) and later in the pandemic. Mobility changes influence regional labor market outcomes primarily via transitions out of unemployment. The estimates indicate that, in line with expectations, regions that experience a smaller decline in mobility (stronger recovery of mobility) display, *ceteris paribus*, a more favorable development of labor market transitions.

The working-from-home potential also influences transitions into employment. However, we find important dampening effects on the outflow from unemployment only towards the end of the period. In contrast, the precrisis unemployment rate starts to adversely affect outflows early in the pandemic, with the strength of the effects increasing until November 2020 and then remaining more or less at this level. The effects of the prepandemic unemployment rate on the transitions into unemployment do not significantly differ from zero throughout the pandemic. However, the net inflow rate shows a significant positive correlation with prepandemic unemployment between autumn 2020 and May 2021 due to the unfavorable impact on the outflows from unemployment.

We find a differentiated impact of the qualification structure on both inflow and outflow rates. Regional labor markets with a relatively high share of low-skilled assistant workers are characterized by a fairly favorable development of transitions into new jobs in the first half of 2021, whereas the percentage of (high-skilled) specialists seems to influence inflow as well as outflow rates. While transitions into unemployment are affected from August 2020 onwards, significant effects on the outflow side do not emerge until April 2021. Interestingly, the impact of a relatively high share of specialists tends to increase outflows as well as inflows, indicating a comparatively strong dynamic in corresponding regional labor markets. Both effects increase in size until June/July 2021 before stabilizing at a similar level thereafter. As a result, the effect on the net inflow rate is statistically significant in January 2021 only. A higher share of experts, which corresponds to the highest skill level, has a smaller effect that is statistically significant only for the transitions into unemployment from the beginning of 2021 onwards. However, the direction of the effects coincides with the results for the specialists. The development of the estimates across different stages of the pandemic suggests that tentative causes for the influence of the qualification structure such as declining consumption demand of high-income workers or a decline of knowledge spillovers in large cities caused by working from home of high-skilled employees emerged gradually during the pandemic.

