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

Silke Hamann[(a)], Annekatrin Niebuhr [(b)], Duncan Roth[(c)], Georg Sieglen[(d)]

Abstract

We estimate spatially heterogeneous effects of the COVID-19 pandemic on labour market dynamics in Germany until December 2021. While initially slightly larger in rural regions, adverse effects quickly become more pronounced and persistent in large agglomerations. 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 spillover effects from reduced product market demand in large cities caused by changes in behaviour such as working-from-home or online shopping are a possible explanation. Second, a higher pre-crisis unemployment rate in large agglomerations is associated with a lower outflow rate out of unemployment. This might reflect the less favourable composition of unemployment in large cities which reduces the probability of transitions into employment during crises.

JEL- Classification: J23, J63, R23

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1 Introduction

Global economic shocks can have heterogeneous regional effects. In analysing 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. Martin, 2012; Martin and Sunley, 2014; Doran and Fingleton, 2018). An extensive literature has provided evidence on the regional disparities concerning strength and consequences of the Great Recession (e.g. Groot et al., 2011; Fratesi and Rodriguez-Pose, 2016; Martin et al., 2016; Di Caro, 2017). Likewise, the Covid-19 pandemic represents a global crisis with 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 (Nathan and Overman, 2020; Florida et al., 2021; Rosenthal et al., 2021). However, empirical evidence concerning regional resilience to the Covid-19 pandemic and a possibly differential impact on agglomerations, in particular, remains scarce.

This paper addresses these points by estimating spatially heterogeneous effects of the Covid-19 pandemic on labour market dynamics in Germany until December 2021. The objective is to assess regional differences in the development of labour 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 labour market impact of the pandemic, but also its subsequent development. According to our results, the unfavourable impact on labour market transitions was initially most pronounced in rural regions. Subsequently, however, most regions quickly started to recover, while the ten largest agglomerations experienced a less favourable development. So far, the differential development turns out to be persistent. Our approach also allows us to decompose the overall effect on labour 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 labour markets. First, the pandemic has led to behavioural changes that seem to differ in their extent across regional labour markets because, among other things, there is important spatial variation in disease severity (e.g. Ascani et al., 2021; Desmet and Wacziarg, 2021; McCann et al., 2022). Chetty et al. (2020), for instance, show that high-income individuals in the U.S. 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 and 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 U.S., 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 et al. (2022a) show that increased working-from-home gave rise to a spatial shift in spending from previously consumption-intensive urban centres towards more residential areas in Germany.

Second, the design of policy measures can give rise to sector-specific shocks. This implies that the economic structure of regional labour 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 and 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 after shocks. Grabner and Modica (2022) examine industrial resilience in the U.S. 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 U.S. 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. (2022) also emphasize the importance of industrial structure for a region's resistance to the Covid-19 induced recession: regional specialisation in essential industries with low interpersonal interactions (e.g. non-store retail, financial and professional services) are significantly related to regional economic resistance. In contrast, U.S. states specialized in non-essential 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 labour markets in response to shocks (Martin et al., 2016; Fusillo et al., 2022). Palomino et al. (2022) show that the skill level is a key mediating factor of the pandemic effect on workers and labour 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). 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 pre-crisis labour market conditions. Analysing local authority districts in Great Britain, Houston (2020) finds that the pre-pandemic 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 for regional resilience. The findings on previous crises point to a beneficial impact of agglomeration on regional recovery (Capello et al., 2015; Di Caro and 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 labour 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., 2022). Containment measures such as social distancing and working-from-home, which reduce face-to-face contact, might reduce learning opportunities that cities provide.[1] Because human interaction and activity is 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

[1] Glaeser (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 labour markets may also decline because employers find it harder to onboard new workers online.

done remotely, which means that cities with their high share of knowledge-intensive jobs may experience a particularly strong decline of 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 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 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 labour market effects induced by the Covid-19 crisis? Only a few studies examine regional differences in the labour 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 non-pharmaceutical interventions on regional labour markets in Scandinavian countries. Their results indicate that all regions were severely hit by the crisis. Dall Schmidt and Mitze (2021) examine the local labour market effects of a regionally differentiated re-opening of public services in Denmark. According to their results, regions benefit from an earlier opening which led to a significant reduction in excess unemployment caused by the pandemic. Carvalo et al. (2022) use information from electronic payments and mobility data to provide evidence on regionally differentiated changes in behaviour 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 in 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 spillover effects from reduced product market demand. Big cities are characterised 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 behaviour 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, a higher pre-crisis unemployment rate in large agglomerations is associated with a lower outflow rate out of unemployment. This might reflect 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 discusses the different data sources and our measure of labour 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 Data and variables

2.1 Pandemic-induced changes in labour market transitions

We use administrative data from the German Federal Employment Agency (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 January 2017 until December 2021. Crucially for our analysis, the number of transitions can be differentiated by region and sector.

At the regional level, we employ the 141 functional labour 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 labour market regions into three categories based on their degree of urbanisation: rural regions, urbanised regions and agglomerations.[2] We further split the third category into large and small agglomerations as some studies indicate that the largest cities suffered from an above-average impact of the pandemic (e.g. Nathan and Overman, 2020).[3] At the sectoral level, we use 88 2-digit sectors according to the 2008 edition of the German classification of Economic Activities.

To evaluate how the pandemic has affected labour 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 two 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 two years earlier (see Lemieux et al. 2020 for a similar approach).[4] Third, we standardise 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 labour market shocks, the 2-year difference in the net inflow rates into unemployment would be expected to be close to zero. A negative labour 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 two years earlier. To better track the development of labour market transitions we use the cumulative sum. The advantage of a cumulative measure is that it allows an easy comparison of the current state of a regional labour market with the pre-pandemic situation. Our measures therefore enable us to directly evaluate two aspects of resilience: resistance to the initial shock and recovery, i.e. return to pre-crisis levels (see Martin and Sunley, 2014 for a discussion of different types of resilience). We refer to this quantity as the excess net inflow rate into unemployment.[5] 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 analyse 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.[6] 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 1,000 employees (relative to two years earlier). Evaluated at the total number of employees in June 2019, this implies an increase of 307,000

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[2] The classification uses the population share living in large and medium size cities, population density and population density excluding large and medium size cities (see https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/regionen/siedlungsstruktuelle-arbeitsmarktregionstypen/Arbeitsmarktregionen_Typen.html).

[3] We 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.

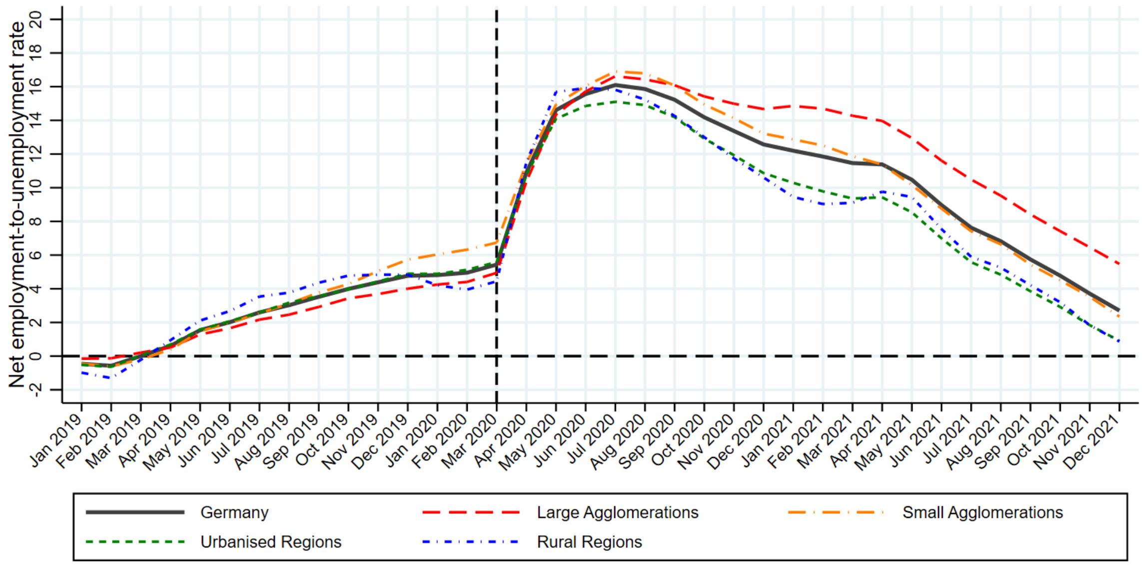
[4] This approach implies that observations from 2020 and 2021 are compared to different reference periods (2018 and 2019, respectively). In principle, differences in the results for these years could therefore be caused by the change in reference period. However, we show that using a constant reference period (the average of the years 2016-18) produces similar results. Table A3 in the Supplementary Material summarizes the results corresponding to Table 1 in the paper.

[5] For brevity, we sometimes drop the term excess.

[6] Figure A1 in the appendix shows corresponding measures for excess inflow rate and outflow rate.

net transitions. The differences between the region types were initially small, with rural areas experiencing a slightly larger increase than agglomerated or urbanised regions.

Figure 1: Development of net transition rate from employment to unemployment



Notes: Unit of observation is region-type-month. The vertical dashed line separates the pre-pandemic and the post-pandemic periods.
Source: Employment unemployment statistics of the FEA.

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 14 months to compensate for the increase in the net inflow rate during the first four 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 urbanised regions, it took longer in agglomerations and especially in large agglomerations, which – on average – recorded higher cumulated measures in every month since July 2020 than other region types. In December 2021, the cumulative measure of large agglomerations continued to exceed the pre-pandemic level and was still more than twice as high than in urbanised and rural regions.

Third, the pre-pandemic development shows that the net inflow rate into unemployment increased relative to the period two years earlier, indicating that the German labour 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 urbanised 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 labour market dynamics.

2.2 Potential sources of regional differences in labour market transitions

To investigate whether changes in mobility during the pandemic result in regional disparities in labour market transitions, we use daily mobility flows which 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 Online Appendix). To account for behavioural 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 labour market region (see also Figure A3 in the appendix).

