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Economic Downturns and Mental Wellbeing*

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April 2020

Abstract

We study the impact of the business cycle on mental wellbeing by linking rich German survey data to over a decade of detailed gross domestic product information. Endogeneity concerns are tackled using a shift-share instrumental variables approach in which exposure to macroeconomic fluctuations is estimated from regional variations in historical industry sector composition. Estimation results reveal strong negative effects of economic downturns on both life satisfaction and a multidimensional measure of mental health. We provide evidence that these effects are mediated by fear of job loss and income reductions, while actual unemployment effects are negligible. A case study of the impact of the global financial crisis reveals that adverse effects on mental wellbeing are persistent and remained even after the economy recovered.

Keywords: business cycle, mental health, life satisfaction, global financial crisis, shift-share instrument

JEL Classifications: C36, E32, I15

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1 Introduction

While there exists little doubt that the economic environment has a profound impact on health, the direction of the effect is strongly context and outcome dependent. Some researchers have concluded that rising economic growth has been the leading contributing factor to improvements in population health over time (Fogel, 1994; Costa, 2015). In contrast, a growing body of literature has documented procyclical patterns of mortality (see, e.g., Ruhm, 2015).[1] The dynamics behind the negative association between economic growth and health have been conjectured to operate through decreases in risky lifestyle behaviors associated with time use and income changes during recessions (Ruhm, 2000; Neumayer, 2004; Gerdtham and Ruhm, 2006; Buchmueller *et al.*, 2007) as well as cyclical fluctuations in the quality of healthcare related to staffing in nursing homes (Stevens *et al.*, 2015) and reductions in motor vehicle accidents (Miller *et al.*, 2009). In particular, observed reductions in cardiovascular mortality, the leading cause of death globally, are consistent with reduced engagement in health-damaging activities, such as drinking (Ruhm and Black, 2002), smoking (Xu, 2013; Ruhm, 2005), obesity (Ruhm, 2005), and sedentary living (Xu, 2013), in times of lower economic activity.[2]

In this paper, we study the causal relationship between the business cycle and mental wellbeing. Whereas previous economic research has almost exclusively focused on the relationship between the macroeconomy and physical health, poor mental wellbeing is likely to be at least as important in terms of economic impact. The World Health Organization has estimated that depression and anxiety, two of the most common mental disorders, costs the global economy one trillion US dollars annually in lost productivity, equivalent to more than 50 million years of work (Chisholm *et al.*, 2016). We aim to close this important contextual gap in the literature by relating over a decade of detailed information on economic development, including the global financial crisis of 2008 (henceforth GFC), to a set of validated measures of mental wellbeing in one of the world's largest economies, Germany. In doing so, we make several important contributions to the existing literature on the interrelation between health and the macroeconomic environment.

First, focusing on mental wellbeing is not only important in its own right (see, e.g., Kahneman and Krueger, 2006) but also relates closely to many of the outcomes previously studied in the literature, such as suicides and other forms of self-harm. Such knowledge could, for example, contribute toward reconciling the mixed empirical findings between the business cycle and suicides, ranging from countercyclical (Ruhm, 2000; Gerdtham and Ruhm, 2006) to procyclical effects (Neumayer, 2004). Economic downturns are likely to

[1] See, for example, Ruhm (2000) and Granados and Roux (2009) for the US, Neumayer (2004) for Germany, Granados (2005) for Spain, Buchmueller *et al.* (2007) for France, Gonzalez and Quast (2011) for Mexico, Ariizumi and Schirle (2012) for Canada, Gerdtham and Ruhm (2006) for OECD countries, and Lin (2009) for Pacific-Asia regions.

[2] However, this view has been challenged by Dávalos *et al.* (2012) and Arkes (2007), who find countercyclical patterns of alcohol and drug consumption, respectively.

generate considerable stress from both anticipated and realized financial strains as well as a loss of psychosocial assets (Macintyre *et al.*, 2018).[3] This may have far-reaching consequences for a wide range of mental and physical health indicators and may inflict large indirect costs for the economy beyond the direct costs of recessions.[4]

Our paper also adds depth to the recent and important literature on the rise of opioid-related harms by shedding light on the potential mental health channel through which economic conditions may impact substance abuse. This literature has found that, as local economic conditions deteriorates, self-reported opioid use (Carpenter *et al.*, 2017), opioid deaths, and overdose ED visits (Ruhm, 2019; Hollingsworth *et al.*, 2017) increase. Also in line with this reasoning, Charles and DeCicca (2008) show that psychological wellbeing for men in the US follows a procyclical trend.

Second, we propose an empirical framework in which can tackle endogeneity concerns arising from both simultaneity bias and other forms of unobserved heterogeneity, which has until now plagued the literature. While some papers study the correlation between (changes in) gross domestic product (GDP) and life satisfaction (Di Tella *et al.*, 2003; Oswald and Wu, 2011) and mental health (Frasquilho *et al.*, 2015), it is unclear to what extent resulting empirical findings represent causal effects. A recent systematic review of medical studies by Frasquilho *et al.* (2015, p. 1) concluded that "periods of economic recession are possibly associated with a higher prevalence of mental health problems" but that "most of the research is based on cross-sectional studies, which seriously limits causal inferences." We address this issue by implementing a shift-share instrumental variables (SSIV) approach to tackle endogeneity concerns and uncover the causal relationship between macroeconomic fluctuations and mental wellbeing.

Our econometric analysis entails the use of linked micro- and macro-level longitudinal data from Germany to study a range of mental health responses to fluctuations in GDP. To provide a venue for the identification of causal effects, we use detailed economic information for each of the 16 German federal states to construct a shift-share adjusted GDP measure based on historical state-specific industry composition. Originally suggested by Bartik (1991), shift-share adjusted variation in economic conditions has been frequently used to instrument for income opportunities (see, e.g., Katz and Murphy, 1992; Blanchard and Katz, 1992; Autor and Duggan, 2003; Aizer, 2010; Bertrand *et al.*, 2015). We provide carefully scrutinized evidence that the context in which our analysis is set is robust to recent concerns about the validity of the shift-share instrument (see, e.g.,

[3] In additional to the above mentioned channels, Eliason and Storrie (2009) and Browning and Heinesen (2012) provide evidence that job loss increases the risk of hospitalization from alcohol-related conditions, traffic accidents, and self-harm.

[4] Another strand of literature in economics relates wellbeing (most often life satisfaction or other happiness measures) to unemployment and inflation as measures of economic distress. A nonexhaustive list of studies includes Di Tella *et al.* (2001), Di Tella and MacCulloch (2009), Clark and Oswald (1994), Clark *et al.* (2001), Wolfers (2003), Kassenboehmer and Haisken-DeNew (2009), Schiele and Schmitz (2016), and Reichert and Tauchmann (2017).

Goldsmith-Pinkham *et al.*, forthcoming; Jaeger *et al.*, 2018).

Third, we exploit the richness of our data to explore potential transmission channels of the effect of the business cycle on mental wellbeing. To this end, we use our econometric framework to study the impact of the macroeconomic environment on subjective (anticipated) and objective (actual) measures of individuals' employment and financial situations, respectively. As mental wellbeing is a complex and multifaceted concept, including both anticipated and actual changes in individuals' economic situations may provide key policy insights on how to efficiently tackle community mental health issues to reduce their economic and social impacts.