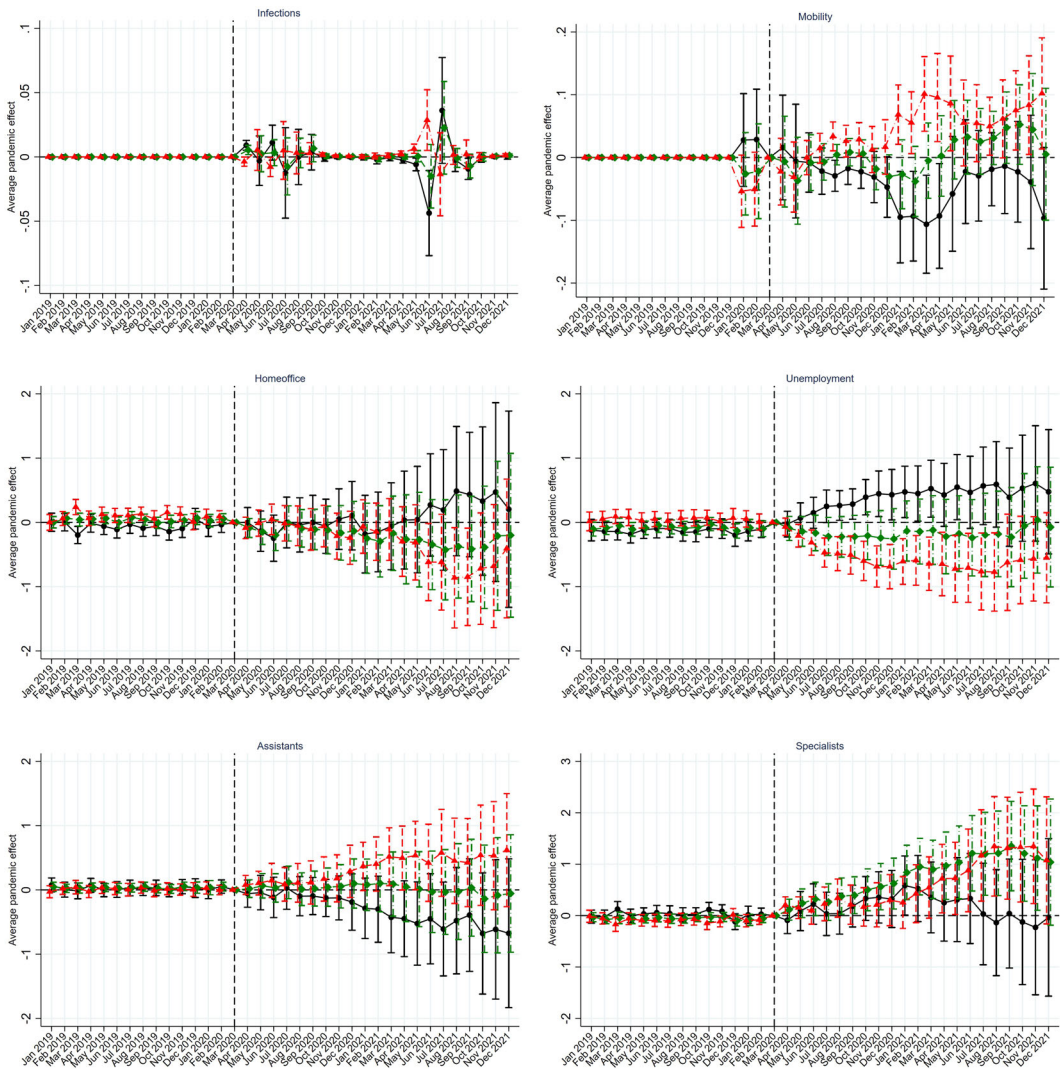


FIGURE 5 Dynamic effects of control variables. Unit of observation is region-month. The plots show the estimated coefficients of the interactions of control variables with month dummies. Estimates are shown separately for the excess net inflow rate, the inflow rate, and the outflow rate. Vertical lines indicate the 95% confidence interval. Robust standard errors clustered at the region level are estimated. Source: Employment and unemployment statistics of the Federal Employment Agency, Teralytics, Corona-Datenplattform.

Finally, we detect various effects of the regional establishment size structure, which operates primarily via inflows into unemployment. According to our results, the influence of a higher share of very small establishments (1–9 workers) changes considerably across the different stages of the pandemic. While a relatively high percentage of very small establishments in local labor markets is associated with unfavorable effects early in the pandemic, there is a change to a more advantageous impact towards the end of the observation period. Shortly after the initial shock, regions with an above-average share of very small establishments experienced a stronger increase in layoffs and fewer transitions into employment. Beginning in May 2020, the impact on the inflow side starts to decrease and becomes insignificant from September 2020 onwards. An adverse effect on transitions into employment is only

