Bachelor's Thesis

# Construction of a COVID-19 lockdown index at the federal state level for Germany.

**An analysis of the mobility trends for places of work during the COVID-19 pandemic.**

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Leipzig, February 22nd, 2022

UNIVERSITÄT
LEIPZIG

Submitted in partial fulfillment of the requirements for the degree of:

B. Sc. Wirtschaftswissenschaften

Supervised by Professor Dr. Süßmuth & Frank Simmen

# List of Acronyms



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# 1 Introduction

The stringency index provided by the Oxford COVID-19 Government Response Tracker (OxCGRT) Hale et al. (2020) has been widely used by scientists and the media during the pandemic to compare and illustrate the strictness of policy responses around the world. However, the OxCGRT stringency index for Germany has two main points of criticism: (i) the heterogeneous policy response in Germany is measured on the nation country-level instead of the provincial country-level and (ii) the methodology to construct the strictness on the national country-level using the maximum values of German districts leads to an overestimation of policy strictness in Germany.

To explain the first point of criticism (i), we first examine the necessity of stringency indices measuring the heterogeneous policy response of Germany on the provincial country-level. Following, we construct stringency indices for Germany on the provincial country-level covering the period March 2020 to November 2020. By analyzing the new stringency indices on the provincial country-level, we provide further evidence of the heterogeneous nature of the German police response, supporting the findings of Buthe et al. (2020a). We create a national index based on the provincial indices using the maximum method of the OxCGRT and our average method. Thus, we provide evidence for (ii) comparing the constructed national stringency indices with the OxCGRT. The main contribution of the first part of the paper is two provide new stringency data on the provincial country-level measuring the overall policy stringency and the strictness of subindices regarding the policy categories school closing, closure and regulation of business, curfews, internal border restrictions, lockdown restrictions, mask-wearing requirements, and social distancing.

In the second part of the paper, we analyze the mobility trends for places of work during the COVID-19 pandemic using the constructed stringency indices and mobility data provided by the COVID-19 Community Mobility Report. We quantify the negative effects of the pandemic on mobility patterns using a fixed-effects (within) regression. Further subject of research is the effect of the share of work-from-home (WFH) jobs throughout German provinces and districts on the mobility trend for places of work. In regards to Irlacher and Koch (2021) we construct WFH shares for the German provinces using recent data (2021) provided by infas360. Subsequently, we use a random-effects GLS regression to: (a) measure the effect of the province-specific variable WFH on mobility for places of work, and (b) measure the effect of income indicators on mobility for places of work. We use (a) and (b) to check for the occurrence of a mobility gap due to differences in the region-specific average income that has been observed by Bonaccorsi et al. (2020) in Italy and by Ruiz-Euler et al. (2020) in the United States of America (US). Finally, we discuss the potential effect of COVID-19 induced changes in mobility trends for places of work on the distribution of income between German districts and between former East and West Germany. We compare our findings to Irlacher and Koch (2021) and provide new insights on the distributional effect of the WFH rate throughout urban and rural areas.

# 2 Construction of a COVID-19 stringecy index at the federal state level

## 2.1 Literature review

### 2.1.1 The COVID-19 policy response in federal and unitarian European democracies

National and subnational policymakers experienced a varying impact of the COVID-19 pandemic across time regarding mortality and infection rates (Buthe et al., 2020a). The varying impact of the pandemic has led to a variety of policy responses around the globe (Hale et al., 2021). In European democracies, the policymaking process is generally subdivided into federal (e.g. Germany and Switzerland) and unitarian (e.g. Italy and France) policymaking (Buthe et al., 2020a). The distinction between a unitarian and federal policy response is based on the extent of power-sharing among the national and subnational governments (Bognetti et al., 1999). During the COVID-19 pandemic, a typical unitarian policy response is characterized by national policymaking and national-homogenous policies (e.g. France). In contrast, a federal policy response is characterized by decentralized sub-national decision making and subnationally differentiated policies (e.g. Germany) (Buthe et al., 2020a). Therefore, subnational separation into federal states is needed to accurately reproduce the COVID-19 policy response strictness of a country with subnationally differentiated policies, like Germany.

Buthe et al. (2020a) empirically measured the heterogeneity of the German policy response for the period January 2020 to July 21st 2020. According to Buthe et al. (2020a), the German policy response is significantly heterogeneous regarding the policy categories: lockdown, school closures and mask-wearing requirements. The policy response on the national country-level is mainly focused on external border restrictions and the provision of health resources (Buthe et al., 2020b). Provincial and municipal governments [1] were primarily responsible for the policy response in the analyzed categories: curfew, lockdown measures, internal border restrictions, closure and regulation of businesses, closure and regulation of schools, social distancing and mask-wearing requirements. Based on the heterogeneity observed by Buthe et al. (2020a), we create a strictness index for Germany that considers a heterogeneous policy response on the provincial country-level.

Siewert et al. (2020) supports the assumption of a heterogeneous policy response by describing Germany's COVID-19 policymaking process as a "multi-level system with power-sharing between the federal, state and local levels" (Siewert et al., 2020, p. 1), where the federal governments take the leading role.

### 2.1.2 The Oxford COVID-19 Government Response Tracker

The Oxford COVID-19 Government Response Tracker (OxCGRT) provides several policy response indices for more than 180 countries worldwide on the national country-level (Hale et al., 2021). The OxCGRT provides the 'Stringency index' to measure the strictness of the COVID-19 policy response. The

[1] The wording 'provincial' refers to the 16 German federal states, while 'municipal' refers to the 401 administrative districts.

data is provided as a daily data series. Subnational indices are provided for selected countries like the United States, Canada or Brazil. However, the OxCGRT lacks subnational stringency indices for Germany. We assume a heterogeneous policy response in Germany as measured by Buthe et al. (2020a) and indicated by Siewert et al. (2020). Therefore, subnational stringency indices are essential for the detailed reproduction of the German COVID-19 policy response.

To measure the heterogeneous policy response on the national level, the OxCGRT reports the most stringent national government policy. Suppose the most stringent policy is only present within a province or a municipal. In that case, the OxCGRT reports the municipal or provincial value as the national stringency value for the corresponding day [2]

In order to identify possible bias due to the OxCGRT methodology, we create a national stringency index based on the average of the provincial stringency indices and compare our result with the OxCGRT stringency index.

## 2.2 Data description

The CoronaNet Research Project provides the data used for the construction of the provincial stringency indices [3]. The publicly available event format data set for Germany covers the COVID-19 policy response from January 2020 to May 2021 at the national, provincial and municipal country-level.

The data is collected by participants of the CoronaNet Research project with a background in Political-, Social- and Public health science using a Qualtrics survey instrument [4]. The hand-coded dataset for Germany contains a total number of 2265 individual policy responses. Every policy response is identified

[2] The OxCGRT accounts for the occurrence by reducing the strictness value by a certain amount, depending on the strictness and the policy category. A detailed explanation is given in the OxCGRT Codebook (https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md) and the OxCGRT working paper of Hale et al. (2020).

[3] The dataset for Germany has last been updated on May 7th 2021, and is available under the following link, https://www.coronanet-project.org/.

[4] For more information on the participants and data collection methods; please see: https://www.coronanet-project.org/methods.html

with a unique policy id and each record with a unique record id. On average, a policy response is updated (strengthened, ended or changed in any other way) at least once. Subsequently, the data set contains a total number of 4421 records. Policy responses are divided into 20 categories (e.g. "Closure and Regulation of Schools") and 49 subcategories (e.g. "Primary Schools (generally for children ages 10 and below)").

The summary statistic of the 20 policy categories (Table 1) represents the data of the analyzed period, subdivided into country-level. According to the CoronaNet codebook. The country-level documents what level of government a policy was initiated from. As theoretically expected, the data indicates that the majority (93.17 %) of policy responses have been initiated from the provincial country-level (4), which supports the assumption that provincial stringency indices are essential for measuring the strictness of the German COVID-19 policy response. The municipal (2) and national governments (3) initiated 2.04% and 4.52% of the recorded policies. Nonetheless, the data set includes 200 policy responses on the national country level throughout 16 policy categories most policy categories. Whenever we encounter overlapping national and provincial policies in the same policy category or subcategory on the same date, we assume that the national policy overrules the subnational policy for reasons of simplicity and programmability.

In contrast to the OxCGRT, we are not considering the policy responses on the municipal country-level. We assume the impact on the municipal country-level is not substantial to the policy strictness on the provincial or national country-level considering the relatively small number of people that are impacted by the policy response on the municipal country-level compared to the total population of the affected federal state (e.g. $\approx$ 250.000 inhabitants in the district of Heinsberg compared to $\approx$18 Million in North Rhine-Westphalia).

Policy responses targeting the categories "Restriction and Regulation of Businesses", "Social Distancing", and "Closure and Regulation of Schools" account for about 62 % of the total number of policy responses (1) recorded within the data set. Nevertheless, the number of policy responses in particular policy categories may correspond to the urge to target those categories with a high

TABLE 1

Summary Statistics of Policy Categories

| Policy Category | (1) N | (2) n Muni. | (3) n Nat. | (4) n. Prov. | (5) Mean t (days) | (6) SD t (days) |
|---|---|---|---|---|---|---|
| Restriction and Regulation of Businesses | 1156 | 15 | 29 | 1112 | 31.5 | 45.79 |
| Social Distancing | 1010 | 6 | 13 | 991 | 35.3 | 53.24 |
| Closure and Regulation of Schools | 560 | 11 | 0 | 545 | 36.2 | 48.48 |
| Restrictions of Mass Gatherings | 419 | 3 | 11 | 399 | 44.8 | 58.82 |
| Quarantine | 343 | 6 | 9 | 327 | 20.4 | 33.39 |
| Health Resources | 251 | 15 | 43 | 193 | 117.6 | 140.3 |
| Restriction and Regulation of Government Services | 179 | 6 | 0 | 173 | 45.5 | 71.75 |
| Lockdown | 95 | 6 | 2 | 87 | 21.2 | 18.25 |
| Health Testing | 93 | 4 | 18 | 71 | 91.3 | 105.6 |
| Public Awareness Measures | 67 | 7 | 17 | 43 | 158.2 | 175.1 |
| Other Policy Not Listed Above | 51 | 1 | 28 | 22 | 139.7 | 228.5 |
| External Border Restrictions | 44 | 0 | 14 | 30 | 56.2 | 48.12 |
| New Task Force, Bureau or Administrative Configuration | 39 | 4 | 6 | 28 | 162.8 | 181.3 |
| Hygiene | 34 | 2 | 0 | 32 | 62.1 | 78.37 |
| Internal Border Restrictions | 32 | 1 | 1 | 30 | 41.1 | 45.95 |
| Health Monitoring | 18 | 0 | 5 | 13 | 248.4 | 160.7 |
| Curfew | 11 | 0 | 0 | 11 | 26.0 | 8.21 |
| Anti-Disinformation Measures | 9 | 1 | 2 | 6 | 60.7 | 147.6 |
| Declaration of Emergency | 6 | 2 | 1 | 3 | 17.0 | 12.88 |
| COVID-19 Vaccines | 5 | 0 | 1 | 4 | 59.0 | 54.17 |
| Total | 4422 | 90 | 200 | 4120 | | |
| % | 100 | 2.04 | 4.52 | 93.17 | | |

frequency of policies or policy changes but do not allow any conclusions on the strictness of the policy response. Further computation of the data set is required to gain inside into the strictness of the policy responses. The average duration within the most targeted policy categories (1) varies from 20 to 45 days (5). High standard deviation levels (6) throughout most policy categories indicate a high variance of policy duration.

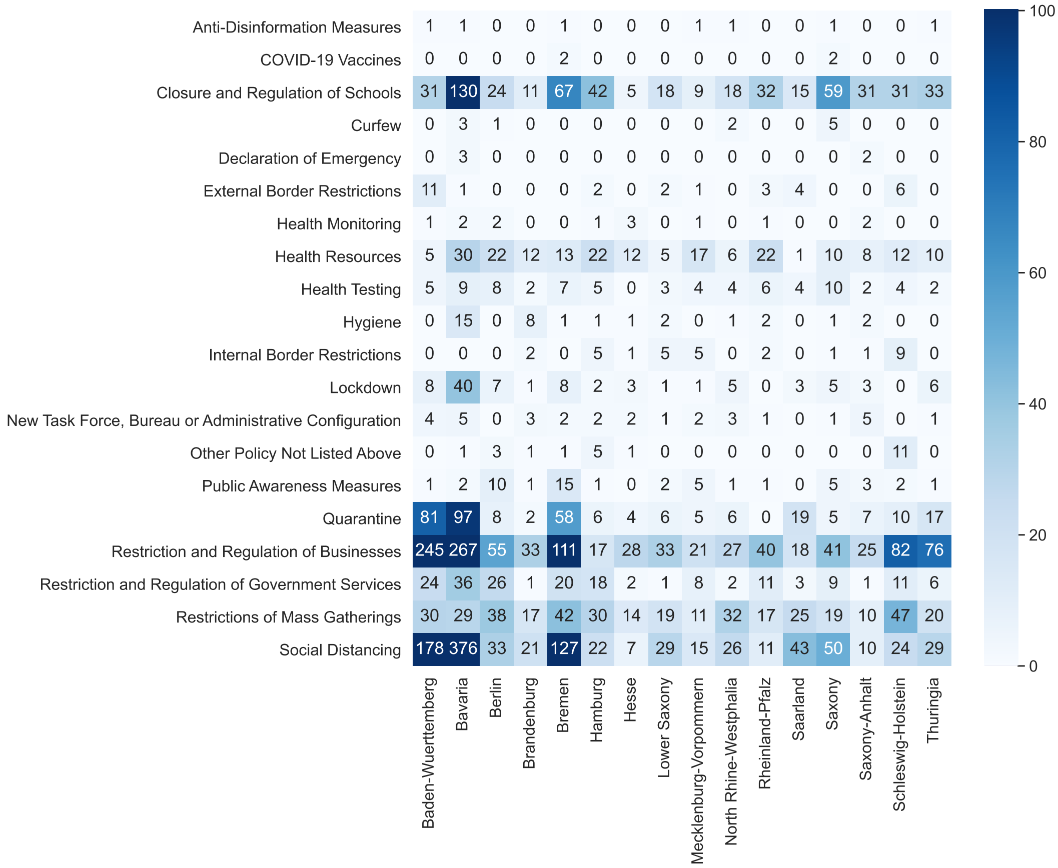
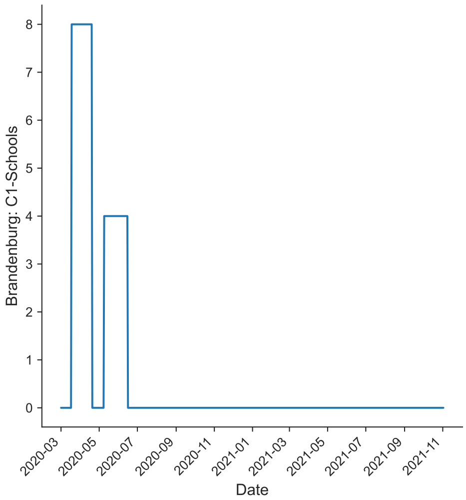
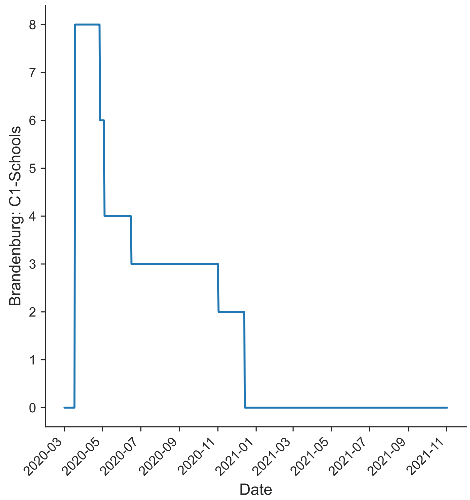



Figure 1: Total number of unique policies in German provinces by policy category.