Fourth, given recent evidence that procyclical mortality patterns began to weaken in the early 2000s (see, e.g., Ruhm, 2015; McInerney and Mellor, 2012), we focus our analysis on the time period between 2001 and 2016. As this period includes the GFC, we complement our main analysis with a specific case study of the financial crisis's impact on mental wellbeing in an event-study framework (see, e.g., Deaton, 2012, for wellbeing responses to US stock prices during the crisis). Since the event-study framework is nested within a difference-in-differences empirical design, we can relate changes in mental wellbeing to both the timing and magnitude of the exposure to the crisis as well as study response dynamics. To obtain a relevant measure of exposure to the recession, we first estimate a regression discontinuity model to predict the shift-share adjusted change in GDP per capita due to the GFC for each German federal state and subsequently use this state-specific measure of crisis exposure in our event study to allow the effect to vary by the size of the economic shock.

Results from estimating our main shift-share instrumental variables model show that variations in the macroeconomic environment have a strong procyclical impact on mental wellbeing, both in terms of life satisfaction (measured on an 11-point Likert scale) and mental health (the Mental Component Summary score from the SF–12v2 health survey). The estimated effects from a one percentage point GDP change are 0.11 and 0.09 standard deviations for life satisfaction and mental health, respectively. These effects are relatively large in relation to other comparable estimates in the literature. For example, using the same data and outcome definition, Krekel and Poprawe (2014) found that a 1 percent increase in reported crimes was associated with a 0.04 standard deviation decrease in life satisfaction in Germany. The shift-share adjustment reveals that ordinary least squares (OLS) estimates are generally biased toward zero, suggesting that selection bias may lead to underestimating the environmental impacts on mental wellbeing in more naïve model specifications. We find no evidence that such endogeneity is mediated through systematic interstate migration. Instead, we argue that asymmetric correlated shocks are more likely to distort inferences.

Assessing effect channels, we find that anticipated changes to one's economic situation are more important than actual changes in explaining the mental wellbeing responses

to macroeconomic fluctuations. In particular, while worries about own employment are strongly countercyclical, actual job loss is not significantly associated with economic fluctuations. The results from our case study of the impact of the GFC on mental wellbeing supports this interpretation. Specifically, we estimate strong negative and persistent effects on life satisfaction in the year before the GFC impacted the German economy and lasted for several years after the economy recovered. This result reinforces our conclusion that changes in the economic environment and mental wellbeing were mainly driven by anticipated, rather than actual, changes in economic conditions. One potential interpretation of these findings is that individuals might have, on average, overestimated the real economic hardships of the recession, at least for the time period we study in this paper.

Our findings have important consequences for social policy in the domain of mental wellbeing. They are also relevant in light of health-induced economic downturns such as the 2020 COVID-19 pandemic as they highlight that the economic consequences themselves may have long-lasting adverse mental wellbeing effects. Layard (2017) estimates that GDP in the UK is reduced by at least 7 percent from unemployment, absenteeism, presenteeism, crime, and healthcare expenditures as a consequence of individuals' poor mental health, equivalent to the share most developed countries spend on education. Large financial savings may hence be possible if negative psychological impacts of economic insecurity could be efficiently addressed. We find the adverse economic effects of recessions are likely to go far beyond the direct costs of lost jobs and exports and that indirect costs from lost productivity due to psychological stress from uncertainties in individuals' financial situations may contribute as much. Fortunately, scaling up the treatment of depression and anxiety disorders is likely to generate substantial returns on investment that could be leveraged in periods of lower economic activity (Chisholm *et al.*, 2016). Paired with active labor market programs, such as improved employment and income protection, these policies may provide a highly cost-efficient remedy to reduce the psychological burden of economic downturns (Knapp and Wong, 2020).

The paper proceeds as follows. Section 2 outlines our econometric framework and identification approach. Section 3 describes the data, estimation sample, and variables we use in our empirical analysis. Section 4 presents the estimation results. Section 5 concludes.

2 Econometric framework

2.1 Data aggregation and industry sorting

A simple and straightforward approach to empirically model the effect of the economic environment on mental wellbeing is to regress the latter on a suitable macroeconomic

indicator, adjusting for a set of observable characteristics:

$$y_{ijrt} = \gamma D_{jrt} + \boldsymbol{X}'_{ijrt}\boldsymbol{\beta} + \boldsymbol{\lambda}_j + \boldsymbol{\lambda}_r + \boldsymbol{\lambda}_t + v_{ijrt}. \tag{1}$$

Here, y_{ijrt} is the outcome of interest for individual i employed in industry j, residing in state r in year t, and D_{jrt} is the chosen indicator of the economic environment. We define D_{jrt} to be the growth rate in GDP per capita across two consecutive years:

$$D_{jrt} \quad = \quad \frac{P_{jrt} - P_{jr,t-1}}{P_{jr,t-1}}, \tag{2}$$

where P_{jrt} is the GDP per capita in industry j, state r, and year t. The parameter γ, quantifying the average change in mental wellbeing from a one percentage point increase in GDP per capita, is the main parameter of interest throughout our analysis. Furthermore, $\boldsymbol{X}'_{ijrt}$ is a (column) vector of individual and potentially time-varying control variables, such as gender, marital status, number of children, highest educational degree, and year of birth with associated parameter (row) vector $\boldsymbol{\beta}$.[5] The vector of controls has state- and industry-level subscripts to allow for the possibility that individuals may move across both states and industry sectors in our panel. Additionally, we include three sets of cluster-specific fixed effects for industry sector, $\boldsymbol{\lambda}_j$, state, $\boldsymbol{\lambda}_r$, and calendar year, $\boldsymbol{\lambda}_t$ (where $\boldsymbol{\lambda}_q \equiv \sum_{k_q} \alpha_q \mathbb{1}(k_q = q)$ is generic for $q = \{j, r, t\}$), capturing cluster-specific unobserved heterogeneity. The error term v_{ijrt} consists of any remaining residual variation in mental wellbeing not captured by the other model components.

While equation (1) is a convenient starting point for the analysis, we can think of at least two disadvantages of using this model for our purposes. First, conditioning on industry fixed effects controls for sorting of individuals into industries related to time-invariant preferences, such as, for example, fixed preferences related to job security: more frail individuals (who are more likely to report lower mental health) may select themselves into industry sectors that are less likely to be hit by recessions. However, controlling for fixed industry effects cannot safeguard against estimation bias due to time-varying sorting of individuals into sectors based on industry trends.[6] Furthermore, the inclusion of individual-level controls is unlikely to capture the full extent of such sorting. To address this concern, we aggregate our empirical model to the year–state level. This modification does not only address time-varying industry sorting but also contributes to analytical transparency and tractability of our approach.[7] To this end, we follow Brewer *et al.*

[5] See Table 1 below for the full list of control variables.

[6] One example of time-varying occupational sorting is the decline of coal mining in the northwestern parts of Germany. A more recent example is the asymmetric rise in renewable energy production across the country, such as solar-powered energy in the south and offshore wind farms in the north.

[7] Specifically, we do not observe individual-level exposure to our measure of economic environment, P_{jrt}. Such exposure is likely to vary across groups of observations within an industry–state–year cell, and ignoring this fact may lead to incorrect inference due to an ecological fallacy (see, e.g., Simpson's

(2018) and first regress each dependent variable on the set of individual-level controls and industry fixed effects[8] in an auxiliary step using OLS:

$$y_{ijrt} = \boldsymbol{X}'_{ijrt}\boldsymbol{\beta} + \boldsymbol{\lambda}_j + u_{ijrt}. \tag{3}$$

Next, we use the predicted residuals $\hat{u}_{ijrt}$ from the estimation of equation (3) to obtain a residualized outcome variable, "purged" from individual-level heterogeneity, by computing the average residual from each industry–state–year cell, $\bar{\hat{u}}_{jrt}$. For analytical brevity, we rename the residualized aggregated outcome $\tilde{y}_{jrt}$.