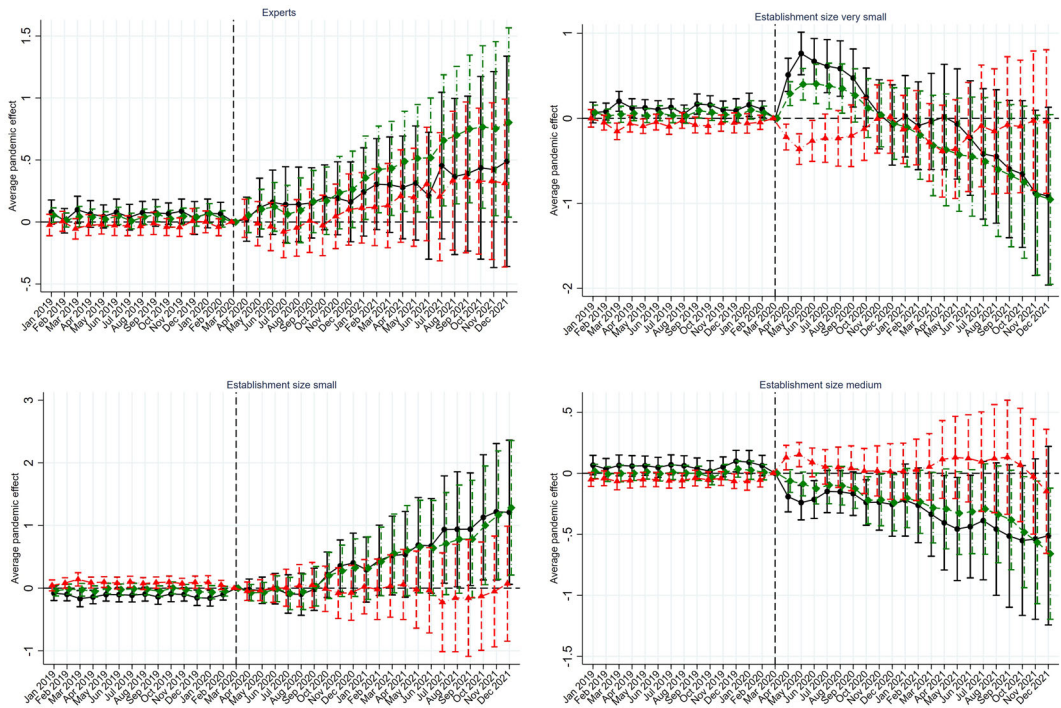


FIGURE 5 (Continued)

found until June 2020. Financial stress might have been stronger on average in areas characterized by a high share of very small establishments, in line with evidence provided by Bartik et al. (2020), leading to more jobs lost in the initial stage of the crisis. Similar changes are observed for the share of medium-sized establishments. In contrast, a relatively high percentage of small firms (10–49 workers) seems to become increasingly a burden for the recovery of regional labor markets—an effect that is driven by relatively more transitions into unemployment from autumn 2020 onwards.

5 | CONCLUSION

We use a two-stage regression approach to examine regional disparities in labor market dynamics in Germany during the pandemic. Our study extends the small number of analyses available so far on differences in the impact of the pandemic on regional labor markets. In contrast to the majority of previous studies, this paper takes a medium-term perspective and examines regional differences in the pandemic shock and subsequent recovery until December 2021. This perspective enables us to provide the first evidence on possible persistence of effects on regional labor markets stemming from the Covid-19 crisis.

Our results suggest that the impact of the pandemic on the excess net transition rate into unemployment was initially strongest among rural labor markets and large agglomerations. However, while most regions subsequently recovered quickly, large agglomerations experienced a less favorable development until the beginning of 2021. The emerging gap in the net transition rates into unemployment turned out to be rather persistent and is primarily due to more lay-offs. Relatively low outflows from unemployment also add to the below-average performance of large cities during the pandemic. However, while the latter effect fades away towards the end of 2021, we observe a sustained disadvantage of large agglomerations on the inflow side throughout the period under investigation.

Differences in sectoral structure and in the size of sector-specific shocks across region types do not explain why the recovery of large agglomerations lagged behind. This finding is in contrast to recent studies that point to a high local concentration of severely hit sectors and more pronounced sectoral shocks in cities as important factors behind above-average regional effects of the Covid-19 crisis (see Carvalho et al., 2022; Marcén & Morales, 2021; Partridge et al., 2022).

A smaller part of the disparities between large agglomerations and other regions is due to differences in precrisis unemployment. Unfavorable initial labor market conditions in large cities seem to impede transitions from unemployment to a new job. Moreover, large agglomerations are characterized by a high share of jobs that are suitable for working from home as well as an above-average percentage of highly skilled workers. This combination of factors might reflect changes in behavior such as working from home or online shopping, which seem to promote net inflows into unemployment during the pandemic. The indicators may thus capture a prolonged decline in demand for goods and services provided especially in big cities. The findings of recent studies suggest that the Covid-19 crisis gave rise to permanent changes in the spatial distribution of consumer demand from which in particular big cities might suffer (Alipour, Falck, Krause, et al., 2022; Althoff et al., 2022). This is in line with the persistent disadvantage that we detect for the large agglomerations and which is driven by more transitions into unemployment. The unfavorable performance of large agglomerations during the pandemic crisis might therefore not be specific to Germany because many countries seem to experience a persistent rise in remote working (e.g., Barrero et al., 2021; De Fraja et al., 2020) and large cities generally show a higher potential for remote work than rural areas (OECD, 2020).