The heat map visualization (Figure 1) represents the distribution of the recorded policy responses on the federal country level across policy categories and federal states. Remarkable is the high number of policy records in the federal states Bavaria, Baden-Wurtemberg, and Bremen across the Restriction and Regulation of Businesses and Social Distancing. Those federal states have highly specific policies in those categories. The policy records target a variety of different subcategories (e.g. 'keeping a distance of at least 1.5 meters apart at bars; public libraries; museums; secondary schools, etc.') while other provinces




(a) Before




(b) After

Figure 2: 'C1-Closure and regulation of schools' data gaps

use a more general policy approach in those policy categories (e.g. 'keeping a distance of at least 1.5 meters apart everywhere'). The uneven distribution of the total number of policies throughout provinces provides evidence for a heterogeneous policy response.

One limitation of the data set is a large number of missing variables and observations. Brandenburg records 11 policies regarding "Closure and Regulation of Schools" according to the dataset. The computation of the strictness indices exclusively with the data provided by the CoronaNet project results in a misrepresentation of the actual stringency (Figure 2 (a)).

The gathering of information on COVID-19 policies is required to fill the gaps of the dataset[5] (Figure 2 (b)). Missing data is a problem across all policy categories and is mainly indicated by irregular gaps in the strictness index (Figure 2 (a)). High amounts of manual research to fill the gaps of the data set increases the likelihood of human errors biasing the strictness indices.

Additionally, the occurrence of data gaps increases over time. Therefore the constructed stringency indices are limited to the period of March 1st 2020 to November 2nd 2020.

[5]Sources used to fill the data gaps are included as notes in the attached Python code.

## 2.3 Construction of stringency subindices

Parts of the methodology used by the OxCGRT to construct the stringency indices is duplicated to construct the stringency indices on the provincial country-level. The OxCGRT stringency index consists of eight ordinal indicators. Each indicator reproduces a different policy response category (e.g. "School closing," "Workplace closing", "Restrictions on internal movement"). The indicators are ranked on an ordinal scale from zero (no policy response) to highest (strictest policy response). For example, the ordinal indicator "School closing" is scaled from 0 to 3. The lowest value of 0 is defined as "no measures", the value of 1 is defined as "recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations", up to the highest value of 3 "require closing all levels". We duplicate the OxCGRT ordinal scaling methodology for subindices with ordinal scales but adjust the ordinal steps according to the CoronaNet dataset.

Following the methodology of the OxCGRT stringency index, we first construct several strictness subindices. Each subindex represents the strictness within a policy category. An overview containing the description, measurement, subcategories and coding constructions of the constructed subindices is given in the Codebook (see Appendix A.1).

*C1 – School closing* monitors the policy response targeting the closure of childcare facilities, schools and universities. The subindex is coded regarding the institution status of each policy record given by the CoronaNet data set (closed; open with conditions; open with no conditions attached). Face-to-face teaching exclusively for graduation classes is considered 'closed' in secondary schools and 'open with conditions' in primary schools. Compared to the OxCGRT, the constructed C1 -School closing index involves childcare facilities and has a more sensitive level of measurement due to the scaling from 0 to 8 instead of 0 to 3. Because the score of the C1-index is based on the institution status of each subcategory (see Appendix A.1), some values of the scale can have a different composition of institution statuses but still share the same level of strictness on the scale. For example, the strictness value of 4 can be composed of either the closure of universities and secondary schools or the status' open with conditions' of all subcategories. Both situations are considered equally strict by the C1 index.

*C2 - Workplace closing (close personal contact)* considers the institutional status (closed; open with conditions; open with no conditions attached) of businesses with close personal contact of the subcategories personal grooming businesses (e.g. hairdressers), bars and restaurants. This specification allows for better comparison because the quantity of policies targeting specific business subcategories varies intensely among the provinces. To improve the representativeness and avoid biases that come with missing data, the C2 index regarding the policy category' closure and regulation of businesses' has been narrowed to record the response for businesses with close personal contact.

*C3 – Curfew* measures the existence of any curfew hours with a ban on leaving home without particular reason, like pursuing a profession.

*C4 - Internal border restrictions* is used to reproduce the restriction on internal movements like restriction on movement within a certain radius from home, prohibition from access to specific regions and provinces and bans on accommodation. Bans of school trips are not considered internal border restrictions.

*C5- Lockdown* captures stay at home requirements or restrictions on visiting healthcare facilities like nursing homes or hospitals. If any policy recorded under the category of 'lockdown' applies, the C5 index measures its existence.

*C6 - Mask wearing* captures information about mask-wearing requirements within specific policy subcategories. Provinces either apply general rules like 'Wearing masks everywhere and 'Wearing a mask in all indoor places' and/or apply mask-wearing policies on various subcategories like Schools or Businesses. For that reason, the first ordinal interval of the C6-index (0 to 1) is subdivided into eight smaller intervals corresponding to subcategory specific mask-wearing requirements. 'Wearing Masks in all indoor spaces' is equal to the ordinal value of 1 and therefore equal to the sum of all category-specific mask-wearing requirements being in place (see Appendix A.1). 'Wearing Masks in all public spaces/everywhere' is considered the strictest mask-wearing policy and indicates a strictness value of 2.

*C7 - Social distancing* captures information about the presence of general social distancing rules that apply in all public spaces. Due to the variety of subcategories targeted by some of the provinces, only general social distancing rules are implemented to assure comparability. We are not considering the subindex 'Restriction of Mass gatherings' used by the OxCGRT. The policy category 'Restriction of Mass gatherings' is classified by Buthe et al. (2020a) as a homogeneous policy category. Omitting 'Restriction of Mass gatherings' might favour the occurrence of different strictness values between provinces. The constructed subindices follow the OxCGRT role model and measure the strictness of the given policy categories on either an ordinal scale lowest to highest (C1 and C2), in a binary way (C3; C4; C7;) or as a combination of both methods (C6). We calculate the strictness value of the ordinal scaled subindices according to the OxCGRT formula (1) (Hale et al., 2021, p. 35),

$$I_{j,t} = 100\frac{v_{j,t}}{N_j} \tag{1}$$

where $N_j$ is the maximum value of the indicator (see Appendix A.2) and $v_{j,t}$ represents the recorded ordinal value on a single day $t$. $I_{j,t}$ is the resulting strictness value measured between 0 and 100 (strictest).

## 2.4 Construction of the stringency index

To construct the stringency index on the provincial country-level, we use the following formula (2),

$$Stringency_{j,t} = \frac{1}{k}\sum_{j=1}^{k} I_{j,t} \tag{2}$$

where $k$ is the total number of subindices, $I_{j,t}$ the subindex on a particular day, and $Stringency_{j,t}$ the stringency index on the provincial country-level on a particular day. Following the methodology of the OxCGRT, each subindex is equally weighted.

We also constructed a weighted stringency index with different weights for each subindex (see Appendix A.3) for the following reasons. The accuracy and completeness of the used policies in subindex C1 and C2 are assumed to be the highest because the use of external sources has reapproved every policy regarding C1 and C2. Therefore, C1 and C2 receive the highest weight of 3/14. The addition 1/14 weight is subtracted from the C3 and C4 subindex as they are measuring policy categories with a low quantity of 11 and 32 policy entries (Table 1). Consequently, the weighted stringency index might overrepresent the strictness of school closing policies and business regulation policies. We constructed the weighted stringency index using formula (3), where $w$ represents the added subindex weights.

$$Weighted\ Stringency_{j,t} = \sum_{j=1}^{k} wI_{j,t} \tag{3}$$

## 2.5 Results

Table 2: Summary statistics of the strictness index

| | (7) Mean SI | (8) SD SI | (9) Min SI | (10) Max SI | (11) Mean wSI | (12) SD wSI | (13) Min wSI | (14) Max wSI |
|---|---|---|---|---|---|---|---|---|
| Bavaria | 40.97 | 14.20 | 0.00 | 59.52 | 50.06 | 17.43 | 0.00 | 73.81 |
| Baden-Wuert. | 38.98 | 15.38 | 0.00 | 59.52 | 48.40 | 18.71 | 0.00 | 73.81 |
| Saarland | 34.82 | 13.26 | 0.00 | 57.14 | 42.64 | 16.49 | 0.00 | 71.43 |
| Saxony | 34.41 | 12.43 | 0.00 | 71.43 | 42.39 | 15.56 | 0.00 | 78.57 |
| Bremen | 32.89 | 10.38 | 0.00 | 45.24 | 41.17 | 13.97 | 0.00 | 59.52 |
| Lower Saxony | 34.32 | 19.74 | 0.00 | 71.43 | 40.64 | 20.51 | 0.00 | 78.57 |
| Thuringia | 32.08 | 12.53 | 0.00 | 57.14 | 40.24 | 15.89 | 0.00 | 71.43 |
| Berlin | 32.13 | 12.67 | 0.00 | 57.74 | 39.35 | 16.21 | 0.00 | 71.43 |
| Mecklenburg-Vorp. | 35.11 | 19.57 | 0.00 | 71.43 | 39.14 | 20.21 | 0.00 | 78.57 |
| Hamburg | 30.17 | 21.87 | 0.00 | 85.71 | 37.34 | 22.90 | 0.00 | 92.86 |
| Brandenburg | 29.10 | 17.18 | 0.00 | 71.43 | 36.11 | 19.02 | 0.00 | 78.57 |
| Saxony-Anhalt | 26.78 | 16.06 | 0.00 | 59.52 | 35.85 | 19.04 | 0.00 | 73.81 |
| Schleswig-Holstein | 28.09 | 17.59 | 0.00 | 59.52 | 35.50 | 18.07 | 0.00 | 66.67 |
| North Rhine-West. | 26.11 | 11.66 | 0.00 | 45.24 | 34.58 | 14.41 | 0.00 | 59.52 |
| Hesse | 25.17 | 15.77 | 0.00 | 57.14 | 33.54 | 19.21 | 0.00 | 71.43 |
| Rheinland-Pfalz | 23.03 | 11.75 | 0.00 | 45.24 | 31.44 | 14.85 | 0.00 | 59.52 |

The resulting subindices (see Appendix A.4) and stringency indices (Table 2) on the provincial country-level provide evidence for a heterogeneous policy response in Germany. The average weighted stringency index (11) varies from 50.06 in Bavaria to 31.44 in Rheinland-Pfalz (Table 2).

Further evidence is provided by different levels of standard deviation (12). Different values of standard variation indicate different variations in the range of the stringency values, which can be interpreted as different policy approaches to contain the pandemic. Hamburg, for example, reaches the highest maximum value of the weighted stringency index (14) with 92.86 (Table 2). Regarding the average weighted stringency index (11), Hamburg is just the 10th strictest province (Table 2). Visually comparing Hamburg to other provinces provides further evidence for a heterogeneous policy approach throughout the German provinces (Figure 3). Hamburgs weighted stringency index over time is characterized by a strong response in the peak of the 7-day average and a following substantial decline (Figure 3). In contrast to Hamburg, Bavaria's policy response is characterized by a high overall response throughout the observed period (Figure 3).

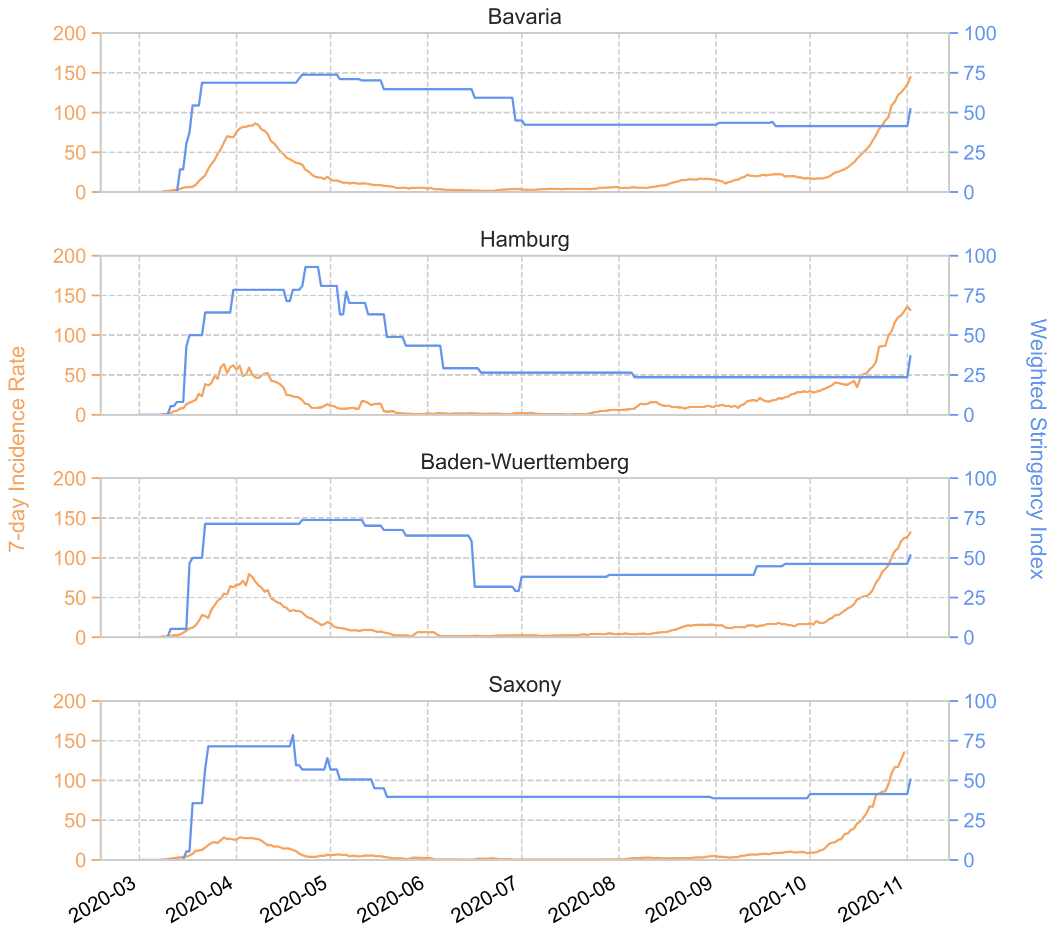



Figure 3: Weighted stringency and 7-day incidence rate.

To examine further parameters indicating a heterogeneous policy response, we examine the correlation of the strictness indices and the correlation of the metric-scaled subindices C1, C2, and C6. We first test the weighted stringency indices of the provinces on normality using D'Agostino's K-squared test. D'Agostino's K-squared test checks on normality based on skewness and kurtosis of the variable. If the p-value of the test is larger than 0.05, we reject the null hypothesis. Rejection of the null hypothesis assumes that our variable is normally distributed. The null hypothesis of 10 out of 16 provinces can not be rejected[6].