Different studies emphasize the role of working-from-home for regional differences in the labour market effects of the pandemic. Following Alipour et al. (2022b), we calculate a measure of potential working-from-home use which 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 labour 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 to 9 workers), small (10 to 49 workers), medium-sized (50 to 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 one year of vocational training), skilled workers (at least two years of vocational training), specialists (advanced vocational training or bachelor degree), and experts (at least four years university education). Furthermore, we use the average regional unemployment rate in 2019 as a measure of initial labour 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 Appendix.

3 Empirical methodology

The aim of the empirical analysis is to assess regional differences in the development of labour 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 De la Roca and Puga (2017).[7] In the first stage, we address the possibility that regionally different labour 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 labour 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:

$$y_{ijt} = \eta_{it} + \sum_{g} \chi_{g(i)jt} I(i \in g) + \varphi_{ij} + u_{ijt} \qquad (1)$$

The excess net inflow rate, y_{ijt}, in region i, sector j and month t is decomposed into three components. First, a region-by-month component, η_{it}, which reflects differences in monthly labour market dynamics between regions. Second, a sector-by-month-by-region-type component, $\chi_{g(i)jt}$,

[7] However, 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.

which controls for sectoral shocks at the region type level.[8] Third, a region-sector-specific constant¸ φ_{ij}. u_{ijt} 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.

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 pre-pandemic period [9] to assess the differences in the development of labour market dynamics during the pandemic between the region types.[10] To account for the trends in the transition measures that are discernible in Figure 1 during the pre-pandemic period (and the seasonal patterns in the case of rural regions), we perform a de-trending procedure to generate adjusted region-month effects $\tilde{\eta}_{it}$ that we use as the dependent variable in the second stage regression (see the Online Appendix for a description of the procedure). The identifying assumption of the event-study model is that the expected development of regional labour market flows would have followed the pre-pandemic trend if the pandemic had not taken place. The difference-in-differences model is given by:

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

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 labour market transition measures differs on average between regional types g (urbanised regions being the reference category) in any month s. For the pre-pandemic period, we expect the estimated coefficients of ψ_s^g to be close to zero, which would indicate that the labour market transitions developed similarly in all region types. By contrast, differences in the estimated coefficients during the pandemic period would indicate that labour markets were differently affected by the pandemic.

To provide more evidence on the factors that give rise to regionally heterogenous effects of the pandemic, we extend the model given by Equation 2 and include different time-varying ($\boldsymbol{x_{it}}$) and time-invariant regional characteristics ($\boldsymbol{z_i}$). 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 structural characteristics of regions (establishment size structure, qualification structure, home office potential, pre-pandemic unemployment rate) and two factors that capture behavioural changes (regional infection rates, mobility changes). In our full model (Equation 3), the effects of the latter variables may also vary over time.

[8] Additional 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).
[9] While infections with SARS-CoV-2 were already detected in January 2020 in Germany, the first lockdown was imposed on 22 March 2020. As the administrative statistics on monthly transitions for March 2020 cover the period 16 February 2020 until 15 March 2020, genuine lockdown effects should not be visible in the March 2020 data.
[10] All region types are potentially affected by the Covid-19 pandemic, so that it is not possible to construct a control group of unaffected regions (Cerqua and 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.

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

The estimated coefficients from Equation 3 provide information on two issues. First, we analyse how these factors affect differences between region types, i.e. 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 labour markets (γ_s, δ_s).

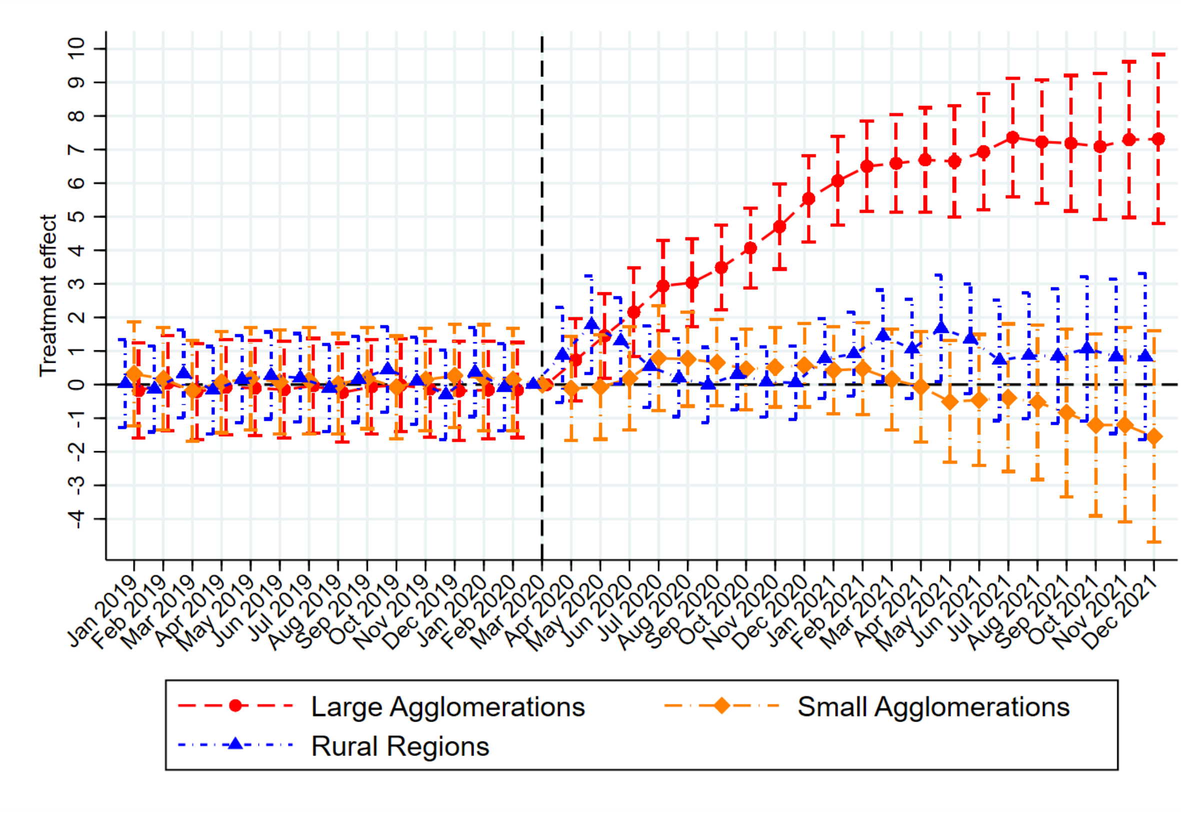
4 Results

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 pre-pandemic development can be seen from April 2020 onwards. The initial shock to labour markets was 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 (urbanised 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 1,600 additional transitions compared to the corresponding change in average urbanised 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 urbanised 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, i.e. 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).

In previous studies (e.g. Kim et al., 2022; 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, e.g. specialization in the tourism industry, that mark regions vulnerability to the economic impact of the pandemic. However, the unfavourable development of large agglomerations here is not due to sector-specific shocks and a specialisation 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.

Figure 2: Baseline difference-in-differences estimates - excess net inflow rate

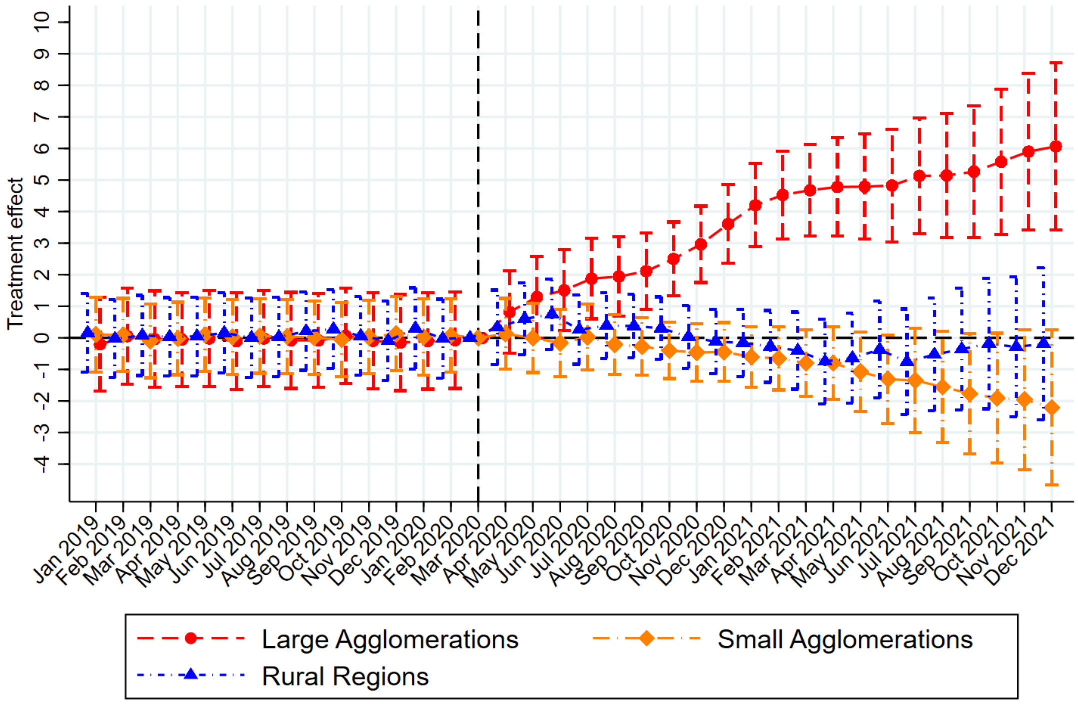


Notes: Unit of observation is region-month. The plot shows the estimated coefficients of the region group-month interactions in Equation 2 using the excess net inflow rate as the dependent variable. Urbanised regions are the reference category. Vertical lines indicate the 95% confidence interval. Robust standard errors are estimated.
Source: Employment and unemployment statistics of the FEA.