The findings also indicate that examining net labor market outcomes likely masks important (partly opposing) effects on inflows and outflows. Moreover, we find considerable variation of effects across different stages of the pandemic. As a result, the impact of some factors such as mobility changes or the establishment size structure seems to be of minor importance for the average effect of the pandemic until December 2021. However, they turn out to be more relevant during specific periods of the pandemic or become increasingly important later in the crisis. Studies that focus on the very early phase of the Covid-19 crisis might therefore give an incomplete picture of factors that influence regional economic resilience during the pandemic.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

- Alipour, J.-V., Falck, O., Krause, S., Krolage, C., & Wichert, S. (2022) The future of work and consumption in cities after the pandemic: Evidence from Germany (CESifo Working Paper No. 10000). CESifo. <https://www.cesifo.org/en/publications/2022/working-paper/future-work-and-consumption-cities-after-pandemic-evidence-germany>
- Alipour, J.-V., Falck, O., & Schüller, S. (2023). Germany's capacities to work from home. *European Economic Review*. Advance online publication. 151. <https://www.sciencedirect.com/science/article/abs/pii/S0014292122002343>
- Althoff, L., Eckert, F., Ganapati, S., & Walsh, C. (2022). The geography of remote work. *Regional Science and Urban Economics*, 93, 103770.
- Ascani, A., Faggian, A., & Montresor, S. (2021). The geography of COVID-19 and the structure of local economies: The case of Italy. *Journal of Regional Science*, 61, 407–441.
- Barrero, J. M., Bloom, N., & Davis, S. J. (2021). *Why working from home will stick* (NBER Working Paper No. 28731). National Bureau of Economic Research. <https://www.nber.org/papers/w28731>
- Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *How are small businesses adjusting to COVID-19? Early evidence from a survey* (NBER Working Paper No. 26989). National Bureau of Economic Research. <https://www.nber.org/papers/w26989>
- Bosen, R., & Thurau, J. (2021). Chronology: How COVID has spread in Germany. (2021. December 28). Deutsche Welle. Retrieved March 24, 2023. <https://www.dw.com/en/covid-how-germany-battles-the-pandemic-a-chronology/a-58026877>
- Brown, R., & Cowling, M. (2021). The geographical impact of the Covid-19 crisis on precautionary savings, firm survival and jobs: Evidence from the United Kingdom's 100 largest towns and cities. *International Small Business Journal: Researching Entrepreneurship*, 39(4), 319–329.
- Bruckner, J., Kahn, M., & Lin, G. C. (2023) A new spatial hedonic equilibrium in the merging work-from-home economy? *American Economic Journal: Applied Economics*. 15(2), 285–319. <https://www.aeaweb.org/articles?id=10.1257/app.20210190>
- Capello, R., Caragliu, A., & Fratesi, U. (2015). Spatial heterogeneity in the costs of the economic crisis in Europe: Are cities sources of regional resilience? *Journal of Economic Geography*, 15, 951–972.
- Di Caro, P. (2017). Testing and explaining economic resilience with an application to Italian regions: Testing and explaining economic resilience. *Papers in Regional Science*, 96(1), 93–113.
- Di Caro, P., & Fratesi, U. (2018). Regional determinants of economic resilience. *The Annals of Regional Science*, 60, 235–240.
- Carvalho, B. P., Peralta, S., & Pereira dos Santos, J. (2022). Regional and sectorial impacts of the Covid-19 crisis: Evidence from electronic payments. *Journal of Regional Science*, 62, 757–798.
- Cerqua, A., & Letta, M. (2022). Local inequalities of the COVID-19 crisis. *Regional Science and Urban Economics*, 92, 103752.
- Chetty, R., Friedman, J., Hendren, N., & Stepner, M. (2020). *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data* (NBER Working Paper No. 27431). National Bureau of Economic Research. <https://www.nber.org/papers/w27431>
- Cochrane, W., Poot, J., & Roskrug, M. (2022). *Urban resilience and social security uptake: New Zealand evidence from the global financial crisis and the COVID-19 pandemic* (IZA Discussion Paper No. 15510). IZA Institute of Labor Economics. <https://covid-19.iza.org/publications/dp15510/>
- Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63, 723–742.
- Couture, V., Dingel, J. I., Green, A., Handbury, J., & Williams, K. R. (2022). JUE Insight: Measuring movement and social contact with smartphone data: A real-time application to COVID-19. *Journal of Urban Economics*, 127, 103328.
- Dall Schmidt, T., & Mitze, T. (2021) Comeback policy after the COVID-19 lockdown in Denmark: Effects of spatially differentiated re-opening policies on regional unemployment. In *Paper presented at the ERSA Congress 2021*. <https://az659834.vo.msecnd.net/eventsairwesteuprod/production-ersa-public/787d1cc996d740bfada3b5cb8a74c0cb>
- Desmet, K., & Wacziarg, R. (2022). JUE Insight: Understanding spatial variation in COVID-19 across the United States. *Journal of Urban Economics*, 127, 103332.
- Doran, J., & Fingleton, B. (2018). US Metropolitan Area Resilience: Insights from dynamic spatial panel estimation. *Environment and Planning A: Economy and Space*, 50(1), 111–132.
- Dörr, J. O., Licht, G., & Murmann, S. (2022). Small firms and the COVID-19 insolvency gap. *Small Business Economics*, 58, 887–917.
- Ebbinghaus, B., Lehner, L., & Naumann, E. (2022). Welfare state support during the COVID-19 pandemic: Change and continuity in public attitudes towards social policies in Germany. *European Policy Analysis*, 8, 297–311.
- Felbermayr, G., Hinz, J., & Chowdhry, S. (2020). Après-ski: The spread of coronavirus from Ischgl through Germany. *Covid Economics*, 22, 177–204.
- Florida, R., Rodriguez-Pose, A., & Storper, M. (2021). Cities in a post-COVID world. *Urban Studies*, 60(8), 1–23. <https://journals.sagepub.com/doi/full/10.1177/00420980211018072>