In order to test Pearson's correlation coefficients for statistical significance, the variable should approximately follow a normal distribution. As this is not the case for 10 out of 16 weighted stringency indices, we use Spearman's rank correlation coefficient to analyze the correlation of the COVID-19 policy response between the 16 German provinces. The limitation of Spearman's rank correlation coefficient is that it uses the ranks of the values rather than the actual values to create a correlation coefficient. The magnitude of the difference in each variable will remain unknown and not noticed using exclusively Spearman's rank correlation coefficients. We additionally created a national strictness index for Germany on the national level by averaging the weighted stringency indices of each province on each day.

All Spearman rank correlation coefficient are highly significant (p-value $<=$ 0.01). 35 policy responses are very highly correlated ($0.9 <= sp < 0.99$), 77 highly correlated ($0.7 <= sp < 0.9$), 24 moderately correlated ($0.5 <= sp < 0.7$) of 136 policy response pairs in total (Figure 4). Pearson's correlation matrix indicates higher positive correlations than Spearman's correlation coefficients (see Appendix A.5). We repeat the process for the ordinal scaled subindices C1 - Closure of Schools ($min\ sp = 0.66$, $mean\ sp = 0.86$) , C2 - Closure Regulation of Business ($min\ sp = 0.73$, $mean\ sp = 0.88$) and C6- Mask wearing $min\ sp = 0.44$, $mean\ sp = 0.80$). Highly, positive correlation patterns occur (see Appendix A.6). We interpret the correlation patterns as a measurement of heterogeneity between province-specific policy responses. The correlation matrix verifies the existence of different degrees of heterogeneity between province-specific policy responses (Figure 4). Based on our findings,

[6]The test outputs of the D'Agostino's K-squared test are included in the attached JupyterNotebook in the 'Results' section

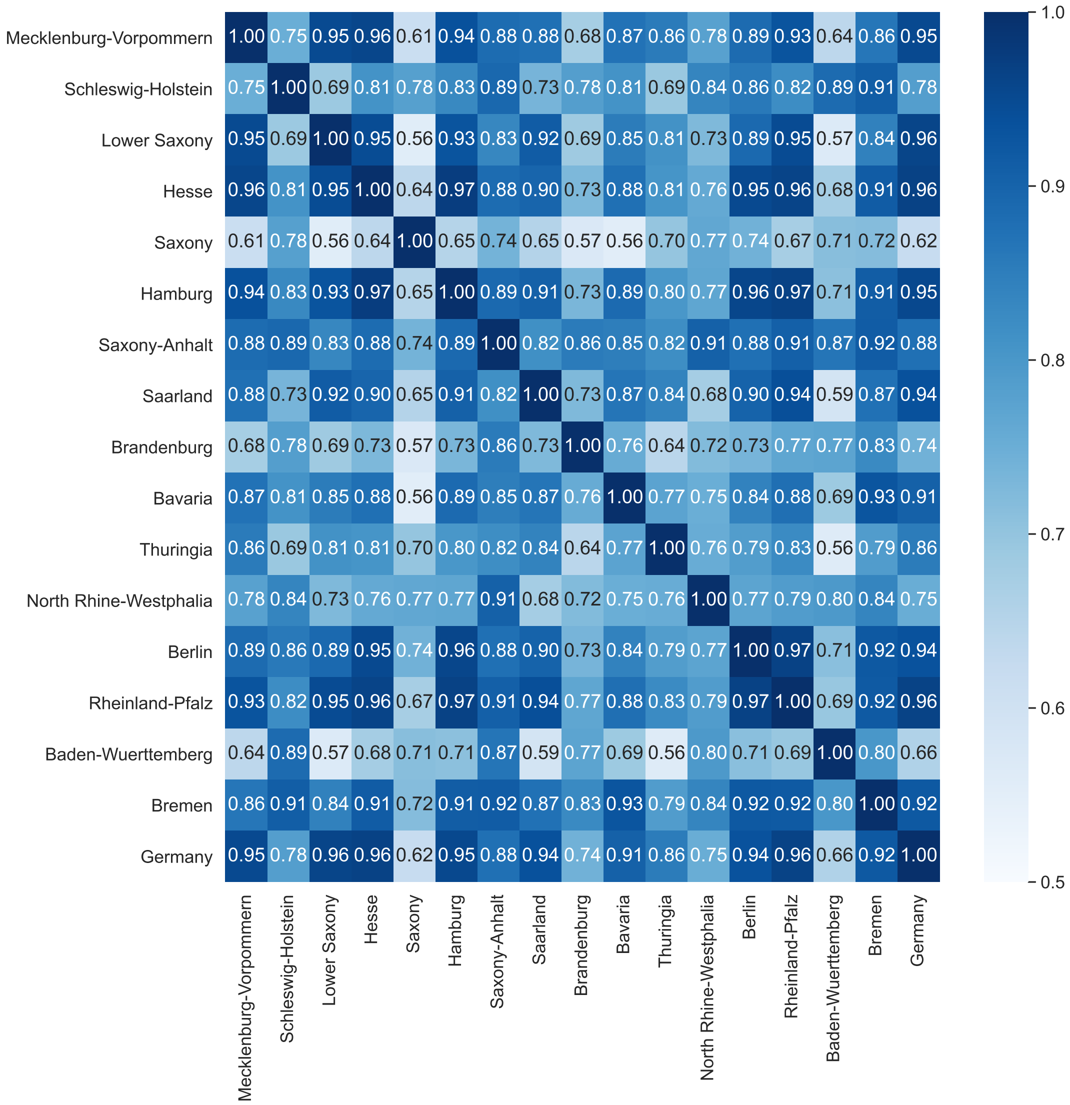



Figure 4: Spearman's correlation matrix weighted stringency index.

we support Buthe et al. (2020a) in interpreting the German policy response as heterogeneous across provinces. To check the weighted national stringency index for robustness, we compare the weighted stringency index to the OxCGRT stringency index (Figure 5). If the national weighted stringency index monitors Germany's COVID-19 policy response correctly, the indices should be highly and positively correlated. Spearman's rank correlation coefficient and the Pearson correlation coefficient both indicate a statistically significant ($p <= 0.01$) high correlation between the OxCGRT data and the weighted stringency index (Figure 5). The stringency gap between the OxCGRT and the weighted stringency index probably occurs due to different methodologies. We can reduce the stringency gap if we duplicate the methodology used by

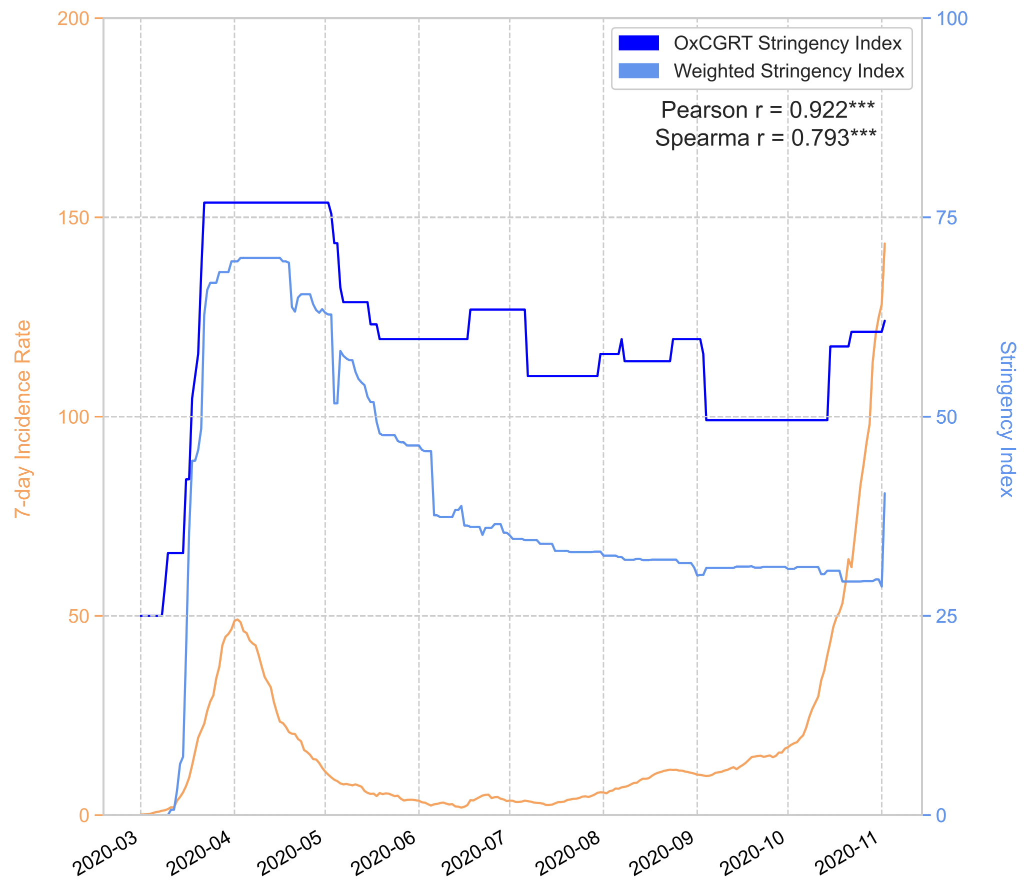



Figure 5: OxCGRT stringency index and weighted national stringency index

Hale et al. (2020) and construct the stringency index on the national country-level by using the maximum strictness values of the corresponding province on a particular day instead of the average (see Appendix A.7). The stringency gap between the OxCGRT and the weighted stringency index provides clear evidence for the bias caused by the methodology of the OxCGRT on the national country-level.

# 3 Mobility trends for places of work during the COVID-19 pandemic

## 3.1 Literature review

We use the constructed stringency index at the provincial country-level to analyze the impact of COVID-19 policy strictness on mobility trends for places of work in Germany. A further subject of research is the effect of the share of work-from-home jobs throughout German provinces and districts on the mobility trend for places of work. Finally, we discuss the potential effect of COVID-19 induced changes in mobility trends for places of work on the distribution of income between German districts and between former East and West Germany.

Previous research analyzing the economic and social impact of COVID-19 mobility restrictions in Italy by Bonaccorsi et al. (2020) reveals two contrary patterns: "Individual indicators (average income) show that the poorest are more exposed to the economic consequences of the lockdown; conversely, aggregate indicators at the level of municipalities, that is, deprivation and fiscal capacity, reveal that wealthier municipalities are those more severely hit by mobility contraction induced by the lockdown" (Bonaccorsi et al., 2020). Bonaccorsi et al. (2020) are using mobility data provided by the Facebook platform to analyze changes in mobility patterns and the individual average income as well as the Italian index of socio-economic deprivation.

The key findings of the analysis of Ruiz-Euler et al. (2020) resembles Bonaccorsi et al. (2020) result of an unequal effect of the COVID-19 pandemic on mobility patterns depending on average income. Ruiz-Euler et al. (2020) research the U.S. mobility patterns in urban centres during the COVID-19 pandemic using anonymous mobile-device location data. Mobility activity is quantified by measuring the distance between unique stops of each mobile device. To assign an estimation variable for income to each mobile-device user, the median household income of the U.S. Census Block Group unit (600 to 3,000 people) where the user spent the most time is assumed to be the place of residence of the individual mobile-device user. The urban centres of Chicago, Detroit, Los Angeles, New York City, San Francisco and Seattle are the units of analysis (Ruiz-Euler et al., 2020).

Before the impact of COVID-19, the mobility rates of the top decile by income were generally higher than the mobility rates of the bottom decile by income. "During the COVID-19 pandemic, mobility rates decline at different speeds for high income and low income levels" (Ruiz-Euler et al., 2020). Figure 6 visualizes the change of mobility rates for the city of Detroit. According to

Ruiz-Euler et al. (2020) we are referring to the different decline of mobility rates as the "mobility gap".

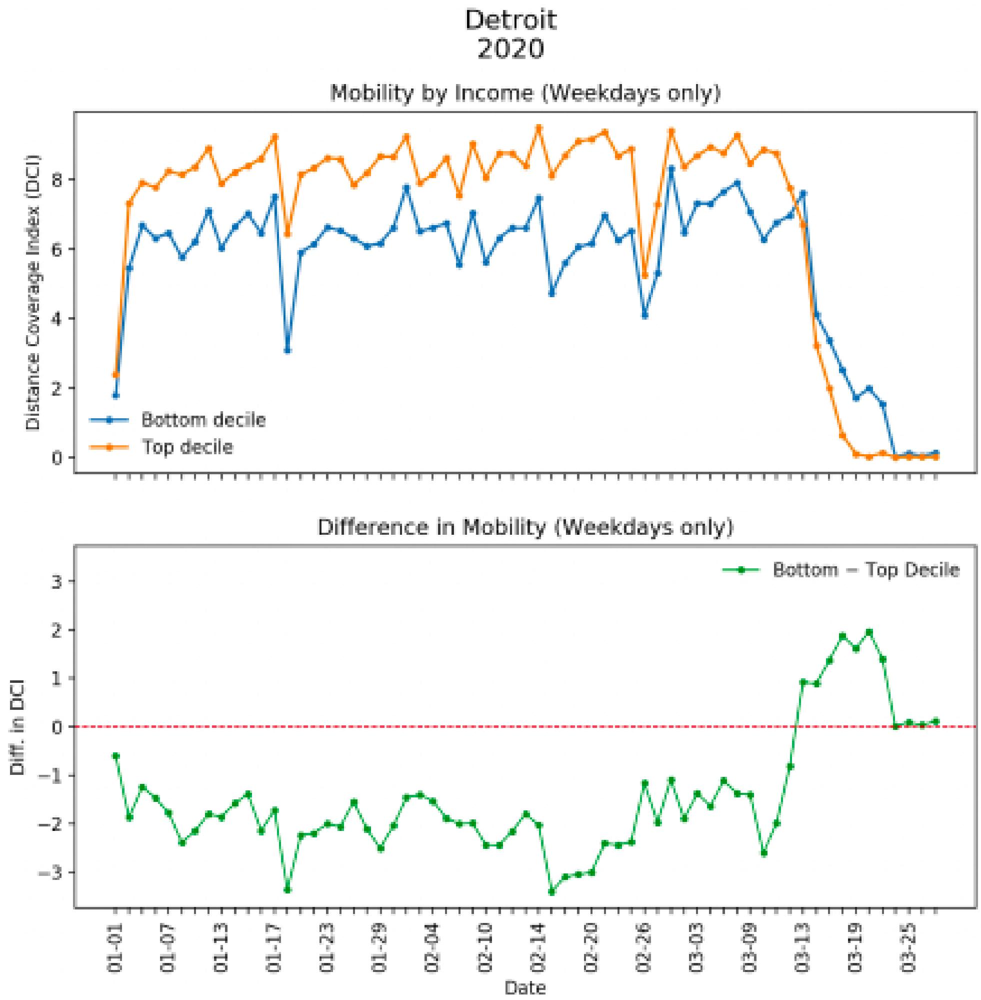



Figure 6: Daily evolution of mobility in Detroit, first quarter of 2020
Source: Ruiz-Euler et al. (2020)

However, the research of Ruiz-Euler et al. (2020) lacks to statistically measure the impact of the COVID-19 pandemic on mobility patterns. Furthermore, the distinction between the effect of the virus and the impact of the virus-containment policies remain unclear. The constructed weighted stringency index and the 7-day incidence value of each German province in combination with a fixed-effect model are used in our analysis to statistically quantify the virus-effect and the policy stringency-effect on the mobility rate for workplaces in Germany.