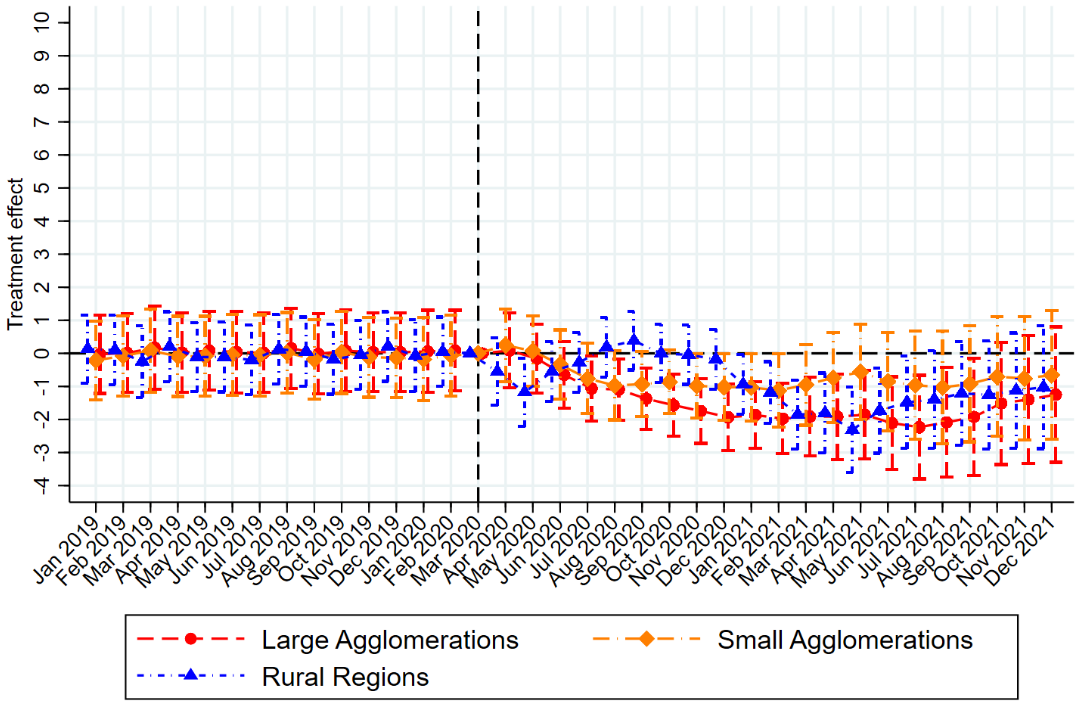
Estimating Equation 2 using the excess inflow rate from employment into unemployment and outflow rate from unemployment into employment allows us to decompose the regional differences in the development of the net rate. The corresponding results are shown in Panel A and Panel B of Figure 3. The results provide evidence that the unfavourable development in large agglomerations can be primarily ascribed to increases in the transition rate from employment into unemployment, which points towards 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 urbanised regions in terms of the inflow rate, while the development of flows into employment is temporarily less favourable.

Figure 3: Baseline difference-in-differences estimates - decomposing the excess net inflow rate

Panel A: Inflow rate from employment into unemployment



Panel B: Outflow rate from unemployment into employment



Notes: 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 (Panel A) and the excess outflow rate (Panel B) as the dependent variable. Urbanised regions are the reference category. Vertical lines indicate the 95% confidence interval. Robust standard errors are estimated. Source: Employment and unemployment statistics of the FEA.

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 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 behavioural changes that in turn may influence labour market outcomes. Potential behavioural 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 disproportionally affect labour markets in large cities.

In the second extension, we add a set of time-invariant variables that capture differences in the pre-pandemic labour 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 pre-pandemic (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.

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.[11] 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 unfavourable development of labour 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 1.3), though it remains statistically significant. 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

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

the former also affects the estimates for the other region types more strongly than the inclusion of mobility changes and infection rates.[12]

Table 1: Average difference-in-differences estimates

Period	**Baseline**	**Extension 1**	**Extension 2**	**Full model**
Panel A				
Excess net inflow rate from unemployment to employment				
Large agglomerations				
Pre-pandemic	-0.119	-0.016	-0.087	-0.195
	(0.523)	(0.535)	(0.764)	(0.691)
Pandemic	5.29***	5.19***	1.37*	1.3*
	(0.524)	(0.535)	(0.771)	(0.702)
Small agglomerations				
Pre-pandemic	0.117	0.155	0.127	-0.002
	(0.56)	(0.563)	(0.524)	(0.502)
Pandemic	-0.006	-0.181	-1.17**	-1.28**
	(0.549)	(0.571)	(0.535)	(0.514)
Rural regions				
Pre-pandemic	0.0922	0.111	0.163	-0.074
	(0.478)	(0.48)	(0.521)	(0.53)
Pandemic	0.835*	1.06**	0.763	0.54
	(0.483)	(0.489)	(0.527)	(0.536)
R^2	0.856	0.856	0.89	0.892
Panel B				
Excess inflow rate from employment to unemployment				
Large agglomerations				
Pre-pandemic	-0.0643	-0.0004	-0.144	0.061
	(0.555)	(0.563)	(0.679)	(0.742)
Pandemic	3.79***	3.76***	1.39**	1.59**
	(0.554)	(0.561)	(0.679)	(0.744)
Small agglomerations				
Pre-pandemic	0.0384	0.0488	-0.0289	0.037
	(0.427)	(0.424)	(0.431)	(0.452)
Pandemic	-0.801*	-0.914**	-1.17***	-1.08**
	(0.42)	(0.428)	(0.431)	(0.454)
Rural regions				
Pre-pandemic	.0863	.0807	.0564	.078
	(0.458)	(0.457)	(0.497)	(0.494)
Pandemic	-0.0941	-0.017	.252	.277
	(0.461)	(0.466)	(0.501)	(0.497)
R^2	.749	.752	.818	.82
Panel C				
Excess outflow rate from unemployment to employment				
Large agglomerations				
Pre-pandemic	0.0548	0.0153	-0.0579	0.256
	(0.438)	(0.44)	(0.624)	(0.583)
Pandemic	-1.5***	-1.43***	0.0183	0.293
	(0.437)	(0.439)	(0.627)	(0.586)
Small agglomerations				
Pre-pandemic	-0.079	-0.106	-0.156	0.0386
	(0.443)	(0.445)	(0.45)	(0.437)
Pandemic	-0.795*	-0.733*	-0.00507	0.201
	(0.431)	(0.444)	(0.453)	(0.441)
Rural regions				

[12] We further show that the findings for large agglomerations are not driven by a single region. Table A4 in the appendix 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.

Pre-pandemic	-0.0059	-0.03	-0.106	0.152
	(0.385)	(0.386)	(0.468)	(0.451)
Pandemic	-0.929**	-1.08***	-0.511	-0.263
	(0.386)	(0.392)	(0.469)	(0.452)
R^2	0.689	0.692	0.754	0.759
N	5,076	5,076	5,076	5,076
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: urbanised regions). Robust standard errors shown in parentheses. ***/**/* indicate statistical significance at the 0.01/0.05/0.1 level. *Control variables are: infection rate, mobility index (time-variant), pre-pandemic home office potential, unemployment rate, skill structure, establishment size structure (time-invariant).*
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

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 out of unemployment there are no significant differences between large agglomerations and the urbanised regions once we include structural characteristics. The estimate of the average pandemic effect for the transition rate into unemployment is also reduced (-58%), but remains statistically significant in the full model. This suggests that there are additional factors which contribute to the relatively strong impact of the pandemic and operate via more inflows into unemployment. The factors that we consider, in sum, 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 only marginally significant for rural regions. However, 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 suggest that the causes, which appear to hamper economic recovery after the pandemic in large and small agglomerations, are similar but stronger in large cities. Labour market dynamics also appear to be negatively affected by these factors in rural regions: while we detect a significant positive effect for the net transition rate in the baseline model, rural regions do not differ from the reference group in the full model. However, in contrast to large agglomerations, this is primarily due to transitions from unemployment to employment. The changes in the average pandemic difference-in-differences estimates caused by the extension of the model are much larger on the outflow side (-0.929 versus -0.263) than on the inflow side (-0.094 versus 0.277).

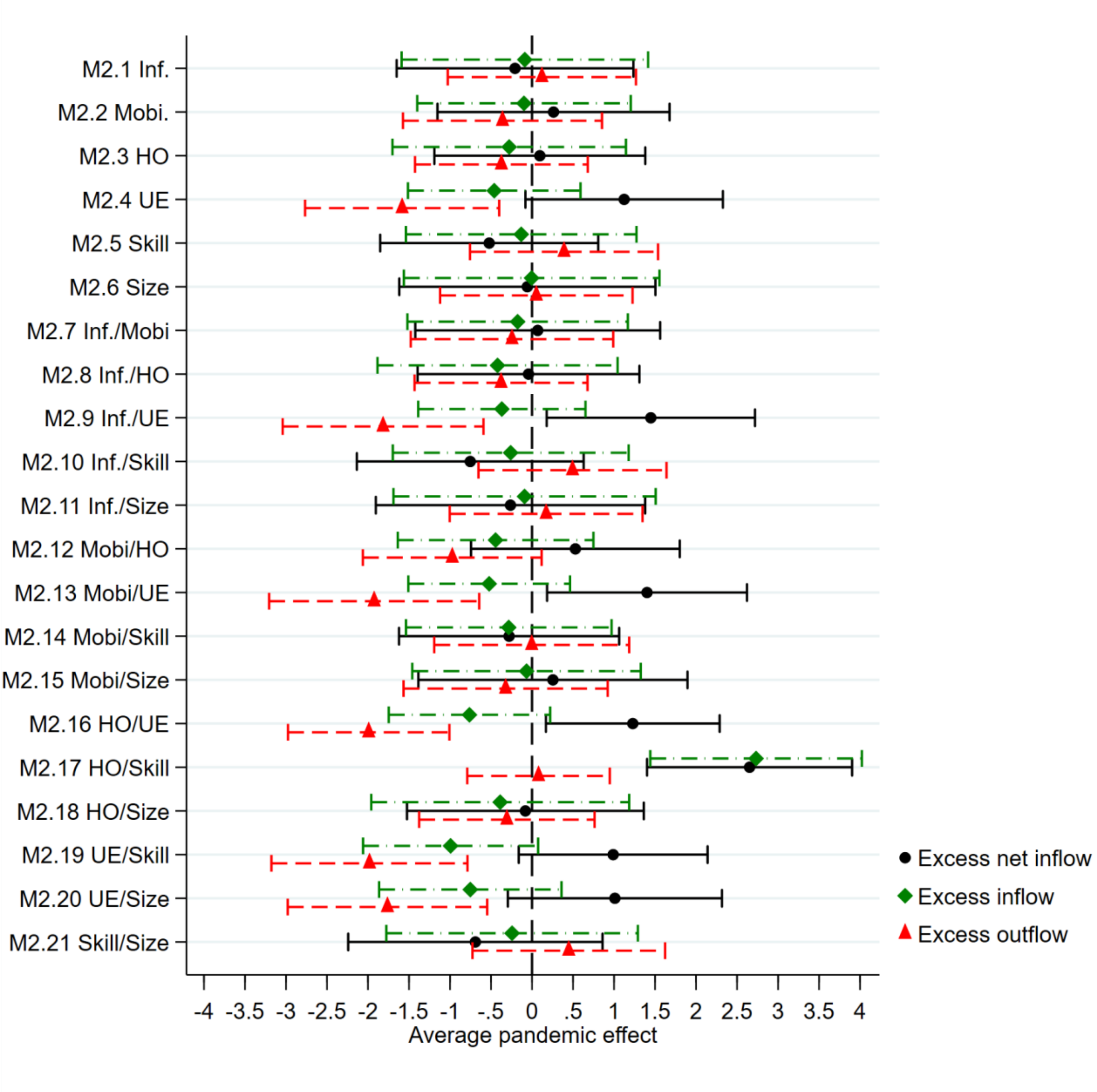
4.3 Relevance of individual factors

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 A5 and A6 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 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 or in combination with other variables (model M2.9, M2.13 or M2.16). This increase is smaller than in model M2.17 and is driven by a reduction in outflows from unemployment into employment. We discuss both findings in turn.