The second disadvantage of specification (1) is the more technical issue of annual production changes potentially causing problems in the interpretation of the regression coefficients. To construct a scale-independent measure of economic activity that can be compared across industries and states, we define a relative measure of production change by relating each year's production to a baseline year according to

$$\Delta P_{rt} \quad = \quad \sum_{j=1}^{J} \left(\frac{S_{jrt}}{\sum_{j=1}^{J} S_{jrt}} \frac{P_{jrt} - P_{jr,t=2000}}{P_{jr,t=2000}} \right), \tag{4}$$

where $P_{jr,t=2000}$ is the GDP per capita in year 2000, our baseline period, and S_{jrt} is the state's share of industry sector j in year t. Thus, ΔP_{rt} differs from D_{jrt} as defined in (2) in two aspects: first, the GDP per capita change is aggregated on the state–year level, and second, we calculate the GDP change relative to the baseline period rather than to the previous period. To further simplify the interpretation of ΔP_{rt}, we index the production change by setting $\Delta P_{r,t=2000}$ equal to one for each state and multiply production change in all years by 100 to obtain the percentage change in a state's GDP relative to its year 2000 level.

After implementing these adjustments, our modified model now regresses the residualized outcome, $\tilde{y}_{jrt}$, on ΔP_{rt} and a full set of state and year fixed effects (with industry fixed effects subsumed into the model from equation (3)):

$$\tilde{y}_{rt} = \gamma \Delta P_{rt} + \boldsymbol{\lambda}_r + \boldsymbol{\lambda}_t + \nu_{rt}, \tag{5}$$

where $\nu_{rt} = \varepsilon_{rt} + (\tilde{y}_{rt} - y_{rt})$ is a zero-mean expectation composite error term under standard regularity assumptions of asymptotic convergence. While these modifications considerably reduce the available empirical variation in our data, we are now more likely to overcome endogeneity bias due to workers endogenously moving between industry sectors in response to industry-specific economic fluctuations. We define model (5) as our benchmark specification in the following analysis.

Paradox). By aggregating the information on the left-hand side to the level of the right-hand side of the regression equation, we make this limitation explicit.

[8] We treat missing industry observations, for example, due to unemployment, as a distinct category.

2.2 Correlated shocks and shift-share adjustment

While our baseline specification in equation (5) tackles time-varying unobserved selection into industries, we may still be concerned about simultaneity bias arising from correlated asymmetric shocks to both mental health and the macroeconomic environment. In particular, reverse causation, in which state-specific shocks to mental health perturb economic growth trajectories heterogeneously across states, or local shocks in unobserved common predictors of both population mental health and regional economic factors, would introduce dependencies between the residual term ν_{rt} and our measure of economic growth ΔP_{rt} and, consequentially, bias the estimate of γ.

To address these concerns, we employ an instrumental variables approach originally proposed by Bartik (1991) and widely used by economists in various empirical applications (see, e.g., Blanchard and Katz, 1992; Aizer, 2010; Bertrand *et al.*, 2015; Acemoglu and Restrepo, forthcoming; and Broxterman and Larson, forthcoming, for a recent review of the literature). The underlying idea for the instrument is based on a so-called shift-share analysis exploring the extent to which economic growth can be attributed to regional ("shift") and industry ("share") factors. The traditional shift-share model exploits variation in industry composition across regions over time to disentangle the two effects by comparing the growth in these factors to national growth in economic indicators. The shift-share instrumental variable (SSIV) uses weighted averages of a common set of shocks, with weights reflecting variation in shock exposure, to estimate the impact of the shock on the outcome of interest. A common approach to implement SSIV, which we also apply in our analysis, is to construct a regional instrument from aggregate shocks to industries with local industry shares measuring the shock exposure. For the purposes of this paper, the task of the SSIV amounts to isolating regional changes in GDP from simultaneous changes in population mental health. SSIV avoids such correlated shocks under the plausible assumption that historical regional industry compositions are uncorrelated with any current year-to-year changes in regional mental health.[9,10]

[9]Identification in SSIV models is somewhat tedious to show, as the underlying identifying assumptions do not conform to the standard quasi-experimental framework. Borusyak *et al.* (2019) develop such a framework for SSIV by showing that it is equivalent to an aggregated *shock-level* IV estimator, in which identification is obtained under the exclusion restriction that variation in shocks are orthogonal to the outcome of interest. A necessary condition for the exclusion restriction to hold is that exposure shares are exogenous. We argue that this holds in our context using historical regional industry compositions that are plausibly unrelated to current trends in population mental health.

[10]We are aware of the recent critique on the use of the shift-share instrument for certain applications. In particular, Goldsmith-Pinkham *et al.* (forthcoming) formalize the implicit underlying assumptions of no spatial spillovers and steady state for each region. Jaeger *et al.* (2018) provide a concrete example of the latter assumption in which short-run shocks to the regional economy may cause longer term general equilibrium adjustment responses, as it takes time for markets to adjust to shocks. We argue that such adjustments are unlikely to be present in our context and provide evidence for this claim below. Specifically, interstate labor migration would create a source of spatial spillover bias if the decision to move was a function of an individual's mental disposition and psychologically resilient workers were more confident that they would find new employment. Table A.1 in Appendix A shows that

To implement SSIV in our setting, we instrument the (endogenous) regional production change from equation (4) by the national industry-specific production change weighted by industry shares from the first year of our analysis period, 2000.[11] To improve the power of the SSIV, we instrument state r's GDP per capita growth rate with either the industry shares-weighted average GDP growth in the East German states (if r is itself in the East) or the West German states (if r is in the West).[12] Furthermore, to avoid relatively large states driving national (i.e., East or West German) GDP per capita growth, we additionally exclude state r's own GDP change (denoted by r^-) in the calculation.

Formally, the SSIV is specified as

$$\Delta P_{rt}^{Z} = \sum_{j=1}^{J} \left(\frac{S_{j,r^-,t=2000}}{\sum_{j=1}^{J} S_{j,r^-,t=2000}} \frac{P_{j,r^-,t} - P_{j,r^-,t=2000}}{P_{j,r^-,t=2000}} \right). \tag{6}$$

The instrument ΔP_{rt}^{Z} in equation (6) differs from the potentially endogenous production ΔP_{rt} in equation (4) in two ways. First, it uses national production changes (the state's own change excluded) relative to the baseline year to instrument state-specific production. Second, it reweights the production change with regional industry shares from the baseline year. Weighting regional GDP growth per capita with the industry shares introduces state-level variation in shock exposure, while using baseline year industry shares avoids picking up potentially endogenous industry trends.

Using our shift-share adjusted production in a two-stage least squares (2SLS) approach yields the first stage:

$$\Delta P_{rt} = \alpha \Delta P_{rt}^{Z} + \boldsymbol{\lambda}_r + \boldsymbol{\lambda}_t + u_{rt}, \tag{7}$$

where the resulting fitted value $\Delta \hat{P}_{rt}$ is used in a second stage analogous to our baseline model from equation (5):

$$\tilde{y}_{rt} = \gamma \Delta \hat{P}_{rt} + \boldsymbol{\lambda}_r + \boldsymbol{\lambda}_t + v_{rt}. \tag{8}$$

Figure A.1 of Appendix A reports the raw, the shift-share adjusted, and the instrumented indexed GDP change over time by federal state. As can be seen from the figure,

only about 3 percent of individuals in our sample moved to another state during the time period we study. Furthermore, Table A.6 and Table A.7 present results from excluding interstate migrants from our analysis sample and including lagged instruments to account for general equilibrium adjustment dynamics, respectively, as suggested by Jaeger *et al.* (2018). Our main findings remain robust to these model alterations.