According to Ruiz-Euler et al. (2020) the mobility gap is a "reflection of *inher-*

*ent differences* in labour markets for high and low paying jobs, with the former being flexible and accommodating to an external shock like a pandemic, while the latter being much more rigid to these types of unpredicted massive disruptions". A possible key component of the *inherent differences* in labour markets described by Ruiz-Euler et al. (2020) and Bonaccorsi et al. (2020), affecting the decline of mobility rates for individuals in high and low paying jobs during the COVID-19 pandemic is the work-from-home (WFH) rate. Irlacher and Koch (2021) investigated the impact of WFH on wages, provincial variation of WFH occurrence and the subsequently effects on income distribution in Germany. The primary source of data used by Irlacher and Koch (2021) is the BIBB/BAuA Employment Survey of 2017/2018, containing information about income, education, profession, place of work and the possibility to work-from-home of 20,018 individual employees in Germany. According to Irlacher and Koch (2021), at the top decile of daily wage distribution, 78% of workers in Germany use the option to work from home, but just 13% in the corresponding bottom decile(see Appendix A.8). Irlacher and Koch (2021) state that the possibility to work-from-home accounts for a 10% cent wage premium and is unevenly distributed throughout the German provinces. Irlacher and Koch (2021) monitor a correlation between the average income inside the region and the corresponding share of WFH jobs. Irlacher and Koch (2021) observe especially low shares in regions of the former German Democratic Republik. In regards to Irlacher and Koch (2021), we use the most recent data measuring the share of WFH jobs in 2020 of each German municipal provided by 'infas360' to reproduce recent WFH shares for each province. Because the share of WFH jobs used in our analysis is measured on the municipal country-level, we use the opportunity to add the binary distinction between urban and rural municipals. By distinguishing between urban and rural districts, our analysis can provide further insights into the variation of the WFH share throughout Germany. Implementing a new geographical analysis level can drive possible implications on the income-distribution effect caused by a higher share of work-from-home jobs during the COVID-19 pandemic. According to Irlacher and Koch (2021), the WFH rate in East Germany is significantly lower than in West Germany. Irlacher and Koch (2021) use a regression plot with the mobility trend for places of work provided by the google mobility report and a work-from-home rate based on the 2017 BIBB/BAuA Employment Survey of 2017/2018 survey to provide visual evidence for the relevance of their findings regarding the COVID-19 crisis (see Appendix A.9). The regression plot indicates a correlation between the work-from-home share of jobs and the decline of mobility rates during the peak of the first lockdown (see Appendix A.9). However, Irlacher and Koch (2021) are not considering different levels of stringency. We are considering province-specific stringency values in our model to verify the findings of Irlacher and Koch (2021). The occurring "mobility gap" between federal states with a low and higher share of WFH jobs shows similarities to Ruiz-Euler et al. (2020) and Bonaccorsi et al. (2020) observations of a greater decline for municipals with lower average income. To provide further evidence if the work-from-home share promotes a mobility gap for places of work, we analyze the impact of the latest work-from-home shares of the German federal states on the mobility for places of work. In addition to Irlacher and Koch (2021) we are considering the effect of the weighted stringency index on the mobility for places of work in our model.

## 3.2 Data description

The observation period is the 17th of March 2020 to the 2nd of November 2020. The 17th of March 2020 is one week after the last German province reported the first COVID-19 infection. Balanced panel data containing information about COVID-19 incidence rates, policy strictness and mobility for places of work is used to construct the panel data model. The data to measure the mobility trend for places of work is provided by the Google Community Mobility Report. Mobility trends for places of work (1) are measured daily for the 16 German provinces (Table 3). Google uses the weekday median values of the 5-week period 3rd of January to the 6th of February 2020 as baseline days for each weekday to measure relative changes in mobility. Relative mobility changes are not measuring seasonal or weekday specific changes and can therefore be biased by seasonal and weekly mobility patterns. Evidence for the existence of seasonality components gives the visualization of the mobility places for work (Figure 7).

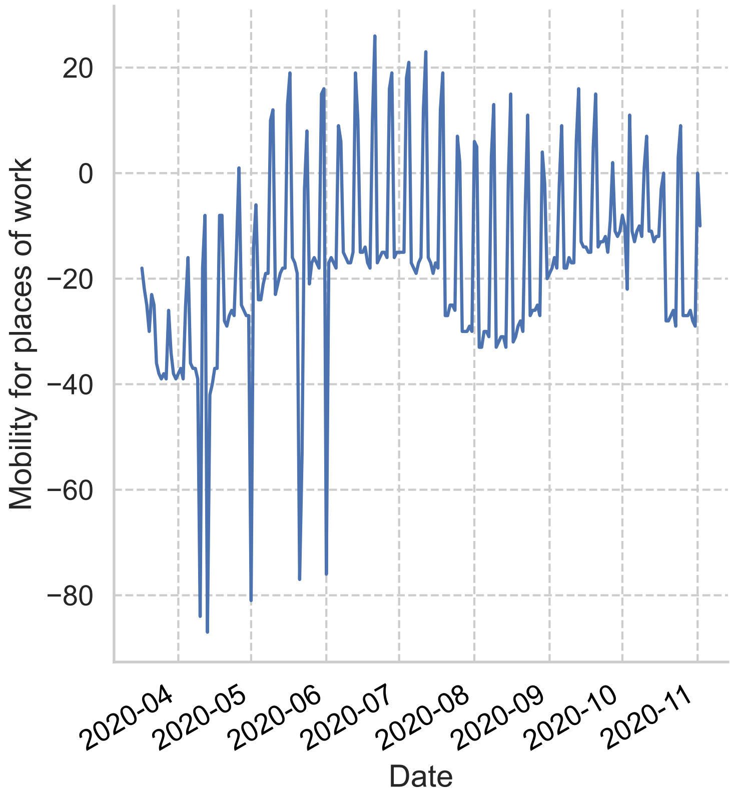



Figure 7: Mobility for places of work in Saxony

Dummy variables for every weekday are used to measure seasonality effects in the model. Additionally, we include a dummy to measure the effect of the German school holidays in summer. The 24-hour average temperature of the capital of each province is used as an approximation to control for a seasonality effect due to temperature changes over time within the each province (Footnote Data from wetter). To remove outliers, we removed any date of observation corresponding to a public holiday. The total number of observed days is 217. 3472 observations are included for each variable used in the panel model. Unfortunately, categorization into groups of income within each province is not given by the mobility data provided by the COVID-19 Community Mobility report. Therefore, changes in mobility patterns within provinces can not be observed.

To measure the virus-effect on the mobility of workplaces, we use the 7-day incidence rate of the province (3) (Table 3). The 7-day incidence rate is calculated

TABLE 3

Summary statistics mobility, stringency and incidence

| | (1) Mobility for workplaces | | | | (2) Weighted stringency index | | | |
|---|---|---|---|---|---|---|---|---|
| Prov. | Mean | SD | Max | Min | Mean | SD | Max | Min |
| BW | -24.39 | 14.18 | 12 | -54 | 51.06 | 14.58 | 73.81 | 29.17 |
| BY | -23.93 | 13.79 | 7 | -49 | 52.94 | 12.57 | 73.81 | 37.50 |
| BE | -26.96 | 16.20 | 15 | -54 | 41.50 | 13.33 | 71.43 | 30.06 |
| BB | -15.43 | 15.51 | 25 | -52 | 38.25 | 16.75 | 78.57 | 21.43 |
| HB | -23.53 | 13.97 | 16 | -52 | 43.67 | 9.39 | 59.52 | 21.43 |
| HH | -27.70 | 15.70 | 15 | -54 | 39.06 | 21.57 | 92.86 | 23.51 |
| HE | -23.71 | 14.48 | 14 | -50 | 35.07 | 17.90 | 71.43 | 21.13 |
| NI | -21.53 | 14.26 | 15 | -54 | 43.13 | 18.04 | 78.57 | 19.05 |
| MV | -11.93 | 16.70 | 35 | -49 | 41.22 | 18.04 | 78.57 | 23.81 |
| NW | -22.31 | 13.77 | 15 | -49 | 36.26 | 12.27 | 59.52 | 26.49 |
| RP | -21.25 | 13.19 | 10 | -50 | 33.18 | 12.76 | 59.52 | 23.81 |
| SL | -23.76 | 12.77 | 8 | -49 | 45.44 | 12.39 | 71.43 | 18.45 |
| SN | -15.65 | 15.45 | 26 | -53 | 45.07 | 11.14 | 78.57 | 5.36 |
| ST | -13.05 | 14.45 | 29 | -51 | 37.61 | 17.36 | 73.81 | 26.49 |
| SH | -19.34 | 15.66 | 21 | -51 | 37.46 | 15.99 | 66.67 | 21.43 |
| TH | -16.31 | 13.87 | 26 | -56 | 42.84 | 11.87 | 71.43 | 21.43 |

| | (3) 7-day incidence | | | |
|---|---|---|---|---|
| Prov. | Mean | SD | Max | Min |
| BW | 20.42 | 24.96 | 131.95 | 1.37 |
| BY | 22.52 | 27.13 | 144.68 | 1.55 |
| BE | 24.50 | 32.98 | 175.79 | 3.25 |
| BB | 8.99 | 12.16 | 71.55 | 0.55 |
| HB | 21.91 | 31.73 | 206.73 | 1.32 |
| HH | 20.33 | 24.88 | 131.45 | 0.16 |
| HE | 18.27 | 27.52 | 165.23 | 1.86 |
| NI | 12.60 | 14.99 | 97.76 | 1.15 |
| MV | 5.19 | 8.78 | 46.75 | 0.00 |
| NW | 20.87 | 26.92 | 167.04 | 3.34 |
| RP | 13.76 | 18.60 | 114.61 | 1.12 |
| SL | 19.81 | 32.44 | 180.18 | 0.20 |
| SN | 12.39 | 22.04 | 125.56 | 0.32 |
| ST | 6.90 | 10.95 | 60.94 | 0.41 |
| SH | 7.75 | 9.60 | 56.96 | 0.17 |
| TH | 9.35 | 11.76 | 66.36 | 0.80 |

by taking the 7-day moving average[7] of the reported COVID-19 infections, divided by the number of inhabitants of the province and multiplied by 100,000. The 7-day incidence rate is an appropriate indicator to measure the effect of the virus in the observed period because the mitigating effects of vaccinations are non-existent. The weighted stringency index (2) is used to measure the

[7]We use the COVID-19 infection data provided by the Novel Coronavirus Visual Dashboard operated by the Johns Hopkins University (https://raw.githubusercontent.com/covid19-eu-zh/covid19-eu-data/master/dataset/covid-19-de.csv).

effect of policy strictness on the mobility trend for places of work (Table 3).

TABLE 4

Summary statistics province-specific variables

| Prov. | (4) WFH | (5) Avg. Mobility | (6) Poverty 2020 | (7) Avg. income 2019 | (8) East/West |
|---|---|---|---|---|---|
| BW | 26.76 | -25.69 | 13.0 | 24892 | west |
| BY | 33.14 | -25.33 | 11.6 | 25309 | west |
| BE | 32.05 | -27.81 | 20.6 | 20972 | east/west |
| BB | 30.01 | -16.50 | 14.5 | 20475 | east |
| HB | 11.69 | -24.55 | 28.4 | 21481 | west |
| HH | 33.43 | -28.61 | 17.8 | 25029 | west |
| HE | 28.95 | -24.90 | 17.4 | 23943 | west |
| NI | 20.39 | -22.69 | 19.7 | 21988 | east |
| MV | 20.17 | -12.98 | 17.6 | 19470 | west |
| NW | 29.36 | -23.55 | 17.4 | 22294 | west |
| RP | 25.25 | -22.56 | 15.9 | 23197 | west |
| SL | 23.72 | -25.17 | 16.9 | 20277 | west |
| SN | 22.98 | -16.73 | 17.9 | 20335 | east |
| ST | 26.36 | -14.16 | 20.6 | 19528 | east |
| SH | 24.01 | -20.43 | 15.9 | 22833 | west |
| TH | 28.53 | -17.56 | 17.7 | 19793 | east |

To analyze the effect of the WFH rate on the mobility for places of work, we use the WFH rate provided by the 2021 report of the structure of the German labour market by 'infas360'. The work-from-home rate measures the proportion of employees subject to social security at the place of residence who work entirely or predominantly from home in February and March 2021. The units of observation are the 294 rural and 107 urban districts. We calculate the provincial WFH rates by summing the WFH rates of the districts, weighted by the total number of employees of the corresponding province (4).

We assume that using values for the WFH rate measured during the COVID-19 pandemic provides us with more relevant insight than the 2017/2018 BIBB/BAuA Employment Survey data used by Irlacher and Koch (2021). We assume the variables listed in Table 4 as constant over time. Therefore, daily, weekly, or monthly adjustment effects of the work-from-home rate triggered by the stringency-effect and the virus-effect cannot be monitored.

To indicate the potential consequences of unequally distributed WFH rates during the pandemic on income distribution, we use various social indicators provided by 'infas360'. On the provincial country level, we use the average income of 2019 (7) and the at-risk-of-poverty rate [8] of 2020 (6). We use a binary variable to distinguish East and West German provinces (8).

### 3.3 Econometric model

Several province-specific differences in variables potentially effecting the mobility for places of work like the WFH rate (4), average income (7) or the state affiliation before the German reunification (8) exist (Table 4). We assume a high likelihood for further unobserved province-specific characteristics. To avoid biased estimators due to omitted time-invariant variables, we use a fixed effect model (FE). FE models control for all time-invariant differences between the provinces. To estimate the effect of COVID-19 policy strictness on mobility trends for places of work in Germany, we apply the following FE model (4),

$$\begin{aligned} MW_{i,t} = \alpha_i + \zeta_2 D1 + \zeta_3 D2 + \zeta_4 D3 + \zeta_5 D4 + \zeta_6 D5 + \zeta_7 D6 + \eta Holiday \\ + \beta_1 SI_{i,t} + \beta_2 VE_{i,t} + \beta_3 Temp_{i,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

where the ζ-dummies estimate the change in the mobility rate for places of work from Monday to Saturday relative to Sunday. η estimates the change in the mobility rate for places of work due to the period of school holidays in summer. $\beta_1$ is the estimated effect of the weighted stringency index on mobility for places of work (*stringency effect*). $\beta_2$ is the estimated effect of the logarithmized 7-day incidence on mobility for places of work. We are using the logarithm of the 7-day incidence $VE_{i,t}$ (*virus effect*), as we assume a linear-log relation between mobility for workplaces and the 7-day incidence rate. $\beta_3$ is used as an additional seasonal control variable to estimate the effect of temperature. $\alpha_i$ is the unknown intercept (*fixed effect*) for each province. $\epsilon_{i,t}$ is the idiosyncratic error term.

We use a Hausman test to verify the suitability of the Fixed-effect (FE) model.

[8] The at-risk-of-poverty threshold is 60% of the median equivalized income. This gives the at-risk-of-poverty threshold for a single-person household (for example, in Baden-Württemberg: 871 euros, in Germany: 801 euros).