Figure 4: Relevance of individual factors and combinations of factors – large agglomerations



Notes: 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

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

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 favourable development of the excess net inflow rate into unemployment in large agglomerations.[13] 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 unfavourable 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 et al. (2022a), we interpret the result as pointing to a drop in consumption spending caused by the absence of (high-income) consumers or commuters in city centres due to working-from-home, which may primarily affect retail sale and restaurants. Other industries in large cities might also be impaired via local input-output linkages. This does not imply that workers in working-from-home jobs experienced excess transitions into unemployment, but rather that the absence of commuting into city centres led to a loss of employment in retail sales or hospitality jobs.[14]

Regional pre-pandemic unemployment and its composition. Higher excess net inflow rates into unemployment in large agglomerations also appear to be due to less favourable 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 A4, 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 the decisive role of the pre-crisis unemployment for regional resilience during the Covid-19 crisis is also provided by Cochrane et al. (2022) who show that the strongest predictor of a post-shock increase in unemployment benefits is the unemployment rate two years earlier. Moreover, results by Brown and Cowling (2021) also underline the importance of unfavourable pre-crisis labour 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 Figure A5 and A6 in the Online Appendix). 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, pointing to weaker effects of the factors that are also relevant for large agglomerations. In particular, the variation introduced by the omission of the regional working-from-home potential and the skill structure is less important in the case of small agglomerations, indicating that the supposed loss of consumer demand might be less pronounced in these regions. For rural regions, we can hardly detect significant differences from the full model and relevant factors seem to differ from those identified for the agglomerations. The most pronounced changes are linked to establishment size and factor combinations that include the establishment size structure. We discuss the role of the size structure in more detail in section 4.4,

[13] In contrast, Grabner and Tsvetkova (2022) show that the pre-pandemic share of jobs that can be performed remotely correlates positively with labour 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.

[14] We further argue that the fact that the deviation from the full model only occurs when both variables are removed is due to the fact that the working-from-home share as well as the share of high-skilled workers are highly correlated (the 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.

which focuses on dynamics and different phases of the pandemic, because these effects vary considerably during the pandemic.

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 pre-pandemic period.

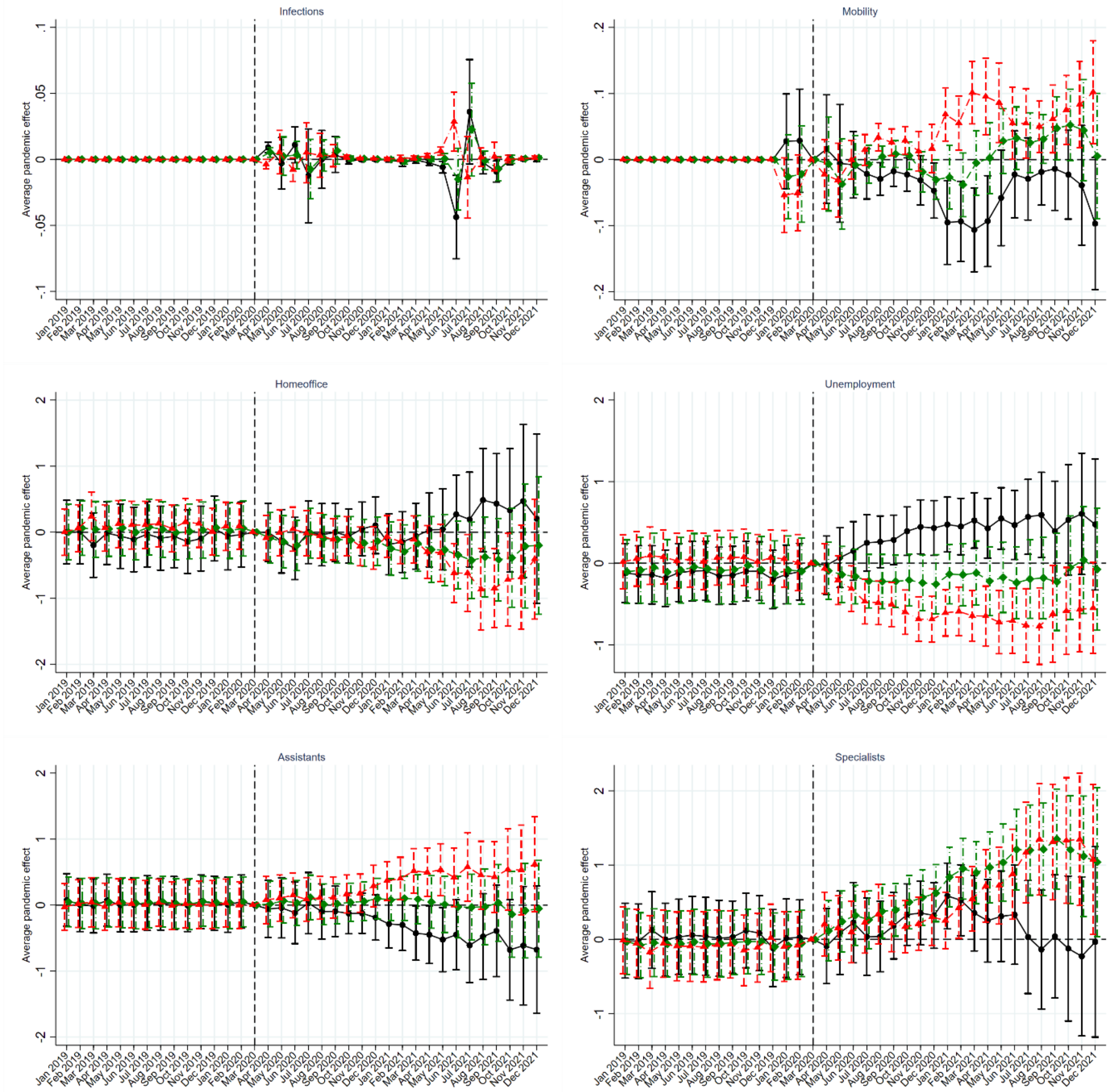
Variation in regional infection rates is not related to changes in the inflow and outflow rates for most of the pandemic period. Larger effects are found during the early stages of the pandemic as well as during the summer of 2021, though they are often statistically insignificant. By contrast, changes in mobility tend to have larger effects, in particular during the second wave of the pandemic (December 2020 to April 2021) and later in the pandemic. Mobility changes influence regional labour 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 favourable development of labour market transitions.

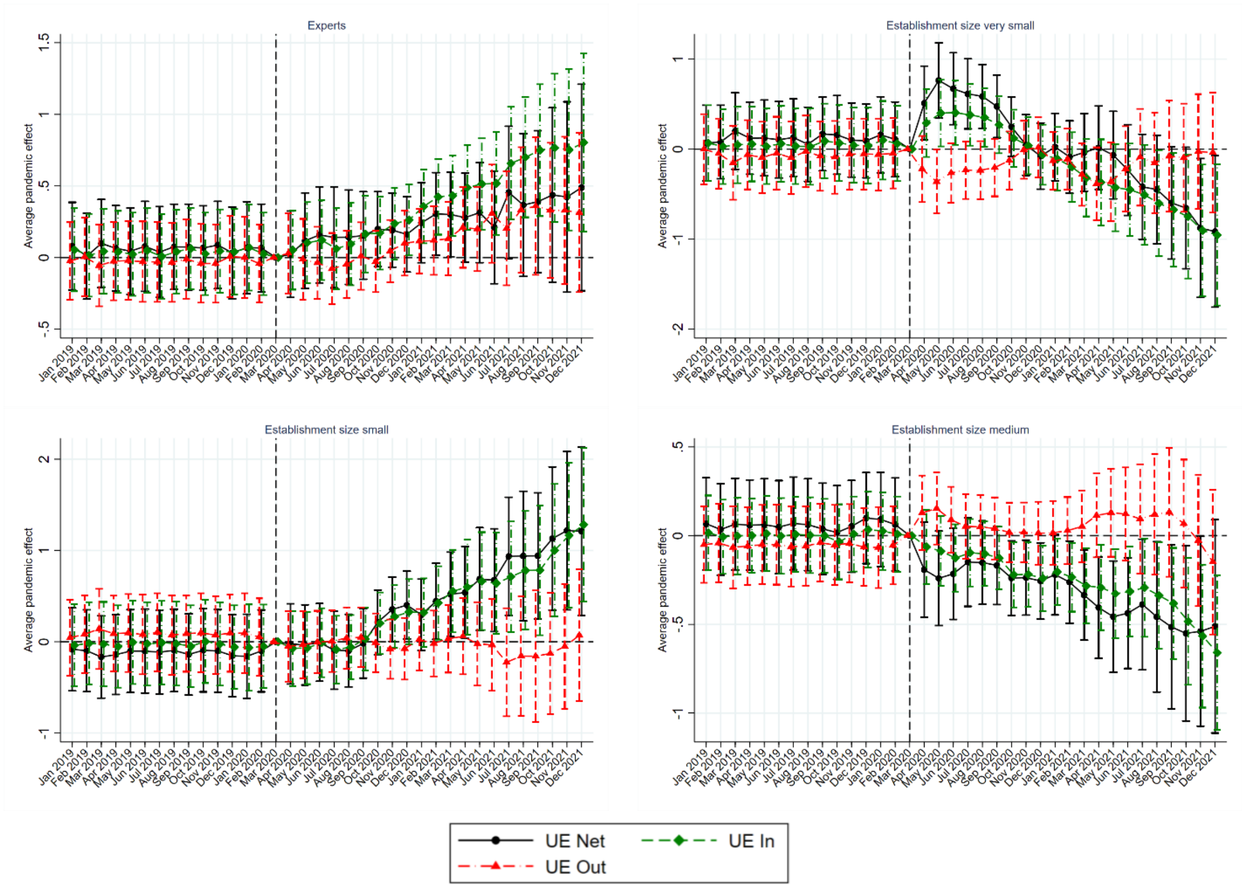
The working-from-home potential also influences transitions into employment. However, we find important dampening effects on the outflow from unemployment only towards the end of the period. In contrast, the pre-crisis unemployment rate starts to adversely affect outflows early in the pandemic, with the strength of the effects increasing until November 2020 and then remaining more or less at this level. The effects of the pre-pandemic 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 pre-pandemic unemployment between autumn 2020 until August 2021 due to the unfavourable impact on the outflows from unemployment.