[11] Table A.5 in Appendix A shows that our main results are robust to using 1991 as an alternative baseline period to construct industry shares.

[12] While this restriction eliminates some of the "share" variation in the data, it also provides additional explanatory power to our instrument due to the, for historical reasons, significant institutional and economic differences between East and West German states.

the different measures of production vary substantially in some states. For instance, consider the three states with the highest GDP per capita in 2000; the geographically small and highly urbanized states of Hamburg, Bremen, and Hesse. Their actual GDP per capita exceeds the instrumented GDP per capita in the early 2000s, indicating that they perform better than the average (West German) state. In later years we observe a reversed pattern where their actual economic development is below their instrumented GDP. Thus, compared to the other states, these regions are underperforming relative to their historical industry structures.

2.3 The impact of the GFC on mental wellbeing

As noted by Deaton (2012, p. 2), while the global financial crisis (GFC) of 2008 "brought harm to many, [...] it provided an unparalleled opportunity to examine how these events affected the standards of living, the emotional experiences, and life evaluations of those who lived through it." To study effect dynamics of macroeconomic fluctuations on mental wellbeing, we heed this advice and extend our shift-share analysis to include a separate case study of the GFC.[13] To this end, we define the magnitude of the GFC-induced shock in GDP per capita in state r by $\mathcal{S}_r$ and estimate regional exposure to the crisis by a measure of the change in production after the crisis, denoted $\mathcal{P}_{r,\text{after}}$, relative to a measure of the change before the crisis, $\mathcal{P}_{r,\text{before}}$:

$$\mathcal{S}_r \quad = \quad \mathcal{P}_{r,\text{after}} - \mathcal{P}_{r,\text{before}}. \tag{9}$$

To provide economically relevant measures for $\mathcal{P}_{r,\text{before}}$ and $\mathcal{P}_{r,\text{after}}$, we could simply use the shift-share-instrumented production values obtained from estimation of equation (7), $\Delta\hat{P}_{r,t=2008}$ and $\Delta\hat{P}_{r,t=2009}$, respectively. However, this narrow one-year before and after comparison does not take into account time trends before and after the crisis year, such as the quick economic recovery. To provide a more relevant measure of the structural break that the GFC incurred on the German economy, we apply a regression discontinuity design. Specifically, to assess the shift in production due to the GFC, we regress the shift-share adjusted production change on a quasi-linear time trend, which we allow to vary before and after the crisis, and a binary indicator for postcrisis years for each federal state.

Formally, we estimate

$$\Delta\hat{P}_t = \alpha_0 + \alpha_1 \mathbb{1}(t \geq 2009) + \alpha_2 t + \alpha_3 \mathbb{1}(t \geq 2009)t + \varepsilon_t \; \forall \; r = 1, ..., 16, \tag{10}$$

[13] The GFC began with a crisis in the US subprime mortgage sector in 2007 that subsequently spread to the entire banking sector, leading the US government to assume control over mortgage companies Freddie Mac and Fannie Mae in September 2008 and causing the fall of Lehman Brothers bank in the same month. However, the economic impact of the crisis in Germany occurred mainly in 2009, which we use as the cutoff year in our analysis.

where $\mathbb{1}(\cdot)$ is the binary indicator function that equals one if its argument is true and zero otherwise. Furthermore, the intercepts α_0 and α_1 capture the average GDP per capita change relative to the baseline period in the precrisis years and any postcrisis discontinuous shift, respectively. Finally, parameters α_2 and α_3 jointly model GDP to follow a quasi-linear trend by allowing for different slopes in pre- and postcrisis years.

We use the estimated parameters from equation (10) to define and predict the crisis-induced regional shocks $\mathcal{S}_r$ using the definitions $\hat{\mathcal{P}}_{r,\text{before}} = \hat{\alpha}_0 + \hat{\alpha}_2 t$ and $\hat{\mathcal{P}}_{r,\text{after}} = \hat{\alpha}_0 + \hat{\alpha}_1 + (\hat{\alpha}_2 + \hat{\alpha}_3)t$ evaluated at $t = 2009$. These quantities are subsequently inserted into equation (9) to obtain an estimate of the shift-share adjusted production change due to the 2009 recession, $\mathcal{S}_r$. Figure 1 illustrates the approach using nationally aggregated data where the markers represent annual values of $\Delta\hat{P}_{rt}$ averaged over the 16 federal states. Estimating equation (10) predicts that $\mathcal{P}_{r,\text{before}}$ and $\mathcal{P}_{r,\text{after}}$ equal 105.6 (indicated by the hollow triangle) and 102.2 (indicated by the black triangle) percent of the 2000 GDP, respectively. Thus, the estimated size of the nationwide shock in production from the GFC, $\mathcal{S}$, is equal to 3.3 percentage points (after rounding).

[Figure 1 about here]

Finally, to obtain an estimate of the effect of the GFC on mental wellbeing, we regress the mental wellbeing measures on a year–crisis interaction in addition to region and year fixed effects:

$$\tilde{y}_{rt} \quad = \quad \boldsymbol{\lambda}_r + \sum_{s=2001}^{2016} \Big(\alpha_t \mathbb{1}(s = t) + \gamma_t \hat{\mathcal{S}}_r \mathbb{1}(s = t) \Big) + \varepsilon_{rt}, \tag{11}$$

where $\boldsymbol{\lambda}_r \equiv \sum_k \alpha_r \mathbb{1}(k = r)$ and α_t represent full sets of state and year fixed effects, respectively. The parameter γ_t represents the average effect of the crisis on wellbeing in each year t, weighted by the regional size of the shock, $\hat{\mathcal{S}}_r$. Specifically, the estimated γ_t coefficients can be interpreted as the unit change in the dependent variable from a one percentage point change in GDP per capita due to the GFC at time t. As several elements in equation (11) are estimated, calculating analytical standard errors for this model is not straightforward. Therefore, we bootstrap the standard errors using 500 replications.

By estimating the γ_t coefficients in equation (11), we obtain a set of pre- and postcrisis effects that can be plotted in an event-study fashion. This is useful for two reasons. First, if there is an effect of the GFC on mental wellbeing, we expect that γ_t will be nonzero in the postcrisis years. The event study will allow us to trace out the dynamic pattern of the causal relationship, in particular the persistence of the effect over time. Second, we can test for spurious pretreatment effects by checking whether the γ_t parameters are zero for the precrisis years, as we do not expect individuals to react to the economic shock (i.e., to $\hat{\mathcal{S}}_r$) before it occurred. Since our event study is effectively nested within a difference-in-differences design, this is equivalent to an assumption of common trends.

3 Data

We combine micro and macro data from official German sources in our empirical analyses. The micro-level data are based on the German Socio-Economic Panel Study (GSOEP), a longitudinal household survey based on annual interviews with all adult members of approximately 11,000 households representative for the German population (see, e.g., Goebel *et al.*, 2019). In addition to several measures of individual wellbeing, the survey also includes extensive socioeconomic and demographic information. For the purpose of our aims, we restrict the sample to years 2000–2016 and exclude individuals who are above 65 years of age (i.e., the mandatory retirement age).[14] Depending on the specification, this leaves us with up to 300,000 person–year observations for around 60,000 individuals. The macro-level data are taken from the National Accounting Systems of the Federal States (*Volkswirtschaftliche Gesamtrechung der Länder*) and are provided by the German Federal Statistical Office (DeStatis, 2017b).