The Hausman test controls if the province-specific error terms ($u_i$) are correlated with the regressors of the model. If the null hypothesis cannot be rejected, the error terms are likely not correlated with the regressors, and a random effect would be appropriate. According to the Hausman test we can reject the null hypothesis ($p < 0.01$) (see Appendix A.10). Therefore, we can assume that our fixed effect estimators (within estimators) are consistent and random effect estimators inconsistent.
However, FE models lack the ability to deeply analyse unique time-constant variables such as the WFH rate, because the individual fixed effect $\alpha_i$ already absorbs all time-constant unobserved factors affecting $MW_{i,t}$. Therefore, effects of the WFH rate can not be estimated by our FE model. A random effect (Random-effect (RE)) model is needed to estimate the effect of the WFH rate on the mobility trend for places of work. In addition to the variables used in our FE model (5), we include the time-constant variables WFH rate, the at-risk-of-poverty rate, a West Germany identifier and the average income in the following RE model (4),

$$\begin{aligned} MW_{i,t} = {} & \alpha + \zeta_2 D1 + \zeta_3 D2 + \zeta_4 D3 + \zeta_5 D4 + \zeta_6 D5 + \zeta_7 D6 + \eta Holiday \\ & + \rho West_i + \beta_1 SI_{i,t} + \beta_2 VE_{i,t} + \beta_3 Temp_{i,t} + \beta_4 WFH_i + \beta_5 Poverty_i \\ & + \beta_6 Income_i + u_i + e_{i,t} \end{aligned} \tag{5}$$

where $\rho$ measures the observed difference between East and West German provinces. $\beta_4$ estimates the effect of the time-invariant WFH rate. We use $\beta_5$ to measure the effect of the at-risk-of-poverty rate from 2020, and $\beta_6$ to measure the effect of the average income of 2019 on the mobility for places of work. $\alpha$ is the intercept, $u_i$ contains the remaining effect of the province-specific characteristics. $e_{i,t}$ is the idiosyncratic error term.
According to the Hausman test, the random effects estimators are likely to be inconsistent ($p < 0.01$) due to the existing covariance between $u_i$ and the regressors (see Appendix A.11). We can reject the null hypothesis of the Breusch and Pagan Lagrangian multiplier test for random effects ($p < 0.01$) (see Appendix A.12). Accordingly, the variance across provinces is not equal to zero,

conditional heteroscedasticity exists, and a pooled OLS model is inappropriate. Robust standard errors are used to adjust our model for the occurrence of heteroscedasticity.

## 3.4 Results

**TABLE 5**

Fixed-effects (within) regression & Random-effects GLS regression

| | | FE | | RE | |
|---|---|---|---|---|---|
| | | i | | ii | |
| Stringency | SI | -0.437*** | (0.026) | -0.429*** | (0.024) |
| infections_log | VE | -0.989*** | (0.214) | -0.989*** | (0.217) |
| Monday | D1 | -25.122*** | (0.975) | -24.848*** | (1.006) |
| Tuesday | D2 | -25.309*** | (0.864) | -25.053*** | (0.888) |
| Wednesday | D3 | -25.002*** | (0.906) | -24.739*** | (0.927) |
| Thursday | D4 | -25.171*** | (0.812) | -25.175*** | (0.820) |
| Friday | D5 | -26.783*** | (0.840) | -26.780*** | (0.868) |
| Saturday | D6 | -4.660*** | (0.532) | -4.664*** | (0.548) |
| Avg. Temperature | *Temp* | 0.373*** | (0.063) | 0.380*** | (0.061) |
| School summer holiday | *Holiday* | -10.053*** | (0.453) | -10.024*** | (0.408) |
| Work-from-home rate | *WFH* | | | -0.506*** | (0.096) |
| West Germany | *West* | | | -7.951*** | (0.838) |
| At-risk-of-poverty 2020 | *Poverty* | | | -0.618*** | (0.173) |
| Avg. income 2019 | *Income* | | | 0.00014 | (0.00036) |
| Constant | | 15.297*** | (1.558) | 40.925*** | (7.899) |
| Corr(u_i, Xb) | | -0.037 | | 0 (assumed) | |
| R-squared: | | | | | |
| within | | 0.7655 | | 0.7618 | |
| between | | 0.1317 | | 0.8618 | |
| overall | | 0.7035 | | 0.7691 | |
| F-statistics / Wald-χ2 | | 3467.8 | | 977475.74 | |
| P-value of: F / Wald-χ2 | | 0.000 | | 0.000 | |
| Number of obs | | 3471 | | 3254 | |
| Number of fed_n | | 16 | | 15 | |

Note: Heteroskedastic consistent standard errors are given in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

An F-value of 3467.8 ($p < 0.01$) suggests the Fixed-effects (within) regression (i) is good fitted. The R-squared (within) value indicates that 76.5% of the variance within provinces is explained by our model (Table 5). A low R-squared (between) value of 13.17 indicates that our model accounts for only 13.17% of the variance between provinces, probably due to omitted time-invariant characteristics of the provinces. We observe a low correlation between the province-specific fixed effects and the regressors, indicating low unobserved heterogeneity. All regressors of the FE model are highly significant ($p < 0.01$). In addition to Ruiz-Euler et al. (2020) and Bonaccorsi et al. (2020) we statistically quantify the magnitude of the *virus-effect* and the *stringency-effect*. Both the *stringency effect*t and the *virus effect* negatively impact the mobility for places of work. According to the *stringency-effect* estimator, the maximum value of policy strictness (100) would lead to a 43.7% decline in mobility for places of work, indicating a strong negative impact of COVID-19 induced policies on the location-dependent labour in the German economy. A high correlation between variables is not observed ($VIF < 2$ for all regressors). Therefore, multicollinearity is not substantially impacting our results. The weekdays Monday to Friday are estimated with a 25.1% to 26.8% decline in mobility for places of work relative to Sunday. Saturdays are estimated with a 4.7% decline relative to Sundays. People generally work less on weekends, regardless of the pandemic. Therefore the decline in mobility for places of work is higher on Monday to Friday than for weekend days. The average 24h-temperature is positively impacting the mobility for places of work, indicating an increase in mobility for places of work throughout the year corresponding to rising temperatures. The mobility for places of work increases after the first wave of COVID-19 infections in the early, relatively cold months of March and April. The positive temperature effect could either be interpreted as an economic recovery process after the first wave of the pandemic or as a general occurring seasonality trend of the mobility for places of work due to rising temperatures (e.g. the mobility for places of work in the construction and agriculture sector is likely to increase with rising temperatures). The German school holidays are negatively impacting the mobility for places of work. Therefore, the observed mobility decline during the summer months is likely to be interpreted as a seasonal effect due to increased holiday activity during summer.

An Wald Chi-Squared value of 977475.74 ($p < 0.01$) suggest that our Random-effects Generalized Least Squares (GLS) regression (ii) is good fitted (Table 5). The R-squared (within) value indicates that our model explains 76.18% of the variance within provinces. A high R-squared (between) value of 86.18 indicates that our model accounts for 86.18% of the variance between provinces. The increase in the R-squared (between) compared to the FE Model (i) is probably due to the implementation of previously omitted time-invariant province-specific variables. The low correlation between the province-specific fixed effects and the regressors in the FE model (i) indicates that the RE model assumption of the correlation between the remaining effects of the province-specific characteristics $u_i$ and the regressors being zero is almost fulfilled. However, the Hausman test ($p < 0.01$) indicates inconsistent estimators of the RE model (ii) (see Appendix A.11).

We dropped the observations for Berlin in the RE model because Berlin can not be considered East or West German.

All estimators used in the RE model (ii) are significant ($p < 0.01$), except for the estimator of the average household income in 2019. The WFH rate estimator is negative, indicating a negative impact of 0.5% on mobility for workplaces for every 1% of employees subject to social security at the place of residence who work entirely or predominantly from home. Our findings support the supposition of Irlacher and Koch (2021) that the WFH rate has a significant negative impact on provinces during the peak of the lockdown. Furthermore, our findings indicate that the WFH rate negatively impacts workplace mobility during the pandemic. We interpret the decline in mobility due to higher WFH rates as flexible and shock resistant characteristics of the regional labour markets. According to Alipour et al. (2021) WFH shields effectively from loss of income by pandemic induced short-time work. As a result, the regional WFH rate needs to be considered to correctly interpret the decline in mobility for places of work as an indicator for economic downfall. According to the West Germany dummy estimator, provinces part of former West Germany encounter an 8% decrease in mobility for places of work. In contrast to the findings of Bonaccorsi et al. (2020), and Ruiz-Euler et al. (2020), the RE model indicates no significant impact of the average income on the mobility for places of work. The estimator for the at-risk-of-poverty rate 2020 suggests that poverty has a significant negative impact on mobility for places of work. Therefore, the RE model (ii) does not provide evidence for the occurrence of a mobility gap between provinces with low and high rates of poverty or income in Germany. According to the WFH rate estimator (ii), differences in WFH rates can lead to mobility gaps throughout provinces in Germany. Employees without the possibility of WFH need to choose between income or mobility reduction. Therefore regions with lower WFH are likely to be characterized with higher mobility for places of work. We interpret the WFH rate a as key component of *inherent differences* in labour markets observed by Bonaccorsi et al. (2020) and Ruiz-Euler et al. (2020). Omitting the West Germany dummy variable reproduces no significant change in the RE model results regarding income and the at-risk-of-poverty rate estimators.

TABLE 6

Summary statistics WFH rate & GDP of German districts

| | (9) WFH rate | | | | (10) GDP pre employee in 1k€ | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Max | Min | Mean | SD | Max | Min |
| Urban | 28.26 | 5.84 | 44 | 10 | 73.14 | 16.33 | 135.80 | 51.80 |
| Rural | 23.91 | 5.32 | 38 | 12 | 65.47 | 11.57 | 101.60 | 52.40 |
| West | 26.28 | 5.94 | 44 | 10 | 71.38 | 11.09 | 135.80 | 52.80 |
| East | 25.11 | 6.15 | 43 | 15 | 60.34 | 5.84 | 81.60 | 51.80 |
| East/urban | 31.12 | 7.44 | 43 | 17 | 60.86 | 4.97 | 71.40 | 51.80 |
| West/urban | 28.00 | 5.64 | 44 | 10 | 74.22 | 12.63 | 135.80 | 54 |
| East/rural | 23.53 | 4.68 | 37 | 15 | 60.20 | 6.08 | 81.60 | 52.40 |
| West/rural | 24.07 | 5.58 | 38 | 12 | 67.73 | 7.57 | 101.60 | 53 |

In contrast to the findings of Irlacher and Koch (2021), significantly lower averages of WFH rates in East German districts are not observed. The average WFH rate in East German districts is 1.17 percentage points smaller than in the West German districts (Table 6). Furthermore, the WFH rate of urban East German districts is 11.11% (3.12 percentage points) higher than in the West German counterpart.

Categorizing the German districts into numbers of employees (workforce) and

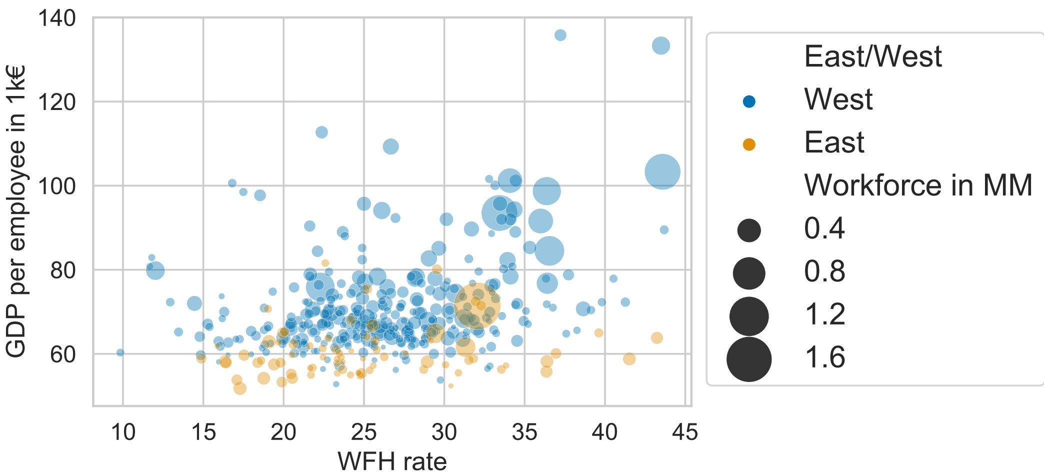



Figure 8: GDP per emplyoee in thousand Euros and the WFH rate of the German districts categorized in East and West German

East and West German districts[9] further indicates the absence of WFH rate differences throughout East and West German districts (Figure 8). The average GDP per employee (10) is generally higher in West Germany (Figure 8 and Table 6). Furthermore, the WFH rate in highly populated urban districts seems to be larger than in less populated districts (Figure 8).

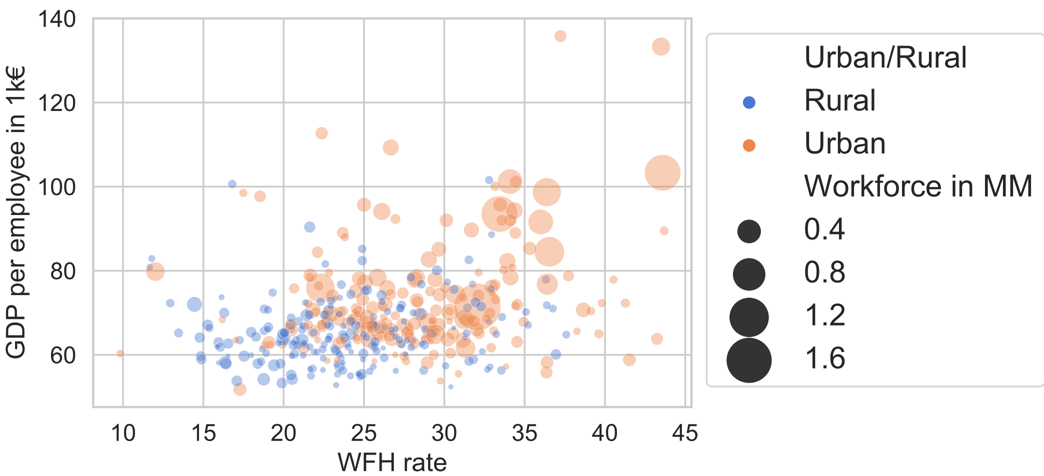



Figure 9: GDP per employee in thousand Euros and the WFH rate of the German districts categorized in urban and rural districts

Categorizing the German districts into urban and rural indicates that the work-from-rate is unequally distributed throughout urban and rural districts

[9]We removed the urban district of Wolfsburg to remove outliers

rather than unequally distributed throughout East and West Germany as assumed by Irlacher and Koch (2021) (Figure 9). The WFH rate (5) confirms that the average WFH rates are higher in urban than in rural districts. In West Germany 16% higher, and in East Germany 32% higher (Table 5).
The geographical visualizations of the German provinces WFH rate compared to the geographical visualizations of the German districts WFH rate supports our finding of unequally distributed WFH rates throughout urban and rural areas. (see Appendix A.13 and Appendix A.14)
WFH effectively shields income losses (Alipour et al., 2021). Therefore, we can expect a positive income effect for urban districts and a negative income effect for rural districts due to the COVID-19 pandemic. The income distribution effect towards urban areas is higher in East Germany because of more considerable differences in the urban and rural WFH rates.
According to Irlacher and Koch (2021), regions with a higher share of WFH jobs are characterized by a higher average income. Figure 10 visualizes linear regression plots for GDP per employee and the work-from-rate with a 95%confidential interval. The wage premium for work from home jobs observed by Irlacher and Koch (2021) seems to only occur in West German districts. Therefore, we expect an additional income effect (limited to West German districts) benefiting districts with higher average income during the pandemic.