We find a differentiated impact of the qualification structure on both inflow and outflow rates. Regional labour markets with a relatively high share of low-skilled assistant workers are characterised by a fairly favourable 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 February 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 labour markets. Both effects increase in size until June/July 2021 before stabilising at a similar level thereafter. As a result, the effect on the net inflow rate is statistically significant in January/February 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 November 2020 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.

Finally, we detect various effects of the regional establishment size structure, which operate primarily via inflows into unemployment. According to our results, the influence of a higher share of very small establishments (1 to 9 workers) changes considerably across the different stages of the pandemic. While a relatively high percentage of very small establishments in local labour markets is associated with unfavourable 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 than other areas. By contrast, a significant adverse effect on transitions into employment is only found in May 2020. Beginning in May 2020, the impact on the inflow side starts to decrease and eventually becomes significantly negative from August 2021 onwards. Financial stress might have been stronger on average in areas characterised 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. However, advantages of very small establishments seem to prevail thereafter. Similar changes are observed for the share of medium-sized establishments. In contrast, a relatively high percentage of small firms (10 to 49 workers) seems to become increasingly a burden for the recovery of regional labour markets - an effect that is driven by relatively more transitions into unemployment from autumn 2020 onwards.

Figure 5: Dynamic effects of control variables





Notes: 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 are estimated.
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

5 Conclusion

We use a two-stage regression approach to examine regional disparities in labour 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 labour 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 first evidence on possible persistence of effects on regional labour 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 labour markets and large agglomerations. However, while most regions subsequently recovered quickly, large agglomerations experienced a less favourable 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 Marcén and Morales, 2021; Carvalo et al., 2022; Partridge et al., 2022).

A significant part of the disparities between large agglomerations and other regions is due to differences in pre-crisis labour market conditions. A higher initial unemployment rate in large cities seems to impede transitions from unemployment to a new job. Moreover, large agglomerations are characterised 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 behaviour 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 et al., 2022a; 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 unfavourable 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. De Fraja et al., 2020; Barrero et al., 2021;) and large cities generally show a higher potential for remote work than rural areas (OECD, 2020).

The findings also indicate that examining net labour 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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Online appendix

Data and variables

De-trending of region-month effects for second stage regression

Due to the trends in the transition measures that are discernible in Figure 1 during the pre-pandemic period (and the seasonal patterns in the case of rural regions), we do not use the estimated region-month effects from Equation 1, $\hat{\eta}_{it}$, as the dependent variable in the second stage. Instead, we perform a de-trending procedure in which the region-month effects from the first stage are regressed against a linear trend and quarterly dummies separately for each region and using observations from the pre-pandemic period only (we use superscript i in the following to indicate that separate models are estimated for each region):

$$\hat{\eta}_t^i = \alpha_0^i + \alpha_1^i t + \sum_{q=2}^{4} \beta_q^i I(i \in q) + v_t^i, if\ t\ \leq March\ 2020$$

Based on the estimated coefficients from this equation, we extrapolate the relationship into the period from April 2020 onwards. The predicted values from this extrapolation present the estimates of how a region's labour market would have developed in the absence of the pandemic. A comparison between the estimated first-stage region-month components and these counterfactuals provide the basis for the empirical evaluation of whether and how regional labour markets were affected differently by the pandemic. We therefore compute the difference between the estimated region-month effects from the first stage on the one hand and the predicted values from the equation above (for the pre-pandemic period) and the linear extrapolation (for the pandemic period) on the other hand, which we label $\tilde{\eta}_{it}$ and use as dependent variable in the second stage regression.

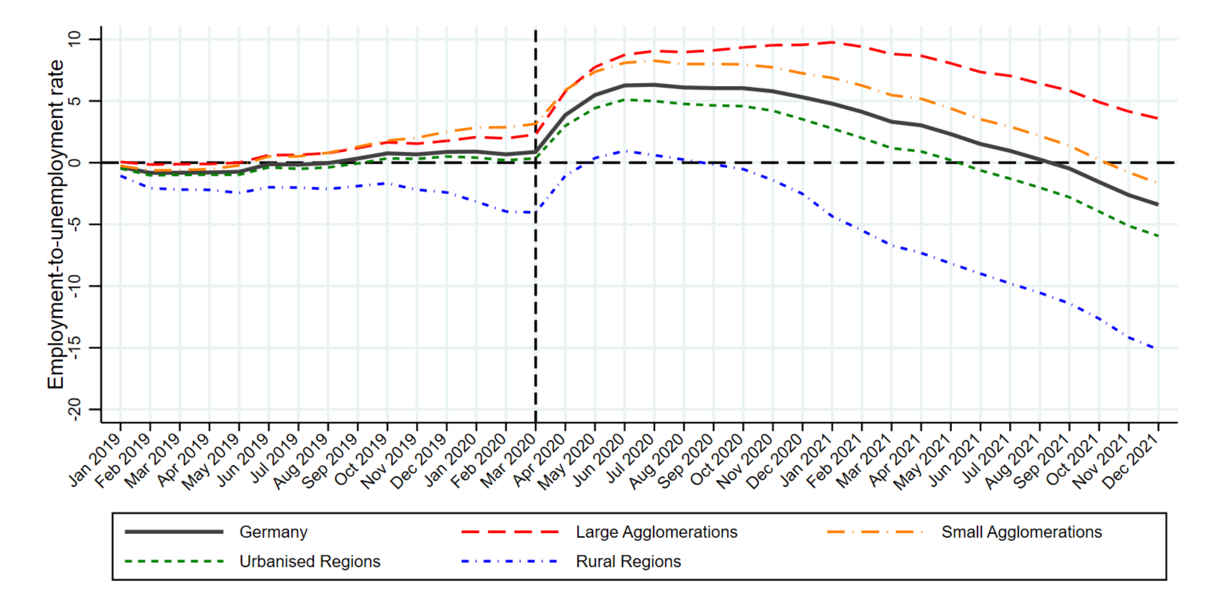
Labour market transitions

Figure A1 provides additional insights into the development of labour market transitions by decomposing net transitions (Figure 1) into an entry-into-unemployment (Panel A) and an exit-from-unemployment (Panel B) component. Both measures are constructed in the same way as the net transitions into unemployment and are based on a comparison of the contemporaneous flow from employment into unemployment and from unemployment into employment, respectively, with the corresponding flow observed two years earlier. For a given month and region-sector cell the difference between the entry-into-unemployment and the exit-from-unemployment measure is identical to the measure of the net transitions into unemployment.

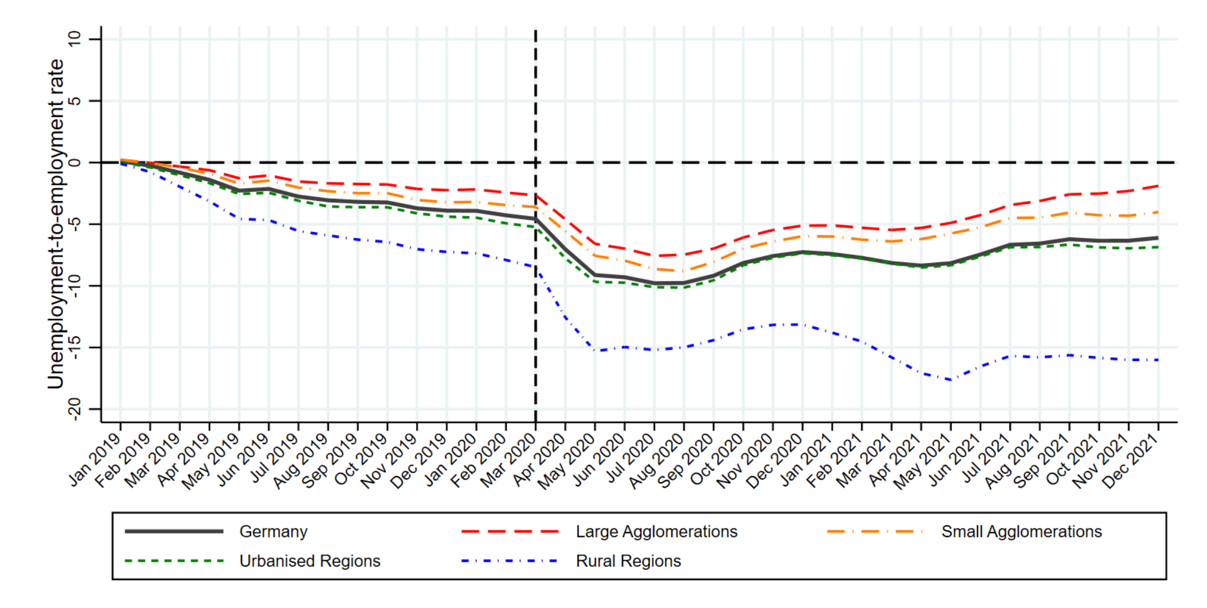
The national pattern of both quantities is similar in as far as there is a jump in value from March to May 2020. The recovery appears to set in earlier for the exits from unemployment than for the entries into unemployment, which implies that transitions from unemployment into employment started increasing before the number of transitions from employment into unemployment began falling. However, while the development of entries into unemployment improved continuously, exits from unemployment plateaued from December 2020 onwards. More importantly, there appear to be considerable differences between the region types with respect to the importance of the two channels. While small and large agglomerations experienced a comparatively large increase of entries into unemployment, the impact on exits from unemployment was less pronounced. The opposite is the case for rural areas where the development of exits from unemployment appears to be more disadvantageous.