We use two different indicators for mental wellbeing as dependent variables in our analysis: life satisfaction and mental health. Life satisfaction is an indicator of subjective mental wellbeing and is included annually in the GSOEP in the form of a discrete variable defined on an 11-point Likert scale, ranging from zero (lowest satisfaction) to ten (highest satisfaction). As a more objective measure of an individual's mental wellbeing, we include the Mental Health Component Summary Score (MCS) from the SF–12v2 short-form health survey. The MCS is assessed biannually in the GSOEP since 2002 and is based on a set of z-transformed subcomponents from the SF–12v2 health survey using principal component analysis. When combined, scored, and weighted, the SF–12v2 results in two scales of mental and physical functioning, respectively, and an overall measure of health-related quality of life.[15] For the purpose of our research question, we focus on the mental health component in our analysis. Figure 2 shows the distributions of the wellbeing measures we use in our analysis.

[Figure 2 about here]

To study potential channels of transmission between the macroeconomic environment and mental wellbeing, we consider two main factors relating to labor market activities: individual employment status and own financial situation. For each channel, we define an *anticipated* and an *actual* measure, capturing responses from individuals' subjective beliefs regarding a possible future event and the actual event, respectively. The actual measure of employment status is defined as a binary indicator for whether an individual is employed and zero otherwise. As an actual measure for an individual's financial situation,

[14] In the baseline specification we keep individuals who are out of the labor force for other reasons than age, enabling us to investigate how economic shocks transmit into individual labor force participation. Excluding individuals out of the labor force does not change our results, however.

[15] See Andersen *et al.* (2007) for details on the construction of the scales.

we include the reported monthly labor market income in euros. For the anticipated measure of employment status, we use a survey question asking respondents to express the extent of their current worries about losing their job defined on a three-point scale (worries a lot, some worries, no worries). Similarly, anticipated financial insecurity is measured by a corresponding question on worries about one's own economic situation. To be more consistent across transmission channels, we define the two latter variables as binary indicators, taking the value one for reporting "no worries" and zero otherwise. Finally, to compare effect sizes, we standardize all transmission channels to have a mean of zero and a standard deviation of one.

The first two panels of Table 1 provide descriptive summary statistics for the key outcome variables we include in our analysis. The following two panels report a set of basic socioeconomic and demographic variables that we extract from the survey. Life satisfaction is relatively high with an average score of 7.1 out of 10,[16] and average monthly income across all years is almost 2,900 euros. In contrast, approximately 17 percent of respondents worry about their economic situation, and 13 percent express a concern about losing their job. Roughly half of the sample are female, and one-third have at least some college education. Furthermore, most individuals are married, and around half have at least one child. The average age of an individual at the start of the analysis period is 33.

[Table 1 about here]

We next link the individual-level information from the GSOEP survey to official statistics on GDP per capita from the 16 German federal states using the year of interview and the respondent's recorded sector of employment.[17] The data allow us to distinguish between seven different industry sectors: manufacturing, finance, trade, public services, construction, agriculture, and energy.[18]

The bottom two panels of Table 1 show that the average annual change in GDP per capita during the time period we study in this paper, 2000–2016, is 1 percent, and the largest industry sector is public services (including, e.g., law enforcement, teachers, healthcare workers, and other civil servants). However, there is considerable heterogeneity in key economic indicators across states. Table 2 shows that finance is the most important sector in 7 out of the 16 federal states, followed by public services in all five East German states, manufacturing in three states (including Baden-Württemberg and Lower Saxony where most car manufacturers are located), and trade only being the most important

[16]Less than 5 percent of respondents report a life satisfaction of ten. Thus, ceiling or censoring in life satisfaction are unlikely to create issues.

[17]We use production and GDP per capita interchangeably in the paper.

[18]See Table A.2 of Appendix A for details on the businesses included in each industry sector. We adjust the National Accounting Systems figures for inflation rates provided by DeStatis (2017a). Population numbers are taken from DeStatis (2018a). We consider industries according to the Classification of Economic Activities, issue 2008 (WZ 2008) by the Statistical Offices of the Federation and the Länder; the most fine-grained classification available on state level for all years contains seven industries.

sector in Bremen, the smallest state (see Figure A.2 in Appendix A). States also vary substantially in their average GDP per capita (in 2000), ranging from 15,000 euros in Thuringia and Saxony-Anhalt to more than 41,000 euros in Hamburg. In contrast, the average increase in GDP per capita exhibits an opposite pattern with a modest increase of only 0.4 percent annually in Hamburg compared to 2 percent in Thuringia. The initial difference and the catch-up pattern can be attributed to several factors. Hamburg (along with Berlin and Bremen) is a self-governing city-state and is therefore more urban. Urban wages are not only higher, but the industries most affected by the 2008–2009 crisis, such as the financial service sector, are also more prominent in urban areas. Furthermore, although immigration may also contribute to the lower GDP per capita increase in some of the West German states, interstate migration plays a less important role in Germany than in most other countries (see Table A.1 of Appendix A).

[Table 2 about here]

Apart from the between-state variation, the industry sector-specific data allow us to study within-state differences across industries. Figure 3 displays trends in national GDP per capita over time by industry sector.[19] The figure displays two important patterns. First, there is considerable variation in economic activity both over time and across industries, with growth rates of up to 18 percent across two consecutive years. Second, the GFC, highlighted by the dashed vertical line in the figure, is responsible for the vast majority of the fluctuations in growth rates. As one might expect, the export-dependent manufacturing sector exhibits the highest volatility, particularly in the years surrounding the financial crisis. In contrast, the public services sector shows little variation across time and even expands slightly during the crisis years, perhaps as a consequence of active labor market policies aimed at diminishing the adverse effects of the recession. Hence, the large regional variation in the industry mix suggests that states with a primarily manufacturing-based economy, such as Baden-Württemberg, were hit harder by the financial crisis compared to states with a stronger reliance on the public sector, such as Mecklenburg-Vorpommern. We exploit this variation in industrial composition across states in our shift-share approach to overcome empirical issues in the identification of causal effects of the macroeconomic environment on mental wellbeing.

[Figure 3 about here]

[19] Figure A.3 in Appendix A shows the corresponding within-state industry variation over time.

4 Results

4.1 Baseline results

Figure 4 plots bivariate correlations between changes in GDP per capita (in bins of 0.5 percentage points) and changes in our two measures of mental wellbeing (in standard deviations), life satisfaction and mental health. The data are organized by industry–state–year cells, and the size of the circles indicates relative cell frequencies. The figure displays clear positive associations between the two variables for both outcome measures. The indicated fitted slope from an OLS regression with observations weighted by cell size suggests that life satisfaction and mental health increase by 0.016 and 0.015 standard deviations for each percentage point growth in GDP per capita, respectively.

[Figure 4 about here]

Table 3 reports point estimates on the relationship between changes in the macroeconomic environment (GDP per capita) and our wellbeing outcomes based on the state–year aggregated OLS model (5) and the SSIV model (8) in the upper and lower panels of the table, respectively. The dependent variables, life satisfaction (measured annually) and mental health (measured biannually), are aggregated according to equation (5), leaving us with a total of 272 and 128 state–year cells, respectively. In all regressions we control for region and year fixed effects such that the empirical variation in the data arises from within-state changes in (instrumented) GDP per capita. To compare estimated parameters across specifications, each outcome is normalized to have a mean of zero and a standard deviation of one.

The reported coefficients from Table 3 show statistically significant procyclical effects on mental wellbeing, consistent across both outcome measures and model specifications. A one percentage point increase in GDP growth per capita in the OLS model is associated with an increase in life satisfaction and mental health of around 0.06 and 0.08 standard deviations, respectively. As the average annual change in GDP per capita in our data is roughly one percentage point, these effect sizes are also economically meaningful.