- De Fraja, G., Matheson, J., & Rockey, J. (2020). *Zoomshock: The geography and local labour market consequences of working from home* (Discussion Paper 20-31). Department of Economics, University of Birmingham. <https://cepr.org/publications/dp15655>
- Fratesi, U., & Rodríguez -Pose, A. (2016). The crisis and regional employment in Europe: What role for sheltered economies? *Cambridge Journal of Regions, Economy and Society*, 9, 33–57.
- Fusillo, F., Consoli, D., & Quatraro, F. (2022). Resilience, skill endowment, and diversity: Evidence from US metropolitan areas. *Economic Geography*, 98, 170–196.
- Glaeser, E. L. (2022). Urban resilience. *Urban Studies*, 59, 3–35.
- Grabner, S. M., & Modica, M. (2022). Industrial resilience, regional diversification and related variety during times of crisis in the US urban–rural context. *Regional Studies*, 56(10), 1605–1617.
- Grabner, S. M., & Tsvetkova, A. (2022). Urban labour market resilience during the Covid-19 pandemic: What is the promise of teleworking? *Regional Studies*. Advance online publication. <https://www.tandfonline.com/doi/full/10.1080/00343404.2022.2042470>
- Groot, S. P. T., Mohlmann, J. L., Garretsen, J. H., & De Groot, H. L. F. (2011). The crisis sensitivity of European countries and regions: Stylized facts and spatial heterogeneity. *Cambridge Journal of Regions, Economy and Society*, 4, 437–456.
- Houston, D. (2020). Local resistance to rising unemployment in the context of the COVID-19 mitigation policies across Great Britain. *Regional Science Policy & Practice*, 12, 1189–1209.
- Inoue, H., Murase, Y., & Todo, Y. (2021). Do economic effects of the anti-COVID-19 lockdowns in different regions interact through supply chains? *PLoS One*, 16, e0255031.
- Juraneck, S., Paetzold, J., Winner, H., & Zoutman, F. (2021). Labor market effects of COVID-19 in Sweden and its neighbors: Evidence from administrative data. *Kyklos: Jahrbuch des Instituts für Geschichte der Medizin an der Universität Leipzig*, 74, 512–526.
- Kim, A., Lim, J., & Coletta, A. (2023). How regional economic structure matters in the era of COVID-19: Resilience capacity of U.S. states. *The Annals of Regional Science*. Advance online publication. 70, 159–185. <https://link.springer.com/article/10.1007/s00168-022-01134-w>
- Kim, J. S., & Kim, T. (2022). Geographic spread of COVID-19 and local economies: Heterogeneous effects by establishment size and industry. *Journal of Regional Science*, 62, 696–731.
- Kosfeld, R., Mitze, T., Rode, J., & Wälde, K. (2021). The Covid-19 containment effects of public health measures: A spatial difference-in-differences approach. *Journal of Regional Science*, 61(4), 799–825.
- Kosfeld, R., & Werner, A. (2012). Deutsche Arbeitsmarktregionen—Neuabgrenzung nach den Kreisgebietsreformen 2007–2011. *Raumforschung und Raumordnung | Spatial Research and Planning*, 70, 49–64.
- Lemieux, T., Milligan, K., Schirle, T., & Skuterud, M. (2020). Initial impacts of the COVID-19 pandemic on the Canadian Labour Market. *Canadian Public Policy*, 46, S55–S65.
- Liu, S., & Sue, Y. (2022). *The effect of working from home on the agglomeration economies of cities: Evidence from advertised wages* (MPRA Paper No. 114429). Munich Personal RePEc Archive. <https://mpra.ub.uni-muenchen.de/102082/>
- Marcén, M., & Morales, M. (2021). The intensity of COVID-19 nonpharmaceutical interventions and labor market outcomes in the public sector. *Journal of Regional Science*, 61, 775–798.
- Martin, R. (2012). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, 12, 1–32.
- Martin, R., & Gardiner, B. (2019). The resilience of cities to economic shocks: A tale of four recessions (and the challenge of Brexit). *Papers of Regional Science*, 98, 1801–1832.
- Martin, R., & Sunley, P. (2014). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography*, 15, 1–42.
- Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. *Regional Studies*, 50, 561–585.
- McCann, P., Ortega-Argilés, R., & Yuan, P.-Y. (2022). The Covid-19 shock in European regions. *Regional Studies*, 56, 1142–1160.
- Nathan, M., & Overman, H. (2020). Will coronavirus cause a big city exodus? *Environment and Planning B: Urban Analytics and City Science*, 47, 1537–1542.
- Naumann, E., Möhring, K., Reifenscheid, M., Wenz, A., Rettig, T., Lehrer, R., Krieger, U., Juhl, S., Friedel, S., Fikel, M., Cornesse, C., & Blom, A. G. (2020). COVID-19 policies in Germany and their social, political, and psychological consequences. *European Policy Analysis*, 6, 191–202.
- OECD. (2020). *Capacity for remote working can affect lockdown costs differently across places*. OECD Policy Responses to Coronavirus (COVID-19).
- Palomino, J. C., Rodríguez, J. G., & Sebastian, R. (2022). The COVID-19 shock on the labour market: Poverty and inequality effects across Spanish regions. *Regional Studies*. Advance online publication. 57(5), 814–828. <https://www.tandfonline.com/doi/full/10.1080/00343404.2022.2110227>