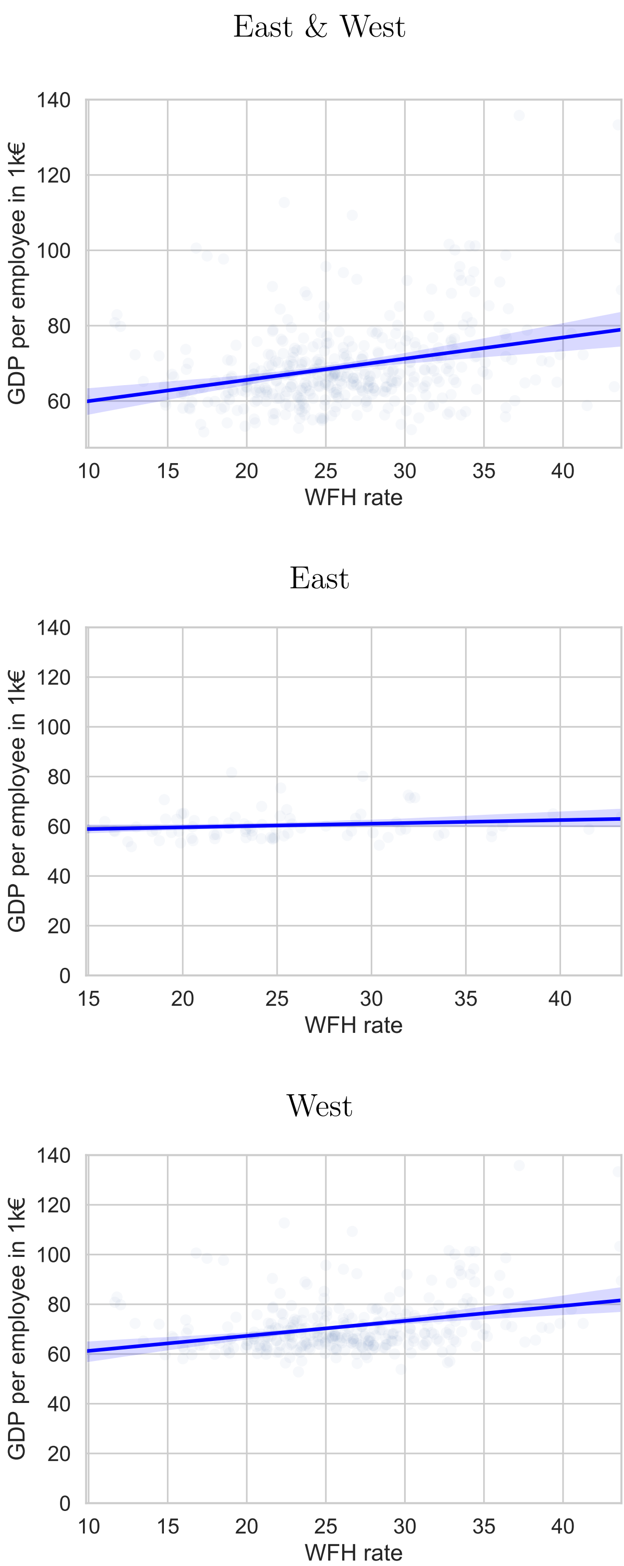



Figure 10: Regression plots of the WFH rate with a 95% confidence interval

# 4 Conclusion

This paper provides researchers with policy stringency data on the provincial country-level measuring the overall policy stringency and the strictness of subindices regarding the policy categories school closing, closure and regulation of business, curfews, internal border restrictions, lockdown restrictions, mask-wearing requirements, and social distancing. The stringency data needs to be updated to cover the entire period of the COVID-19 pandemic. New subindices should be added to increase the accuracy of the stringency indices on the provincial country-level.

We provide profound confirmatory evidence for a heterogeneous policy response in Germany as indicated in the study by Buthe et al. (2020a).

According to our results, the OxCGRT stringency index by Hale et al. (2020) likely overestimates the strictness value for Germany on the national country-level.

Policy strictness and COVID-19 infections negatively impact the mobility of places of work. According to our Fixed-effects (within) regression, the maximum value of policy strictness (100) would lead to a 43.7% decline in mobility for places of work. We observe a significant negative impact of the province-specific WFH rate. In contrast to Bonaccorsi et al. (2020) and Ruiz-Euler et al. (2020) the impact of income on the mobility for places of work is not significant, and the impact of the at-risk-of-poverty is significantly negative. We conclude that mobility gaps in Germany are likely to be affected by the region-specific differences in WFH rates instead of differences in income. The different results compared to the findings of Bonaccorsi et al. (2020) and Ruiz-Euler et al. (2020) might occur due to different correlations between WFH and income in Germany. The income variables used by Bonaccorsi et al. (2020) and Ruiz-Euler et al. (2020) might correlate with different WFH rates between units of observation and might absorb the underlying effect of different WFH rates. We suggest analyzing the correlation between the WFH rates and average income within districts in Italy and the US.

However, the Hausman test indicates that the random-effects GLS regression estimators are insignificant. A correlated random coefficient model could be used to verify our results.

In contrast to the Irlacher and Koch (2021), significantly lower averages of WFH rates in East German districts are not observed. The average WFH rate in East German districts is 1.17 percentage points smaller than in the West German districts (Table 6). Furthermore, the WFH rate of urban East German districts is 11.11% (3.12 percentage points) higher than in the West German counterpart.

Considering that WFH jobs effectively shield from income losses due to pandemic induced short-time work (Alipour et al., 2021), we expect an additional income effect for districts and groups if income with higher WFH rates during the pandemic. Therefore, we can expect a positive income effect for urban districts and a negative income effect for rural districts. The income distribution effect towards urban areas is higher in East Germany because of more considerable differences in the urban and rural WFH rates. We expect an additional income effect (limited to West German districts) benefiting districts with higher average income during the pandemic. Employees without the possibility of WFH need to choose between income or mobility reduction. Therefore we can expect regions with lower WFH (rural districts) to be characterized with higher mobility for places of work during the pandemic. Accordingly, rural districts and districts with a low average income in West Germany are more severely hit by the pandemic in terms of income losses and risk of infection.

# A Appendix

## A.1 Codebook

| Codebook of the Strictness Subindices | | | | | |
|---|---|---|---|---|---|
| ID | Name | Description | Measurement | Subcategories | Coding instructions |
| C1 | School/ childcare closing | Record closings of childare facilities, schools and universities | Ordinal scale | [Preschool or childcare facilities (generally for children ages 5 and below); Primary Schools (generally for children ages 10 and below); Secondary Schools (generally for children ages 10 to 18); Higher education institutions (i.e. degree granting institutions)] | 0 : open with no conditions attached<br>1 : open with conditions<br>2 : closed/locked down* (*only graduation classes allowed counts as closed for Secondary School) |
| C2 | Workplace closing (close personal contact) | Record closings of workplaces with close personal contact (e.g. personal grooming businesses, bars, restaurants) | Ordinal scale | [Restaurants; Bars; Personal Grooming Businesses (e.g. hair salons)] | 0 : open with no conditions attached.<br>1 : open with conditions 2 : closed/locked down* (*open for take-away only counts as closed) |
| C3 | Curfew | Record curfews with ban on goint out of house without special reason | Binary flag | | 0 : no curfew<br>1 : curfew with mandatory closing hours |
| C4 | Internal border restrictions | Record internal borde restrictions | Binary flag | | 0 : no internal border restrictions<br>1 : curfew with mandatory closing hours |
| C5 | Lockdown | Record lockdown regulations | Binary flag | | 0 : no lockdown regulations.<br>1 : lockdown regulations (e.g. stay-at-home requirements or closing of care facilities for visitors) |
| C6 | Mask wearing | Record mask waering requirments for: schools; personal businesses; non personal businesses; all indoor spaces; everywhere | Binary flag (Mask wearing required in subcategory) / Ordinal Scale (Scaling regarding quantitiy of subcategorie with mask waearing requriemnts) | [Indoor mask wearing requirements in place for: subcategories C1; subcategories C2; non_personal business (e.g. supermarkets); Wearing mask in all indoor places; Wearing Masks in all public spaces/everywhere ] | 0 : no mask wearing policy in place<br>1 : mask wearing policy |
| C7 | Social distancing | Record if general keeping distance rules apply | Binary flag | | 0 : no general 1,5m distancing rule<br>1 : Keeping a distance of at least 6 feet or 1.5 meters apart |

## A.2 Maximum ordinal values of subdindices

| Max Values of Subindices | |
|---|---|
| ID | Max value (N_j) |
| C1 | 8 (0,1,2,3,4,5,6,7,8) |
| C2 | 6 (0,1,2,3,4,5,6) |
| C3 | 1 |
| C4 | 1 |
| C5 | 1 |
| C6 | 2 ([0-1],1,2)* |
| C7 | 1 |

* value from 0 to 1 can be decimal, see section C6 for further information

## A.3 Subindex weights

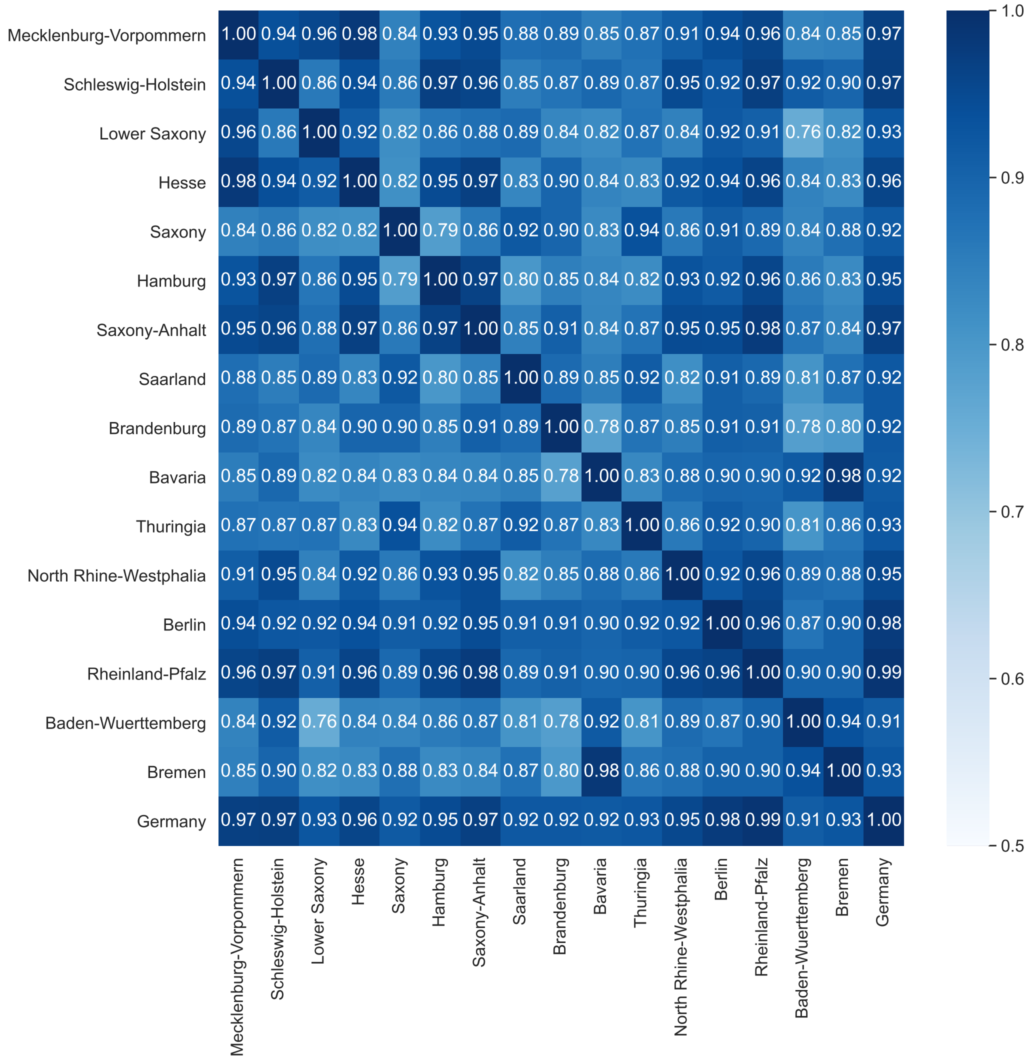
| Subindex Weights | |
|---|---|
| ID | Weigth (w) |
| C1 | 3/14 |
| C2 | 3/14 |
| C3 | 1/14 |
| C4 | 1/14 |
| C5 | 2/14 |
| C6 | 2/14 |
| C7 | 2/14 |