Turning next to the corresponding SSIV estimates, the corresponding effect on life satisfaction is around 0.11 standard deviations, nearly twice as high as in the aggregated OLS model. The IV estimate for the effect on mental health of 0.09 standard deviations is also somewhat higher than the corresponding OLS result. These effects are large compared to the impacts on wellbeing of other factors investigated in the literature. For example, using the same data and outcome measure, Krekel and Poprawe (2014) find that a 1 percent increase in the crime frequency ratio is associated with a 0.043 standard deviation decrease in life satisfaction. The relatively larger IV estimates suggest the presence of attenuation bias in the OLS model from, for example, correlated asymmetric

shocks to both mental wellbeing and the macroeconomic environment. Hence, the impact of economic downturns on mental wellbeing may be underestimated in studies that fail to account for such distortions.[20,21]

[Table 3 about here]

4.2 Transmission channels

Next, we study potential pathways of transmission of the estimated effects from Table 3 by replacing the mental wellbeing outcomes with our four proposed channels: employment status and labor earnings (actual channels) and worries about own economic situation and job loss (anticipation channels), respectively. Results from this analysis are reported in Table 4, equivalent to Table 3 save for the change of dependent variables. For comparability, each outcome variable is again standardized to have a mean of zero and a standard deviation of one.[22]

Table 4 displays stark differences of the effects of GDP changes between the actual and the anticipated channels. In contrast to the small, and in the case of unemployment, insignificant, GDP effects on the actual channels, the effects on the anticipated channels are both economically and statistically significant. A one percentage point increase in GDP per capita in the OLS model reduces worries of job loss and about one's own economic situation by around 0.09 and 0.06 standard deviations, respectively. As in Table 3, the corresponding results for the SSIV model are larger in magnitude; when GDP changes are instrumented, the coefficient estimates increase to 0.15 and 0.10 standard deviations, respectively. In contrast, GDP changes do not appear to have a statistically significant effect on the probability of being employed, and the estimated effects on labor income, while precisely estimated, are small in magnitude. Estimating the model using the original variable scales, both OLS and IV coefficients suggest effects sizes below 1 percent and below 0.05 percentage points for income and employment, respectively (see Table A.8 in Appendix A).

[20] Table A.3 of Appendix A reports coefficients from the first-stage estimation of equation (7). The partial F-statistics for the instrument in both regressions are highly significant. In the larger life satisfaction sample, a one percentage point increase in the shift-share adjusted GDP per capita increases state r's GDP by about 0.9 percentage points (0.88 for the mental health sample).

[21] The effects from Table 3 are largely robust to a set of alternative specifications reported in Appendix A. In Table A.4 we rerun the baseline models (OLS and IV) but leave the financial crisis period out of our sample (i.e., we drop the years 2007–2010). Table A.5 repeats the analysis using industry shares from the first year after the reunification, 1991, as the baseline period in the IV approach instead of the year 2000. Table A.6 and Table A.7 address the Goldsmith-Pinkham *et al.* (forthcoming) and Jaeger *et al.* (2018) critiques of the SSIV. In Table A.6 we only keep individuals who resided in the same state over the entire analysis period to avoid spatial spillover bias from selective migration. Table A.7 adds a one-year lag in production change to account for dynamic general equilibrium adjustments.

[22] See Table A.8 in Appendix A for equivalent estimations keeping the dependent variables' original scales.

The negligible employment and income effects reported in Table 4 are not unexpected given the institutional features of the German labor market. For instance, Dustmann *et al.* (2014) report that Germany did not experience mass layoffs as a consequence of the GFC, although the drop in GDP per capita was similar to the US. Instead, firms relied on flexible short-time work compensation schemes.[23] The left panel of Figure A.4 plots the year-to-year changes in overall and manufacturing sector employment over time, respectively. While Figure 3 suggests that the production drop in the manufacturing sector was more than 15 percent between 2008 and 2009, the corresponding drop in employment was less than 2.5 percent. On average over all sectors, there was no drop in employment around the year 2009. The right panel of Figure A.4 plots the change in short-time work compensation over time. From 2008 to 2009, the number of (full-time equivalent) employees affected by short-time work compensation rose by over 600 percent, from 550,000 to over 3.8 million. Individuals on short-time work contracts are not laid off if firms suffer a demand shock; rather, their working hours are reduced (possibly even to zero) until the demand recovers. The salary loss from reduced working hours is partly compensated by the unemployment agency, potentially explaining the small but statistically significant income drop.

[Table 4 about here]

4.3 Event study of the GFC

Last, we present the results from our case study of the GFC's impact on mental wellbeing. The left and right panels of Figure 5 shows estimation results from the event-study model (11) for life satisfaction and mental health outcomes, respectively. The plotted coefficients are interpreted as the standardized response in mental wellbeing from the shift-share and exposure-adjusted estimate of the GFC for each year in our data.

Three observations stand out from Figure 5. First, there are no discernible systematic trends for either of our measures of mental wellbeing for the years leading up to the GFC, indicating that our empirical approach is valid in the sense that it is likely to capture the causal effect of the crisis on the outcomes we consider.[24] Second, the visible sharp drop in life satisfaction in 2008 occurs in the year preceding the GFC's main impact on the German economy. Although the production drop in Germany mainly occurred in 2009, the mortgage crisis in the US started already in the summer of 2007. This "anticipatory" drop in life satisfaction is in line with the conclusions from the previous subsection, suggesting that individuals' worries about their future economic situations seem to affect their mental wellbeing even in the absence of actual changes. Using daily cross-sectional

[23] See, e.g., Cahuc and Carcillo (2011) for a review of this type of employment arrangements.

[24] A joint hypothesis test of whether the precrisis coefficients are jointly zero cannot be rejected at conventional significance levels. The p-value of the joint test is 0.16 for life satisfaction and 0.87 for mental health. See the note to Figure 5 for details.

life satisfaction data for US citizens, Deaton (2012) finds that life satisfaction reacts strongly to daily stock price drops during the financial crisis. As a likely explanation, he points out that stock prices presumably function as a forward-looking indicator for income and employment, as most do not hold stocks. This explanation aligns well with our finding that the perception, more than the realization, of an income or employment shock drives business-cycle-induced changes in mental wellbeing.[25]

Finally, the GFC had an adverse impact on both measures of mental wellbeing in the years after the crisis took place. In particular, for life satisfaction we estimate strong negative and persistent effects lasting for several years after the economy recovered. The mental health outcome is seemingly less impacted by the GFC in the short run but catches up in later years. This difference can potentially be attributed to the fact that the mental health component score, unlike life satisfaction, is a composite measure of wellbeing with potentially offsetting elements. In summary, this result further strengthens our conclusion that changes in the economic environment and mental wellbeing were mainly driven by anticipated, rather than actual, changes in economic conditions.[26]

[Figure 5 about here]

5 Conclusion

While there exists a large body of research on the effects of the business cycle on physical health, significantly less is known about its consequences for psychological wellbeing. Productivity losses due to mental health disorders, such as stress and depression, and their effects on substance abuse harms are becoming a rapidly increasing public health concern in many countries. A closer investigation of the underlying channels of such health problems could generate key policy implications to moderate their damaging impacts in periods of economic recession. Specifically, Ruhm (2012, p. 12) notes that "future research could fruitfully provide further information on whether macroeconomic conditions differentially affect physical and mental health." This paper attempts to bridge this gap by focusing on the impact of the macroeconomic environment on established indicators of mental wellbeing in Germany.

We explore the causal effects of the business cycle on life satisfaction and mental health using rich Germany survey data linked to aggregate economic data on state-level produc-

[25] Figure A.5 in Appendix A shows Google Trends data for "mortgage crisis" searches (German *Hypothekenkrise*) in Germany over time. Searches peaked in August 2007 after the GSOEP interviews of the 2007 wave were conducted (between February and July 2007). Less than 2.5 percent of the 2007 interviews took place in August or later in the year.