- Partridge, M., Chung, S., & Wertz, S. S. (2022). Lessons from the 2020 Covid recession for understanding regional resilience. *Journal of Regional Science*, 62, 1006–1031.
- Patterson, M. G. (1991). A note on the formulation of a full-analogue regression model of the shift-share method. *Journal of Regional Science*, 31, 211–216.
- Reissl, S., Caiani, A., Lamperti, F., Guerini, M., Vanni, F., Fagiolo, G., Ferraresi, T., Ghezzi, L., Napoletano, M., & Roventini, A. (2022). Assessing the economic impact of lockdowns in Italy: A computational input–output approach. *Industrial and Corporate Change*, 31, 358–409.
- Roberts, D. L., Rossman, J. S., & Jarić, I. (2021). Dating first cases of COVID-19. *PLoS Pathogens*, 17, e1009620.
- Roca, J. D. L., & Puga, D. (2017). Learning by working in big cities. *The Review of Economic Studies*, 84(1), 106–142.
- Rodríguez-Pose, A., & Burlina, C. (2021). Institutions and the uneven geography of the first wave of the COVID-19 pandemic. *Journal of Regional Science*, 61, 728–752.
- Rosenthal, S. S., Strange, W., & Urrego, J. (2021). Are citey centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19. *Journal of Urban Economics*, 127, 103381. <https://www.sciencedirect.com/science/article/abs/pii/S0094119021000632>
- Schlosser, F., Maier, B. F., Jack, O., Hinrichs, D., Zachariae, A., & Brockmann, D. (2020). Covid-19 lockdown induces disease-mitigating structural changes in mobility networks. *Proceedings of the National Academy of Sciences of the United States of America*, 117, 32883–32890.
- Xiao, J., Boschma, R., & Andersson, M. (2018). Resilience in the European Union: The effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations. *Industrial and Corporate Change*, 27, 15–47.

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