Figure A1: Development of labour market transitions

Panel A: Excess inflow rate from employment into unemployment



Panel B: Excess outflow rate from unemployment into employment



Notes: Unit of observation is region-type-month. The vertical dashed line separates the pre-pandemic and the post-pandemic periods.
Source: Employment unemployment statistics of the FEA.

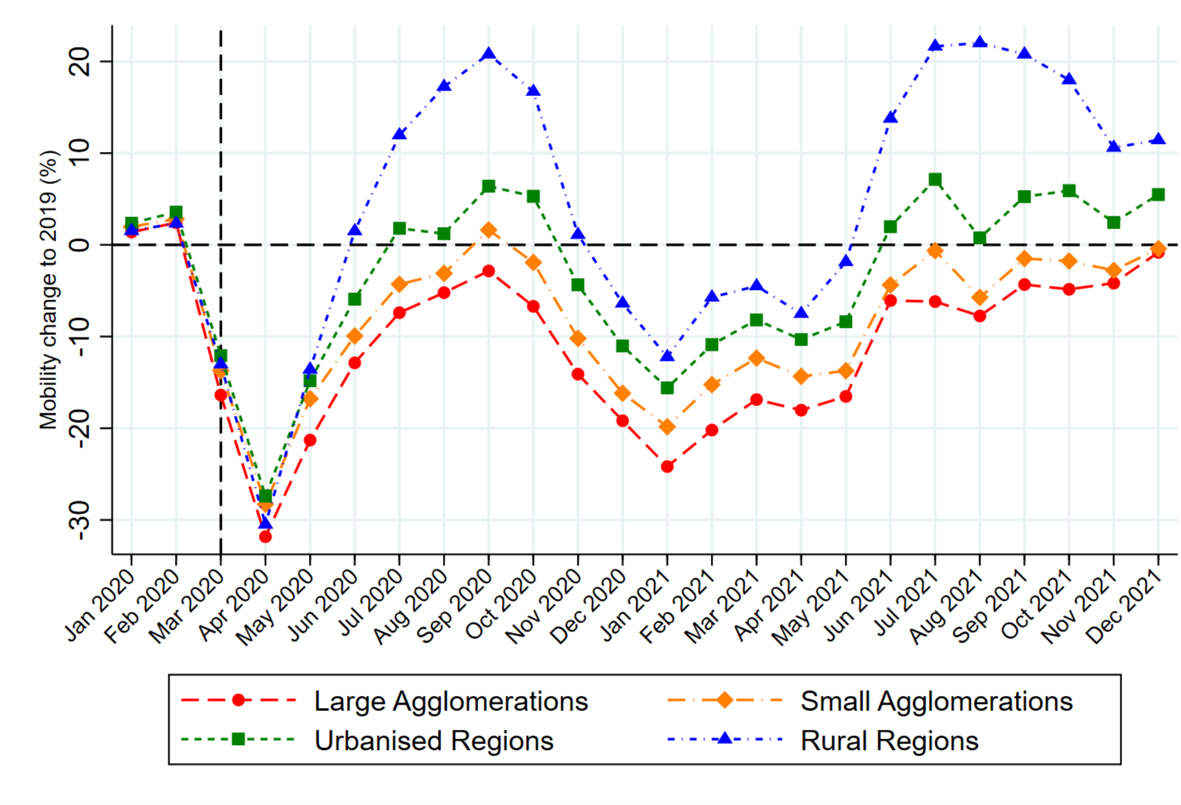
Control variables

The mobility flows are collected by the provider Telefónica who registers which devices are connected to specific cell towers. A movement is identified as a switch of the cell tower area. The raw data are aggregated by Teralytics. In order to determine the mobility change, a daily flow in 2020 is compared with the flow observed for the corresponding weekday in the same month in 2019 (see Schlosser et al. 2020 for a detailed description). The information on the movements is available for the period January 2019 to December 2021. Thus, we cannot calculate the change in mobility between 2019 and 2018.

For the empirical analysis, we assume that there are no significant changes between the two years. In the regression analysis, we use the monthly average of daily changes relative to the base year 2019.

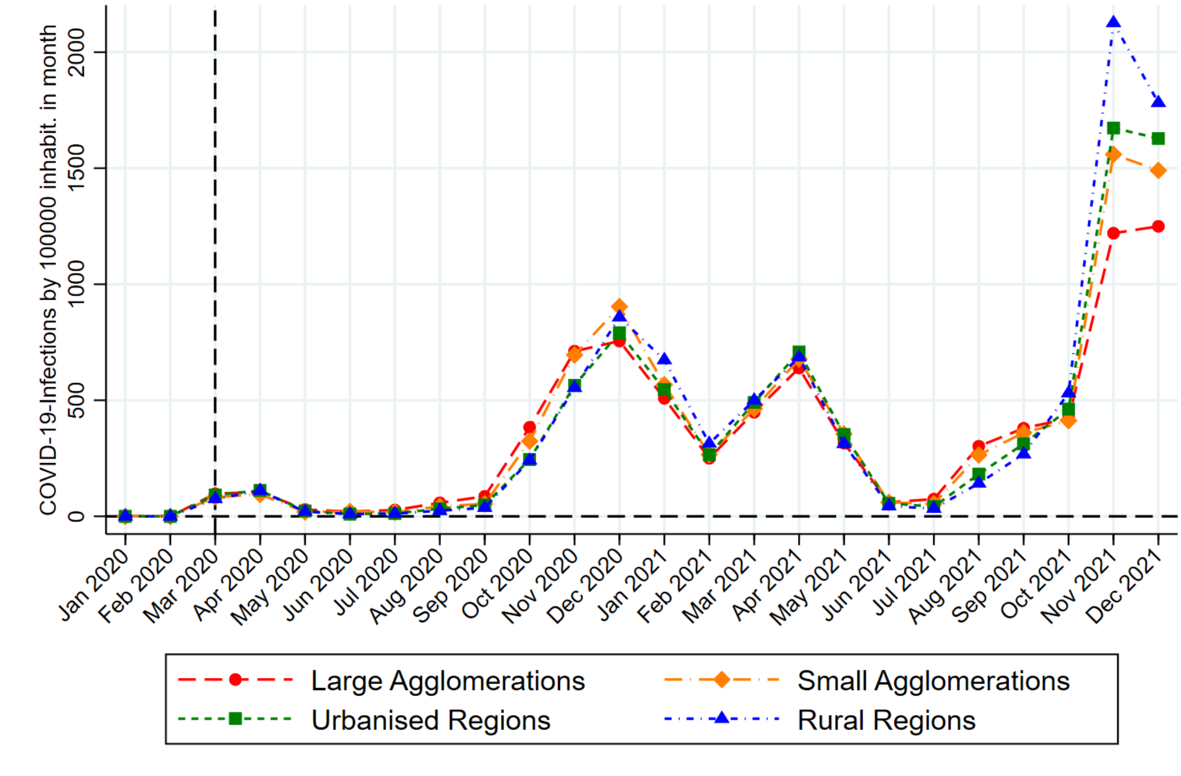
The initial shock in Spring 2020 gave rise to a strong decline of movements by around 30% in all region types (see Figure A2). Mobility in large agglomerations remained below the level in 2019 throughout the period under consideration, while rural areas in particular quickly returned to the pre-crisis level and actually experienced a significant excess mobility in summer and early autumn in both years of the pandemic.

Figure A2: Change in mobility



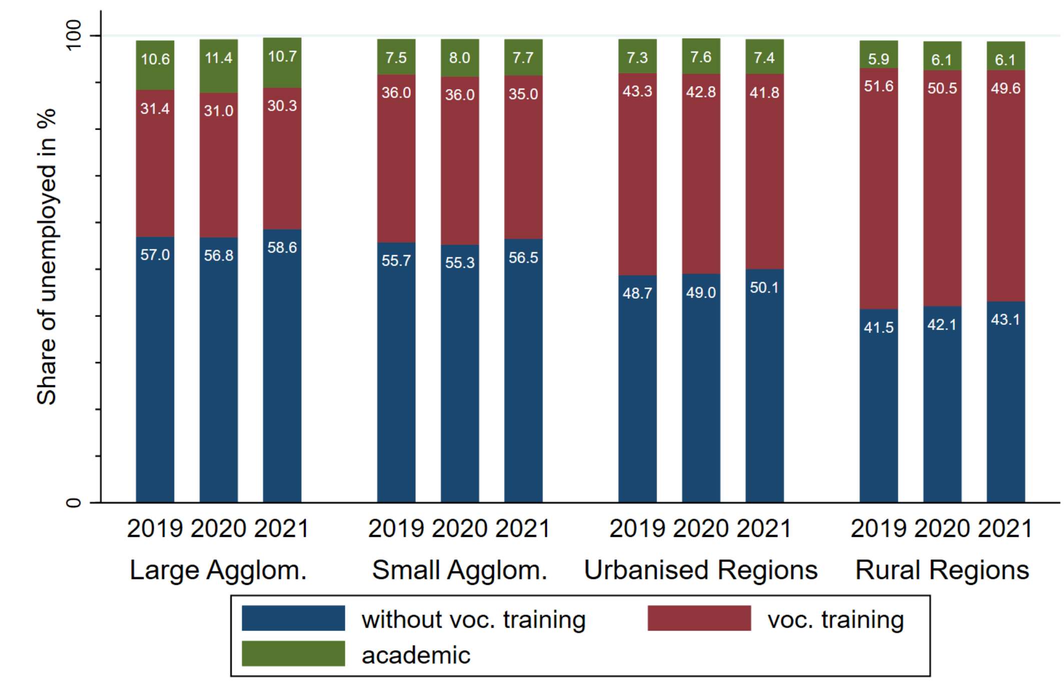
Notes: The unit of observation is region-type-month. The figure shows monthly changes in mobility (relative to the corresponding month in 2019) based on mobile phone data.
Source: COVID-19 Mobility Project, Teralytics.