[26] Comparing the effect size with the baseline IV results in Table 3 is not straightforward. The standard deviation of state–year production changes $\Delta\hat{P}_{rt}$ used to produce the IV estimates in Table 3 (cf. equation 8) is 7.8, while the standard deviation in state-level shock sizes, $\mathcal{S}_r$, used in the event studies is only 0.8. With this in mind, dividing the effect estimate in the event study by ten yields comparable point estimates.

tion for the years 2000–2016. Exploiting variation in industry composition across federal states, we construct a shift-share adjusted measure of regional gross domestic product to assess how individuals are affected by a change in their macroeconomic environment. To complement this analysis, we also provide a case study of the impact of the 2008 global economic crisis (GFC) by relating the size of the economic shock to population changes in wellbeing before and after the crisis. For both analyses, we find strong procyclical effects on both measures of mental wellbeing and in particular on life satisfaction. Furthermore, the estimated effects persist several years after the economy recovered from the GFC, suggesting that economic downturns can have long-run adverse effects. Finally, assessing effect channels, our results suggest that wellbeing effects appear to be mainly mediated by anticipated (worries about job loss and own economic situation), rather than realized (actual changes to employment and income), changes in personal economic conditions.

In terms of policy implications, our findings suggest that, while institutional features of the German labor market substantially moderated the adverse income and employment effects of the GFC, it appeared to have been less successful in protecting individuals from psychological distress. This finding is also relevant in light of health-induced economic downturns such as the 2020 COVID-19 pandemic as they highlight that the economic consequences themselves may have long-lasting adverse mental wellbeing effects. Thus, active labor market policies (i.e., unemployment benefits or subsidized short-time work compensation) in isolation might be insufficient to fully protect against the adverse effects of recessions on mental wellbeing. The strong reactions to individuals' own perceived, rather than realized, economic situations we have estimated suggest that better communication of the existing economic and social safety net as well as increased investments in the treatment of common mental health distorders, such as anxiety, can play a crucial role in moderating such effects. Future work in this area could focus on providing a more comprehensive understanding of the specific behavioral mechanisms through which individuals' worries about uncertain economic prospects translates into lower mental wellbeing and the impacts of these factors on long-run economic outcomes.

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Tables and figures

TABLE 1.
Descriptive statistics

	(1) Mean	(2) Std.	(3) Min.	(4) Max.
Mental wellbeing measures				
Mental Health Summary Score	0.0	1.0	-5.0	3.0
Life satisfaction (original scale)	7.1	1.7	0	10
Transmission channels				
Employment	1.00	0.06	0	1
Income (in Euro)	2,884	2,444	2	99,999
Income (in log)	7.8	0.7	0.7	11.5
No worries: job loss	0.87	0.33	0	1
No worries: own economic wellbeing	0.83	0.38	0	1
Individual-level control variables				
Female	0.52	0.50	0	1
Education: secondary schooling (baseline)	0.66	0.47	0	1
Education: university entrance degree	0.12	0.32	0	1
Education: university graduation	0.22	0.41	0	1
Marital status: single/widowed (baseline)	0.30	0.46	0	1
Marital status: married	0.59	0.49	0	1
Marital status: divorced	0.08	0.28	0	1
# kids: 0	0.46	0.50	0	1
# kids: 1	0.23	0.42	0	1
# kids: 2	0.21	0.41	0	1
# kids: $\geq$3	0.10	0.30	0	1
Year of birth (FE)	1967	14	1937	1998
Demographics				
Average annual population change	0.0	0.6	-1.7	1.2
Living in East German state	0.21	0.41	0	1
Production measures				
Average annual GDP change	1.0	2.0	-4.6	4.0
Relative GDP change to year 2000	105.7	5.6	100.0	117.5
...shift-share adjusted	105.5	5.5	99.9	117.1
Industry sectors (average contribution to GDP, all years)				
Manufacturing	0.22	0.01	0.20	0.23
Trade	0.21	0.00	0.20	0.21
Finance	0.26	0.00	0.25	0.27
Public	0.22	0.01	0.21	0.23
Others	0.09	0.00	0.08	0.10

NOTE.— Own calculations. Mental wellbeing measures, individual-level control variables, potential channels of transmission, and share of people living in East Germany are based on the German Socioeconomic Panel (GSOEP) survey. Statistics on production measures, industry sectors, and average annual population change refer to nationally aggregated data from the German Federal Statistical Office. For the nationally aggregated data the standard deviation (std.) and the minimum (min.) and maximum (max.) values give the variation over time, but not deviations across federal states. The mean of the industry sectors gives their average contribution to the nationally aggregated GDP over all years from 2000–16, see Table A.2 for the businesses they include. "FE" indicates that the variables enter the regression through a set of fixed effects.

TABLE 2.
Key variables on state level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Population		GDP per capita		2009 crisis downturn (in percentage points)	
Federal state	Location	Main industry (in 2000)	in mil. (in 2000)	change 2001–16 (in percent)	in Euro (in 2000)	change 2001–16 (in percent)	raw shock	shift-share adj.
Baden-Württemberg	West	Manufacturing	10.5	0.3	26,533	1.1	4.1	3.5
Bavaria	West	Finance	12.2	0.3	26,460	1.1	1.9	3.5
Berlin	West	Finance	3.4	0.4	22,760	0.9	3.4	2.3
Brandenburg	East	Public service	2.6	-0.3	15,492	1.5	2.1	4.6
Bremen	West	Trade	0.7	0.2	30,552	0.7	9.4	3.2
Hamburg	West	Finance	1.7	0.3	41,084	0.4	4.2	3.4
Hesse	West	Finance	6.1	0.1	28,916	0.5	5.6	3.1
Lower Saxony	West	Manufacturing	7.9	0.0	20,923	0.9	0.1	3.1
Mecklenburg-Vorpommern	East	Public service	1.8	-0.6	14,797	1.4	0.1	3.4
North Rhine-Westphalia	West	Finance	18.0	0.0	23,486	0.9	3.2	2.9
Rhineland-Palatinate	West	Manufacturing	4.0	0.0	21,045	1.0	1.4	3.1
Saarland	West	Finance	1.1	-0.4	21,451	1.1	10.0	3.1
Saxony	East	Public service	4.4	-0.5	15,394	1.9	5.9	4.3
Saxony-Anhalt	East	Public service	2.6	-1.0	14,635	1.7	4.3	4.3
Schleswig-Holstein	West	Finance	2.8	0.2	20,743	0.5	1.9	2.4
Thuringia	East	Public service	2.4	-0.7	14,720	2.0	4.8	5.5

NOTE.— Own calculations based on data from the German Federal Statistical Office. States classified as being in the east in column 1, were part of the German Democratic Republic before the reunification. In the analysis, Berlin is considered as West German, even so the eastern part of the city was part of the German Democratic Republic. The main industry in column 2 refers to the industry with the highest contribution to the state's GDP. Column 3 states population in million (mil.) for the year 2000. Berlin, Bremen, and Hamburg are so-called city states and are smaller and more urbanized than most other states. Column 4 gives the average year-to-year population change in percent between 2001–16. Columns 5 and 6 give the GDP per capita in 2000 and the average annual change between 2001–16. Column 7 shows the effect of the 2009 crisis on the states' GDP as assessed by equation (10) when the dependent variable is the actual GDP change relative to 2000, ΔP_t. In column 8, we use the shift-share-instrumented GDP change as the dependent variable, $\Delta \hat{P}_t$.