## A.4 Summary statistics subindices

| | (15)<br>Mean C1 | (16)<br>SD C1 | (17)<br>Mean C2 | (18)<br>SD C2 | (19)<br>Mean C3 | (20)<br>SD C3 | (21)<br>Mean C4 | (22)<br>SD C4 |
|---|---|---|---|---|---|---|---|---|
| Bavaria | 69.13 | 25.60 | 58.23 | 25.32 | 0.00 | 0.00 | 0.00 | 0.00 |
| Baden-Wuert. | 71.26 | 25.95 | 60.66 | 25.66 | 0.00 | 0.00 | 0.00 | 0.00 |
| Saarland | 51.67 | 26.63 | 57.83 | 25.27 | 0.00 | 0.00 | 0.00 | 0.00 |
| Saxony | 55.41 | 24.91 | 57.15 | 24.84 | 0.40 | 6.36 | 0.40 | 6.36 |
| Bremen | 66.30 | 29.41 | 49.66 | 28.89 | 0.00 | 0.00 | 0.00 | 0.00 |
| Lower Saxony | 58.10 | 26.56 | 59.51 | 25.16 | 0.00 | 0.00 | 29.15 | 45.54 |
| Thuringia | 58.05 | 30.19 | 56.21 | 25.10 | 0.00 | 0.00 | 0.00 | 0.00 |
| Berlin | 44.53 | 33.29 | 56.48 | 23.15 | 0.00 | 0.00 | 0.00 | 0.00 |
| Mecklenburg-Vorp. | 64.52 | 23.66 | 57.56 | 24.54 | 0.00 | 0.00 | 65.59 | 47.60 |
| Hamburg | 62.04 | 28.85 | 58.23 | 25.05 | 0.00 | 0.00 | 19.84 | 39.96 |
| Brandenburg | 48.13 | 26.31 | 58.10 | 25.27 | 0.00 | 0.00 | 8.10 | 27.33 |
| Saxony-Anhalt | 67.91 | 22.07 | 59.04 | 25.22 | 0.00 | 0.00 | 0.00 | 0.00 |
| Schleswig-Holstein | 68.52 | 25.17 | 59.92 | 25.67 | 0.00 | 0.00 | 24.70 | 43.21 |
| North Rhine-West. | 69.59 | 22.80 | 56.75 | 24.22 | 7.69 | 26.70 | 0.00 | 0.00 |
| Hesse | 59.97 | 29.24 | 57.29 | 24.71 | 0.00 | 0.00 | 0.00 | 0.00 |
| Rheinland-Pfalz | 60.83 | 23.68 | 56.88 | 24.96 | 0.00 | 0.00 | 0.00 | 0.00 |

| | (23)<br>Mean C5 | (24)<br>SD C5 | (25)<br>Mean C6 | (26)<br>SD C6 | (27)<br>Max C6 | (28)<br>Mean C7 | (29)<br>SD C7 |
|---|---|---|---|---|---|---|---|
| Bavaria | 43.72 | 49.71 | 23.77 | 13.81 | 40.28 | 91.90 | 27.33 |
| Baden-Wuert. | 37.25 | 48.44 | 18.27 | 11.62 | 36.11 | 85.43 | 35.36 |
| Saarland | 12.96 | 33.65 | 35.83 | 21.18 | 50.00 | 85.43 | 35.36 |
| Saxony | 11.74 | 32.26 | 24.22 | 14.03 | 40.28 | 91.50 | 27.95 |
| Bremen | 0.40 | 6.36 | 22.33 | 11.82 | 33.33 | 91.50 | 27.95 |
| Lower Saxony | 13.77 | 34.52 | 13.71 | 7.23 | 20.83 | 65.99 | 47.47 |
| Thuringia | 10.12 | 30.22 | 13.16 | 6.81 | 16.67 | 87.04 | 33.65 |
| Berlin | 18.22 | 38.68 | 13.78 | 7.18 | 20.83 | 91.90 | 27.33 |
| Mecklenburg-Vorp. | 14.98 | 35.76 | 13.16 | 6.81 | 16.67 | 29.96 | 45.90 |
| Hamburg | 20.24 | 40.26 | 20.85 | 16.82 | 100.00 | 29.96 | 45.90 |
| Brandenburg | 11.74 | 32.26 | 19.73 | 11.06 | 30.56 | 57.89 | 49.47 |
| Saxony-Anhalt | 17.41 | 38.00 | 13.16 | 6.81 | 16.67 | 29.96 | 45.90 |
| Schleswig-Holstein | 0.40 | 6.36 | 13.16 | 6.81 | 16.67 | 29.96 | 45.90 |
| North Rhine-West. | 3.64 | 18.78 | 14.30 | 8.15 | 29.17 | 30.77 | 46.25 |
| Hesse | 15.79 | 36.54 | 13.16 | 6.81 | 16.67 | 29.96 | 45.90 |
| Rheinland-Pfalz | 0.40 | 6.36 | 13.16 | 6.81 | 16.67 | 29.96 | 45.90 |

## A.5 Pearson-correlation matrix weighted stringency index

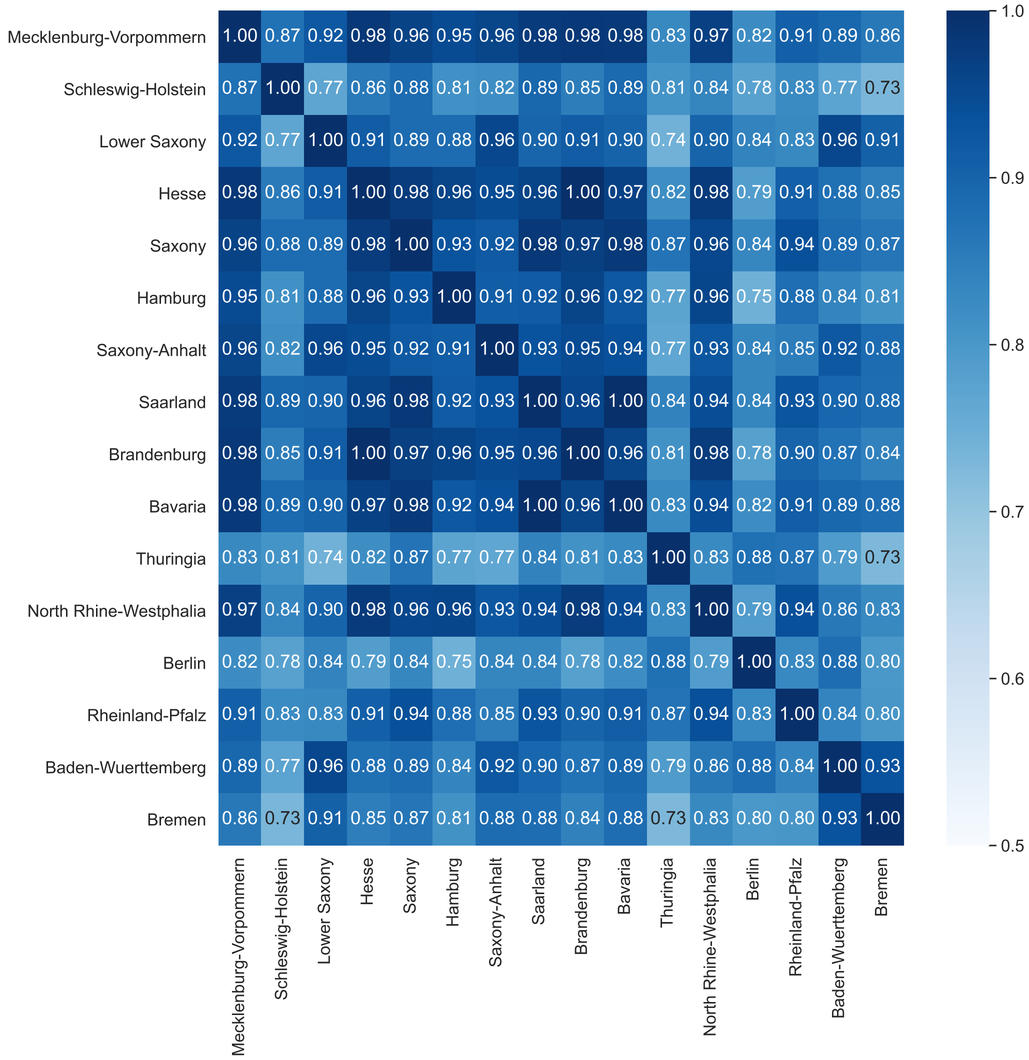


## A.6 Spearman-correlation matrix subindices

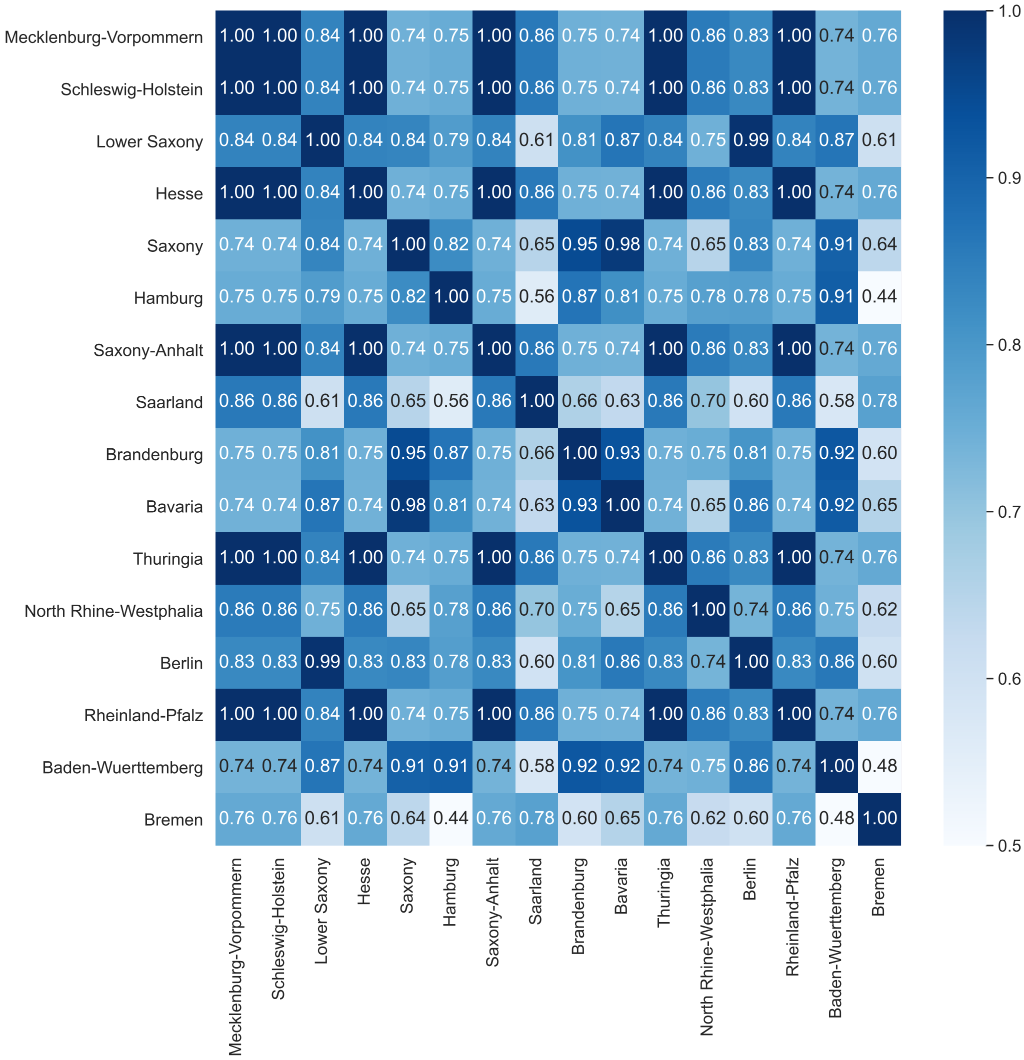
### C1 - School closing

| | Mecklenburg-Vorpommern | Schleswig-Holstein | Lower Saxony | Hesse | Saxony | Hamburg | Saxony-Anhalt | Saarland | Brandenburg | Bavaria | Thuringia | North Rhine-Westphalia | Berlin | Rheinland-Pfalz | Baden-Wuerttemberg | Bremen |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mecklenburg-Vorpommern | 1.00 | 0.93 | 0.92 | 0.92 | 0.79 | 0.90 | 0.85 | 0.90 | 0.83 | 0.86 | 0.91 | 0.81 | 0.89 | 0.87 | 0.70 | 0.85 |
| Schleswig-Holstein | 0.93 | 1.00 | 0.94 | 0.93 | 0.74 | 0.92 | 0.84 | 0.91 | 0.88 | 0.91 | 0.91 | 0.81 | 0.92 | 0.87 | 0.80 | 0.93 |
| Lower Saxony | 0.92 | 0.94 | 1.00 | 0.95 | 0.78 | 0.94 | 0.81 | 0.99 | 0.82 | 0.84 | 0.91 | 0.78 | 0.95 | 0.97 | 0.74 | 0.84 |
| Hesse | 0.92 | 0.93 | 0.95 | 1.00 | 0.83 | 0.97 | 0.84 | 0.95 | 0.87 | 0.89 | 0.94 | 0.80 | 0.98 | 0.95 | 0.82 | 0.91 |
| Saxony | 0.79 | 0.74 | 0.78 | 0.83 | 1.00 | 0.80 | 0.78 | 0.81 | 0.86 | 0.66 | 0.86 | 0.77 | 0.83 | 0.81 | 0.77 | 0.76 |
| Hamburg | 0.90 | 0.92 | 0.94 | 0.97 | 0.80 | 1.00 | 0.84 | 0.95 | 0.87 | 0.89 | 0.92 | 0.83 | 0.97 | 0.94 | 0.81 | 0.91 |
| Saxony-Anhalt | 0.85 | 0.84 | 0.81 | 0.84 | 0.78 | 0.84 | 1.00 | 0.81 | 0.85 | 0.70 | 0.81 | 0.95 | 0.82 | 0.80 | 0.80 | 0.83 |
| Saarland | 0.90 | 0.91 | 0.99 | 0.95 | 0.81 | 0.95 | 0.81 | 1.00 | 0.84 | 0.82 | 0.91 | 0.79 | 0.96 | 0.98 | 0.77 | 0.84 |
| Brandenburg | 0.83 | 0.88 | 0.82 | 0.87 | 0.86 | 0.87 | 0.85 | 0.84 | 1.00 | 0.83 | 0.90 | 0.81 | 0.89 | 0.82 | 0.88 | 0.93 |
| Bavaria | 0.86 | 0.91 | 0.84 | 0.89 | 0.66 | 0.89 | 0.70 | 0.82 | 0.83 | 1.00 | 0.88 | 0.66 | 0.86 | 0.79 | 0.74 | 0.91 |
| Thuringia | 0.91 | 0.91 | 0.91 | 0.94 | 0.86 | 0.92 | 0.81 | 0.91 | 0.90 | 0.88 | 1.00 | 0.77 | 0.94 | 0.90 | 0.77 | 0.88 |
| North Rhine-Westphalia | 0.81 | 0.81 | 0.78 | 0.80 | 0.77 | 0.83 | 0.95 | 0.79 | 0.81 | 0.66 | 0.77 | 1.00 | 0.78 | 0.77 | 0.77 | 0.78 |
| Berlin | 0.89 | 0.92 | 0.95 | 0.98 | 0.83 | 0.97 | 0.82 | 0.96 | 0.89 | 0.86 | 0.94 | 0.78 | 1.00 | 0.96 | 0.83 | 0.90 |
| Rheinland-Pfalz | 0.87 | 0.87 | 0.97 | 0.95 | 0.81 | 0.94 | 0.80 | 0.98 | 0.82 | 0.79 | 0.90 | 0.77 | 0.96 | 1.00 | 0.76 | 0.83 |
| Baden-Wuerttemberg | 0.70 | 0.80 | 0.74 | 0.82 | 0.77 | 0.81 | 0.80 | 0.77 | 0.88 | 0.74 | 0.77 | 0.77 | 0.83 | 0.76 | 1.00 | 0.89 |
| Bremen | 0.85 | 0.93 | 0.84 | 0.91 | 0.76 | 0.91 | 0.83 | 0.84 | 0.93 | 0.91 | 0.88 | 0.78 | 0.90 | 0.83 | 0.89 | 1.00 |