Figure A3: Covid-19 infection rates



Notes: The unit of observation is region-type-month. The figure shows monthly incidence rate per 1000,000 inhabitants by region- type.
Source: Corona-Datenplattform.

Figure A4: Unemployment by vocational degree



Notes: The figure shows average yearly shares of unemployed by vocational degree in all unemployed and by region type.
Source: Unemployment statistics of the FEA.

Table A1: Descriptive statistics

Variables	N	Mean	SD	Min	Max
Excess transition rate					
Net employment-to-unemployment	421,872	-1.45	1,640	-179,000	103,000
Employment-to-unemployment	421,872	-28.03	1,604	-181,000	31,500
Unemployment-to-employment	421,872	-26.58	783	-122,000	6,000
Estimated region-month effects from first-stage					
Net employment-to-unemployment	5,076	-0.87	7	-40	20
Employment-to-unemployment	5,076	-0.28	5	-51	19
Unemployment-to-employment	5,076	0.59	4	-34	28
Regional qualification structure					
Employment share assistants	141	16.73	2	11	23
Employment share skilled worker	141	60.46	3	49	67
Employment share specialists	141	11.31	2	8	17
Employment share experts	141	10.81	3	6	23
Employment share unknown	141	0.69	1	0	3
Regional firm size structure					
Employment share 1 - 9 employees	141	16.41	3	9	25
Employment share 10 - 49 employees	141	25.83	3	15	34
Employment share 50 - 249 employees	141	28.95	3	16	36
Employment share > 249 employees	141	28.81	8	11	59
Monthly COVID-Infections per 100,000 inhabitants	5,076	245.64	499	0	5809
Change in mobility relative to 2019 (%)	5,076	-0.09	14	-56	133
Share of employees in occupations suitable for working-from-home	141	52.67	3	47	63
Average unemployment rate 2019	141	4.71	2	2	11
Average number of employees 2019 (region-sector)	11,388	2,933.39	7,115	1	133,731
Average number of employees 2019 (region)	141	236,918.00	287,615	20,049	1,727,354

Notes: Unit of observation is region-sector-month (421,872 observations), region-sector (11,388), region-month (4,794) or region (141 observations).
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

Table A2: Descriptive statistics by region-type

Variables	Large agglomerations		Small agglomerations		Urbanised regions		Rural regions	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Excess transition rate								
Net employment-to-unemployment	2.15	229	8.50	435	6.69	395	-15.59	2585
Employment-to-unemployment	-15.63	371	-14.28	438	-8.09	382	-57.51	2533
Unemployment-to-employment	-17.78	250	-22.77	401	-14.78	275	-41.92	1170
Estimated region-month effects from first-stage								
Net employment-to-unemployment	1.69	5	-1.52	7	-1.31	7	-0.65	7
Employment-to-unemployment	1.57	4	-0.73	5	-0.26	5	-0.45	6
Unemployment-to-employment	-0.12	3	0.79	4	1.04	5	0.21	4
Regional qualification structure								
Employment share assistants	14.12	2	17.04	3	16.83	2	16.98	2
Employment share skilled worker	55.13	3	57.70	3	60.44	3	62.61	2
Employment share specialists	14.30	2	12.26	2	11.31	2	10.36	1
Employment share experts	15.99	3	12.48	3	10.75	3	9.23	2
Employment share unknown	0.45	0	0.53	0	0.68	0	0.82	1
Regional firm size structure								
Employment share 1 - 9 employees	14.14	1	15.38	2	15.44	2	18.18	3
Employment share 10 - 49 employees	21.68	1	23.77	2	25.26	3	28.01	3
Employment share 50 - 249 employees	26.51	1	27.73	2	29.14	3	29.73	3
Employment share > 249 employees	37.67	3	33.12	6	30.16	7	24.08	6
Monthly COVID-Infections per 100,000 inhabitants	224.03	337	237.70	434	238.93	473	259.35	567
Change in mobility relative to 2019 (%)	-7.08	9	-4.79	8	-1.18	11	4.18	17
Share of employees in occupations suitable for working-from-home	58.98	3	54.79	3	52.72	2	50.59	2
Average unemployment rate 2019	6.07	2	5.13	2	4.15	2	4.83	2
Average number of employees 2019 (region-sector)	12,680	18,952	3,737	6,021	2,330	4,284	1,242	2,266
Average number of employees 2019 (region)	1,094,280	419,983	308.902	149,020	187,825	111,573	98,240	61,225

Notes: The table shows descriptive statistics for the regions contained in each region type.
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

Results

Table A3: Average difference-in-differences estimates – 2016-2018 reference period

Period	Baseline	Full model
	Panel A	
	Excess net inflow rate from unemployment to employment)	
	Large agglomerations	
Pre-pandemic	0.0192	0.0683
	(0.498)	(0.52)
Pandemic	3.75***	1.37***
	(0.492)	(0.525)
	Small agglomerations	
Pre-pandemic	0.167	0.141
	(0.436)	(0.367)
Pandemic	0.246	-0.969***
	(0.423)	(0.374)
	Rural regions	
Pre-pandemic	-0.178	-0.208
	(0.352)	(0.359)
Pandemic	0.965***	0.234
	(0.354)	(0.363)
R^2	.851	.911
	Panel B	
	Excess inflow rate from employment to unemployment	
	Large agglomerations	
Pre-pandemic	-0.12	-0.0338
	(0.484)	(0.663)
Pandemic	4.14***	2.54***
	(0.481)	(0.663)
	Small agglomerations	
Pre-pandemic	-0.0133	0.00532
	(0.341)	(0.373)
Pandemic	.103	-0.338
	(0.334)	(0.373)
	Rural regions	
Pre-pandemic	.108	.0466
	(0.368)	(0.347)
Pandemic	-1.35***	-0.431
	(0.368)	(0.35)
R^2	.806	.885
	Panel C	
	Excess outflow rate from unemployment to employment	
	Large agglomerations	
Pre-pandemic	0.209	-0.152
	(0.461)	(0.462)
Pandemic	0.754*	1.13**
	(0.457)	(0.463)
	Small agglomerations	
Pre-pandemic	0.0823	-0.0254
	(0.418)	(0.315)
Pandemic	0.11	0.748**
	(0.407)	(0.318)
	Rural regions	
Pre-pandemic	-0.0671	0.126
	(0.463)	(0.31)
Pandemic	-2.68***	-0.808***
	(0.461)	(0.312)
R^2	0.626	0.859
N	5,076	5,076

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 for large agglomerations (reference category: urbanised regions). Each column shows the results when a single region is excluded from the sample. Robust standard errors shown in parentheses. ***/**/* indicate statistical significance at the 0.01/0.05/0.1 level. The baseline model includes no additional control variables. The full model includes time-variant (*infection rate, mobility index) and time-invariant control variables (pre-pandemic home office potential, unemployment rate, skill structure, establishment size structure). All control variables are interacted with month dummies.*

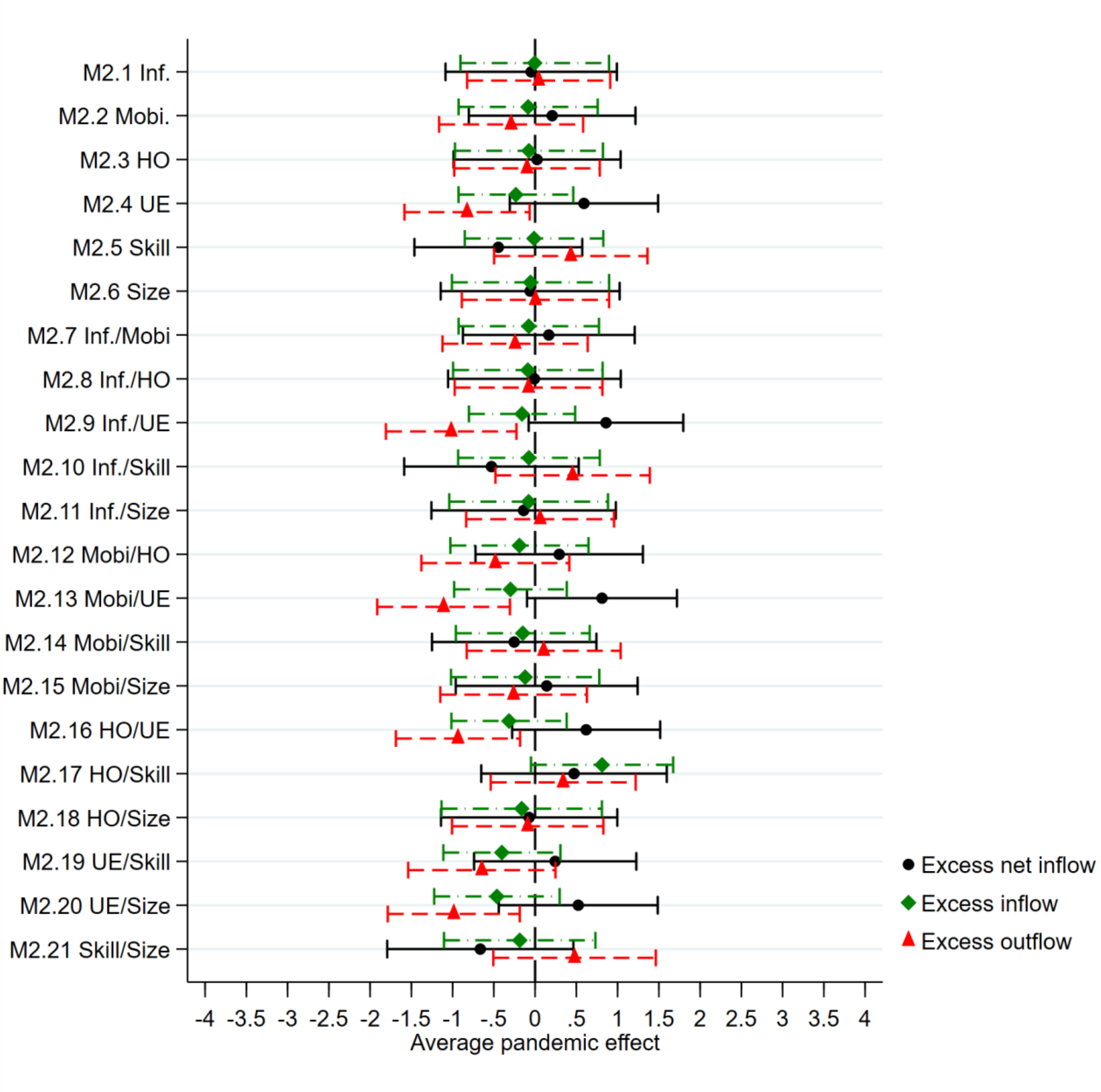
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

Table A4: Average difference-in-differences estimates – removing single regions (large agglomerations)

Period	Hamburg	Hannover	Düsseldorf	Essen	Köln	Bochum	Frankfurt	Stuttgart	München	Berlin
					Panel A					
					Excess net inflow rate from unemployment to employment					
					Baseline model					
Pre-pandemic	-0.123	-0.102	-0.0923	-0.119	-0.113	-0.125	-0.124	-0.141	-0.123	-0.131
	(0.55)	(0.533)	(0.549)	(0.537)	(0.562)	(0.532)	(0.57)	(0.433)	(0.574)	(0.542)
Pandemic	4.9***	5.42***	5.46***	5.44***	5.29***	5.4***	5.23***	5.89***	4.95***	4.8***
	(0.55)	(0.534)	(0.549)	(0.538)	(0.563)	(0.533)	(0.57)	(0.438)	(0.573)	(0.542)
R^2	0.853	0.855	0.853	0.855	0.853	0.856	0.853	0.861	0.853	0.85
					Full model					
Pre-pandemic	-0.16	-0.106	-0.176	-0.24	-0.212	-0.219	-0.131	-0.205	-0.263	-0.205
	(0.679)	(0.74)	(0.691)	(0.695)	(0.701)	(0.725)	(0.717)	(0.619)	(0.749)	(0.7)
Pandemic	0.791	1.39*	1.36*	1.23*	1.31*	1.32*	1.2*	2.26***	1.24	1.24*
	(0.692)	(0.753)	(0.702)	(0.706)	(0.712)	(0.737)	(0.727)	(0.631)	(0.759)	(0.709)
R^2	0.89	0.891	0.89	0.891	0.89	0.891	0.89	0.897	0.889	0.887
					Panel B					
					Excess inflow rate from employment to unemployment					
					Baseline model					
Pre-pandemic	-0.0684	-0.0387	-0.0674	-0.0705	-0.0742	-0.0711	-0.0642	-0.0743	-0.0559	-0.058
	(0.625)	(0.582)	(0.589)	(0.55)	(0.598)	(0.528)	(0.611)	(0.549)	(0.536)	(0.59)
Pandemic	3.78***	3.83***	3.99***	4.07***	3.71***	4.08***	3.69***	4.18***	3.12***	3.29***
	(0.623)	(0.58)	(0.588)	(0.55)	(0.597)	(0.527)	(0.609)	(0.548)	(0.531)	(0.589)
R^2	0.743	0.747	0.743	0.752	0.746	0.759	0.744	0.753	0.749	0.738
					Full model					
Pre-pandemic	-0.0101	0.152	0.0598	0.0523	0.0357	0.0321	0.103	0.244	0.0293	0.0643
	(0.78)	(0.746)	(0.744)	(0.761)	(0.733)	(0.736)	(0.788)	(0.548)	(0.805)	(0.739)
Pandemic	1.77**	1.25*	1.66**	1.54**	1.53**	1.94***	1.55*	2.75***	1.43*	1.71**
	(0.783)	(0.749)	(0.745)	(0.763)	(0.735)	(0.739)	(0.79)	(0.551)	(0.805)	(0.741)
R^2	0.817	0.821	0.817	0.82	0.819	0.819	0.816	0.831	0.807	0.812
					Panel C					
					Excess outflow rate from unemployment to employment					
					Baseline model					
Pre-pandemic	0.0547	0.0634	0.0248	0.0485	0.0383	0.0542	0.0594	0.0664	0.0667	0.0735
	(0.415)	(0.455)	(0.464)	(0.444)	(0.462)	(0.427)	(0.475)	(0.448)	(0.413)	(0.492)
Pandemic	-1.12***	-1.59***	-1.47***	-1.36***	-1.58***	-1.31***	-1.53***	-1.71***	-1.83***	-1.51***
	(0.414)	(0.454)	(0.463)	(0.444)	(0.461)	(0.426)	(0.473)	(0.447)	(0.413)	(0.49)
R^2	0.69	0.686	0.69	0.688	0.683	0.692	0.687	0.686	0.686	0.679
					Full model					
Pre-pandemic	0.149	0.259	0.236	0.293	0.248	0.252	0.234	0.449	0.292	0.27
	(0.518)	(0.577)	(0.586)	(0.611)	(0.576)	(0.568)	(0.605)	(0.607)	(0.594)	(0.543)
Pandemic	0.984*	-0.143	0.301	0.315	0.224	0.616	0.347	0.489	0.187	0.471
	(0.524)	(0.581)	(0.588)	(0.613)	(0.579)	(0.572)	(0.607)	(0.61)	(0.597)	(0.547)
R^2	0.767	0.759	0.767	0.756	0.757	0.757	0.759	0.755	0.75	0.756
N	5,040	5,040	5,040	5,040	5,040	5,040	5,040	5,040	5,040	5,040

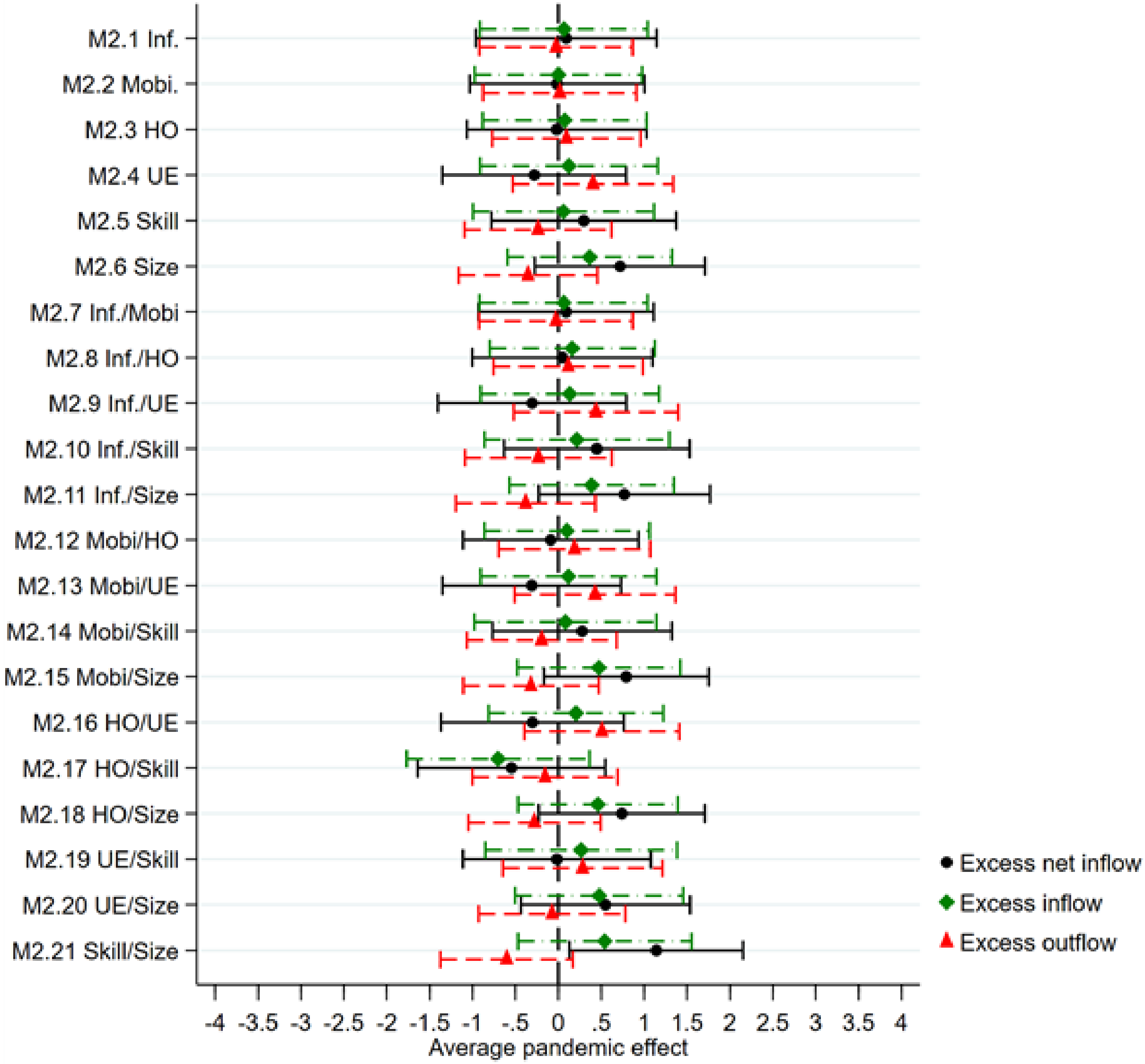
Notes: The table shows the average estimated effects of the region-type-months interactions in the pre-pandemic and the pandemic period for the excess net inflow, the inflow and the outflow rate for large agglomerations (reference category: urbanised regions). Each column shows the results when a single region is excluded from the sample. Robust standard errors shown in parentheses. ***/**/* indicate statistical significance at the 0.01/0.05/0.1 level. The baseline model includes no additional control variables. The full model includes time-variant (*infection rate, mobility index) and time-invariant control variables (pre-pandemic home office potential, unemployment rate, skill structure, establishment size structure). All control variables are interacted with month dummies.*
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

Figure A5: ***Relevance of individual factors and combinations of factors*** **– small agglomerations**



Notes: The Figure shows the deviation of the average coefficient estimate of the region-month dummies in the pandemic period for small 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.
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.

Figure A6: ***Relevance of individual factors and combinations of factors*** **– rural regions**



Notes: The Figure shows the deviation of the average coefficient estimate of the region-month dummies in the pandemic period for rural regions 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.
Source: Employment unemployment statistics of the FEA, Teralytics, Corona-Datenplattform.