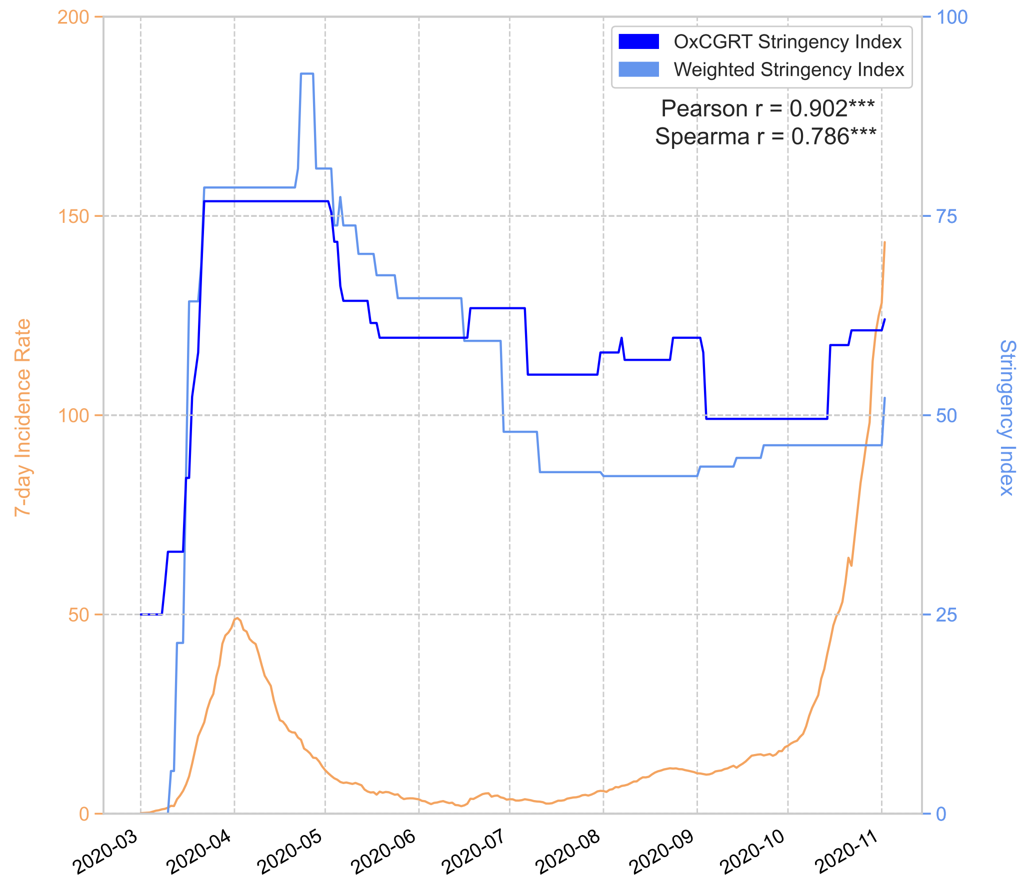
## C2 - Workplace closing (close personal contact)



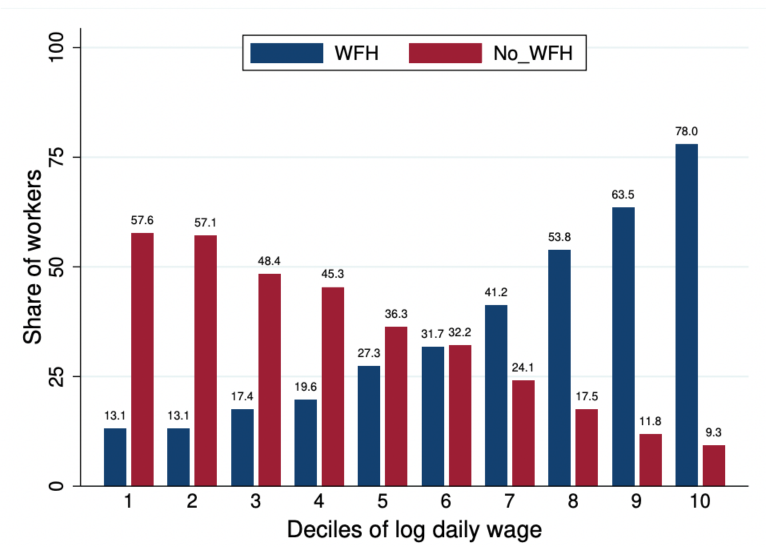
## C6 - Mask wearing



## A.7 OxCGRT and weighted national stringency index with maximum-method

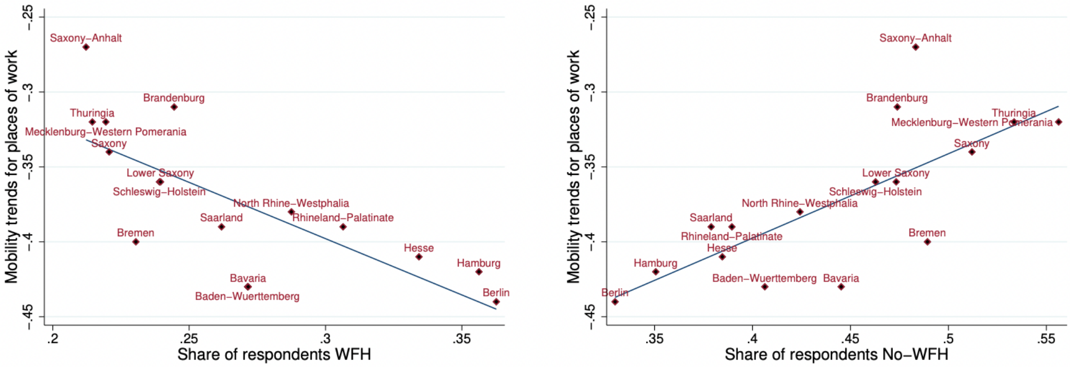



## A.8 WFH across the wage distribution




Source: Irlacher and Koch (2021)

## A.9 Changes in mobility trend for workplaces and working from home




Source: Irlacher and Koch (2021)

## A.10 Hausman-Test fixed-effect

| | Coefficients (b) fe5 | (B) re5 | (b–B) Difference | sqrt(diag(V_b–V_B)) S.E. |
|---|---|---|---|---|
| Stringency | –.437242 | –.4359071 | –.0013349 | . |
| infections~g | –.9890921 | –1.056254 | .0671623 | .0048864 |
| temp | .394662 | .3878207 | .0068413 | . |
| weekday | | | | |
| 2 | –25.12175 | –25.11468 | –.0070679 | . |
| 3 | –25.30932 | –25.3087 | –.0006203 | . |
| 4 | –25.00224 | –24.99688 | –.0053615 | . |
| 5 | –25.43722 | –25.42661 | –.0106113 | . |
| 6 | –27.00777 | –26.99491 | –.0128648 | . |
| 7 | –4.515116 | –4.516005 | .0008895 | . |
| 1.summer_h~i | –9.811758 | –9.811895 | .0001371 | . |

```
                  b = consistent under Ho and Ha; obtained from xtreg
   B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

              chi2(10) = (b–B)'[(V_b–V_B)^(–1)](b–B)
                       =       71.64
            Prob>chi2 =       0.0000
            (V_b–V_B is not positive definite)
```

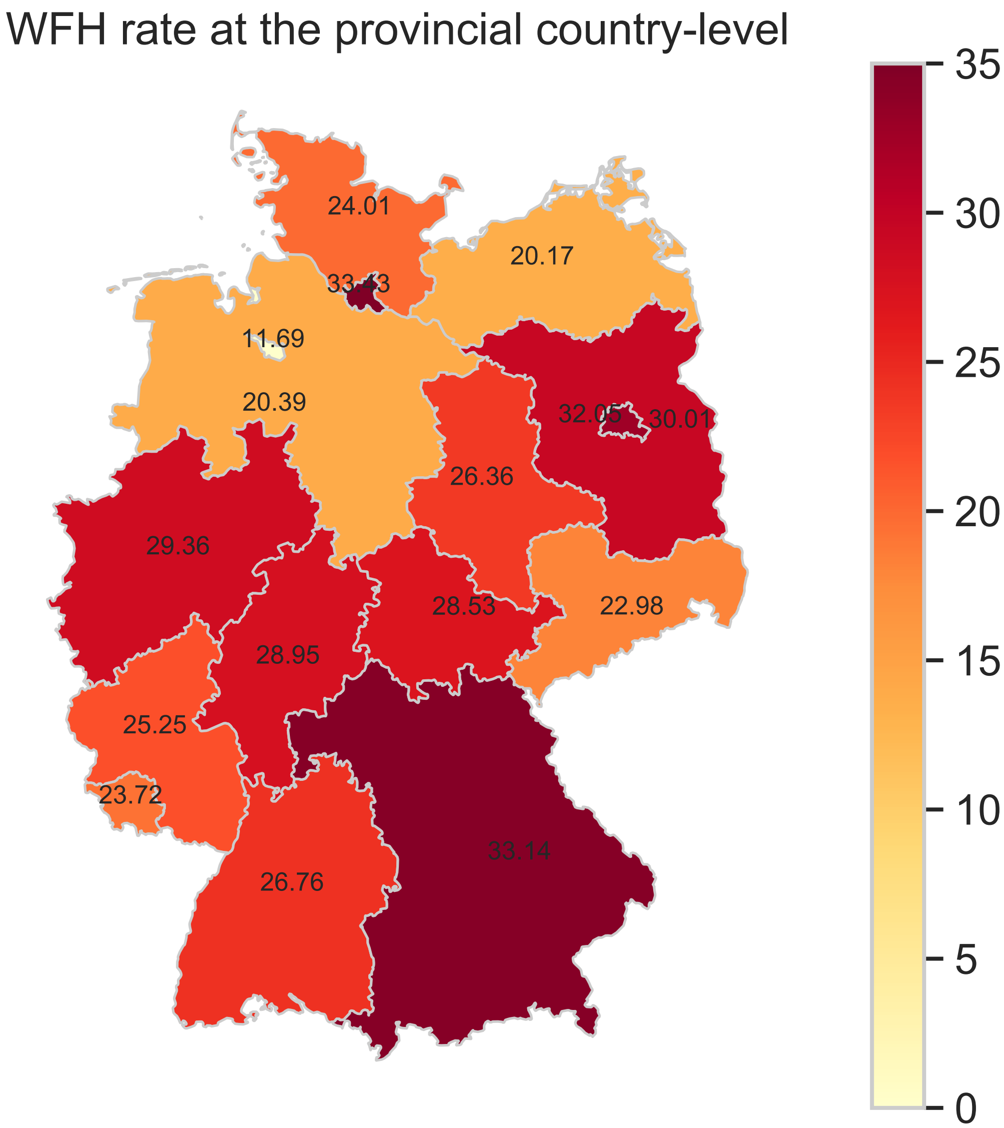
## A.11 Hausman-Test random-effect

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      fe6          re6         Difference          S.E.
-------------+----------------------------------------------------------------
  Stringency |   -.4344601    -.4294678       -.0049923        .0011259
infections~g |   -1.010637    -.9891774       -.0214591        .0115732
     weekday |
          2  |   -24.85391    -24.84812       -.0057891               .
          3  |   -25.05813    -25.05328       -.0048499               .
          4  |   -24.73619    -24.73895        .0027647               .
          5  |   -25.17089    -25.17502        .0041245               .
          6  |   -26.78299    -26.78028       -.0027038               .
          7  |   -4.659525     -4.66365         .004125               .
        temp |    .3728674     .3797474        -.00688         .0029229
1.summer_h~i |   -10.05272    -10.02357       -.0291483               .
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(10) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       32.76
                Prob>chi2 =      0.0003
                (V_b-V_B is not positive definite)
```

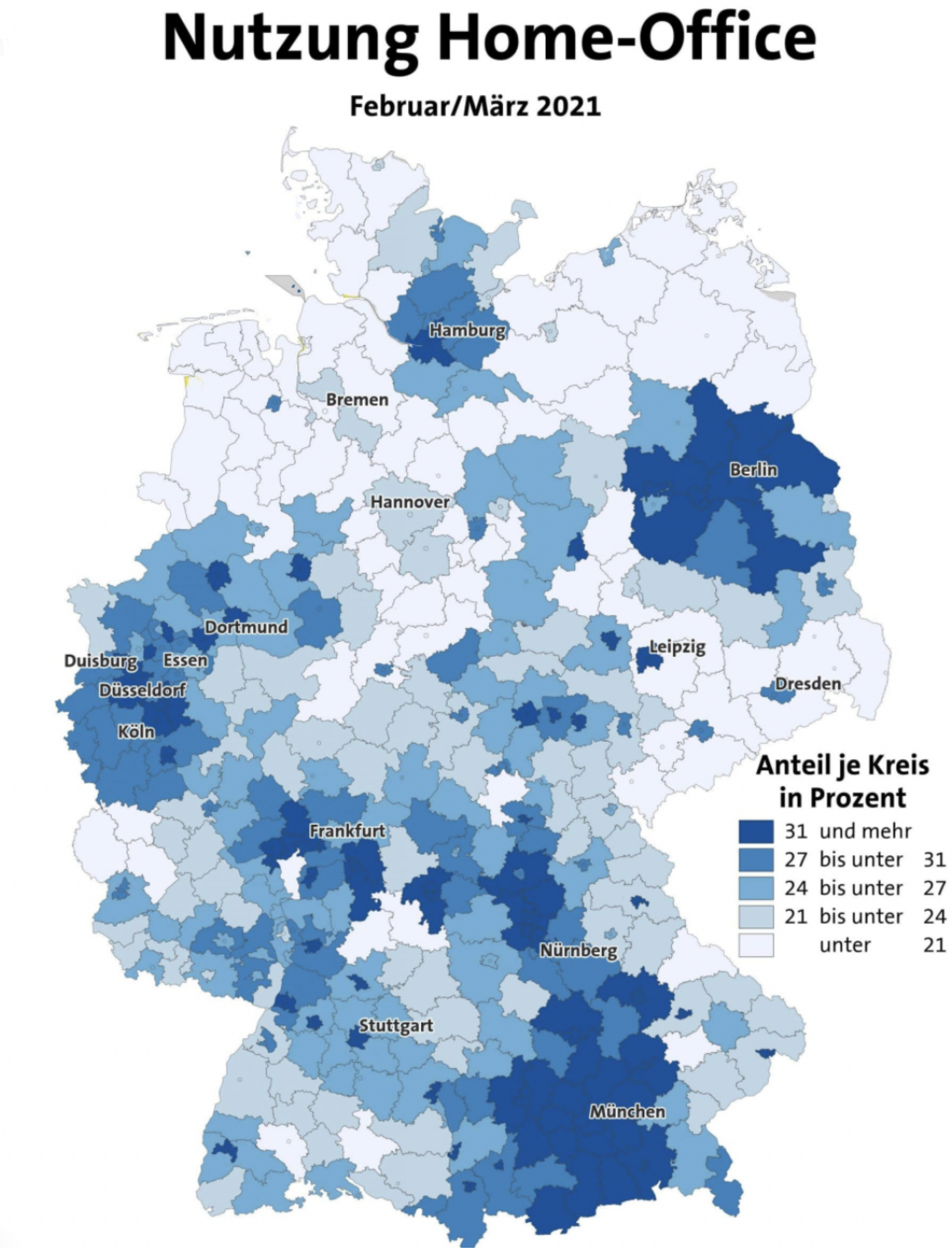
## A.12 Breusch and Pagan Lagrangian multiplier test for random effects

```
Breusch and Pagan Lagrangian multiplier test for random effects

        mobility[fed_n,t] = Xb + u[fed_n] + e[fed_n,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                mobility |   231.6194       15.21905
                       e |   50.62212       7.114922
                       u |   1.459498       1.208097

        Test:   Var(u) = 0
                             chibar2(01) =   896.07
                          Prob > chibar2 =   0.0000
```

## A.13 Geographical visualizations of the WFH rate in German provinces



## A.14 Geographical visualizations of the WFH rate in German districts




Source: infas360

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Matrikelnummer

Ich versichere, dass ich die Bachelorarbeit selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Darüber hinaus versichere ich, dass die elektronische Version der Bachelorarbeit mit der gedruckten Version übereinstimmt.

Leipzig, 22.02.2022

Ort, Datum

T. Winkler

Unterschrift