TABLE 3.
Estimated effect of GDP per capita change on mental wellbeing

	(1)	(2)
	Dependent variable	
	Life satisfaction	Mental Health Summary Score
Aggregated OLS		
ΔP_{rt}	0.0636***	0.0752*
	(0.0152)	(0.0304)
Shift-share IV		
$\Delta \hat{P}_{rt}$	0.1146***	0.0931***
	(0.0188)	(0.0181)
Number of observations	302,779	138,941
Number of state–year cells	272	128
First-stage F-statistic	40.5	24.4

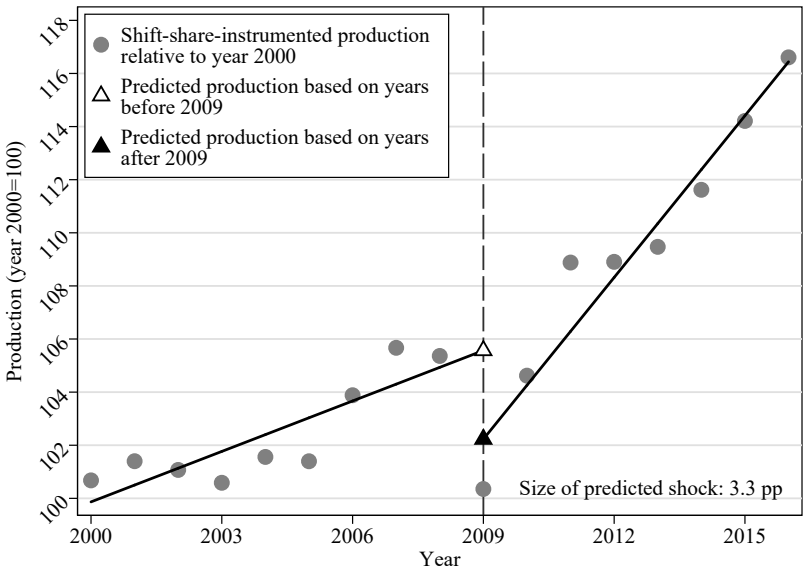
NOTE.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. Outcome variables are adjusted for individual-level characteristics according to equation (3). Both outcome measures are standardized to mean 0 and standard deviation 1. Observations are weighted by the number of individuals making up each cell. The first row gives the coefficient of production change (calculated according to equation (5)) on life satisfaction in column 1 and the Mental Health Summary Score in column 2, respectively. The second row repeats the analysis using instrumented production change using the IV approach (equation (8)). The F-statistic stated at the bottom of the table refers to instrument in the first stage of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

TABLE 4.
Estimated effect of GDP per capita change on potential effect channels—standardized effect sizes

	(1)	(2)	(3)	(4)
	Dependent variable			
	Employment		Income	
	Have employment	No worries: job loss	Labor income	No worries: own econ. situation
Aggregated OLS				
ΔP_{rt}	−0.0317	0.0852***	0.0244**	0.0601**
	(0.0200)	(0.0185)	(0.0093)	(0.0190)
Shift-share IV				
$\Delta \hat{P}_{rt}$	−0.0610	0.1509***	0.0287**	0.0999***
	(0.0321)	(0.0319)	(0.0103)	(0.0271)
Number of observations	184,255	184,255	164,480	164,480
Number of state–year cells	272	272	272	272
First-stage F-statistic	40.5	40.5	40.5	40.5

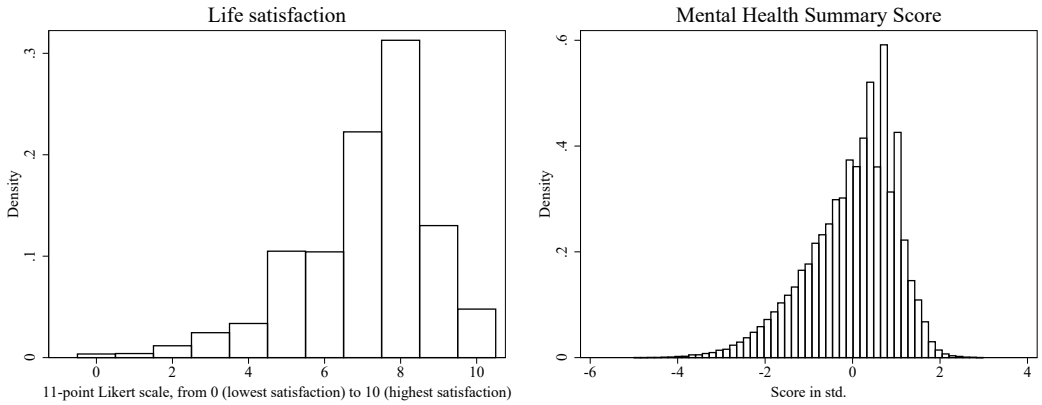
NOTE.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. Outcome variables are adjusted for individual-level characteristics according to equation (3). To ease of interpretation, all outcomes variables are standardized to mean 0 and standard deviation 1. See Table A.8 in Appendix A for estimation results when using the variables measured on their original scales instead. Observations are weighted by the number of individuals making up each cell. Individual observations are dropped when the dependent variable is missing for either channel type. Income is conditional on employment. The first row gives the coefficient of production change (calculated according to equation (5)) on the outcome stated in the column. The second row repeats the analysis using instrumented production change using the IV approach (equation (8)). The F-statistic stated at the bottom of the table refers to instrument in the first stage of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

FIGURE 1.
Measurement of the magnitude of the 2008–09 crisis



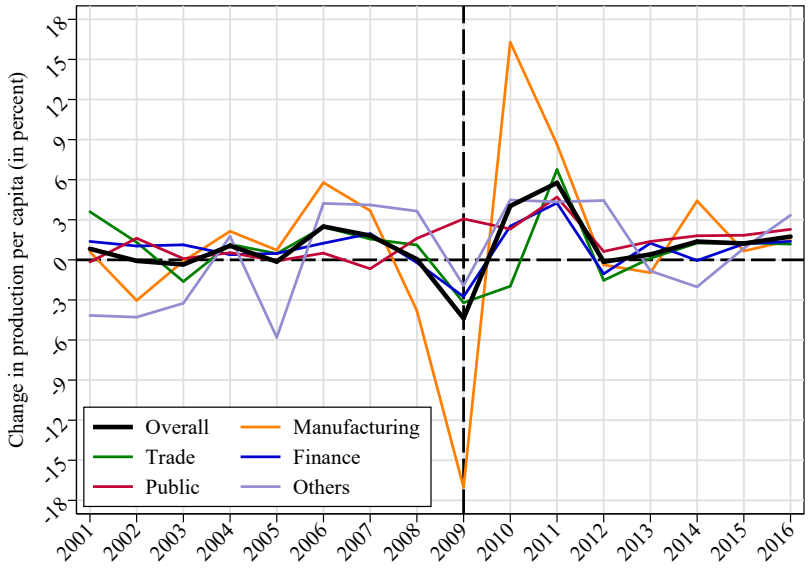
NOTE.— Own illustration based on data from the German Federal Statistical Office. The circular markers state the shift-share-instrumented relative GDP change between the year stated on the x-axis and 2000. We do not re-scale the index after instrumenting it, thus the 2000 marker does not lie at exactly 100. The fitted lines on the left- and the right hand side correspond to α_2 and α_3 in equation (9), respectively. The estimated effect of the crisis year 2009 (α_1) is the (rounded) difference between the trend in the GDP growth in 2009 when predicted using the years 2000–2008 (105.6 percent of the year-2000 level, hollow triangle) and 2009–2016 (102.2 percent, black triangle).

FIGURE 2.
Distribution of mental wellbeing measures



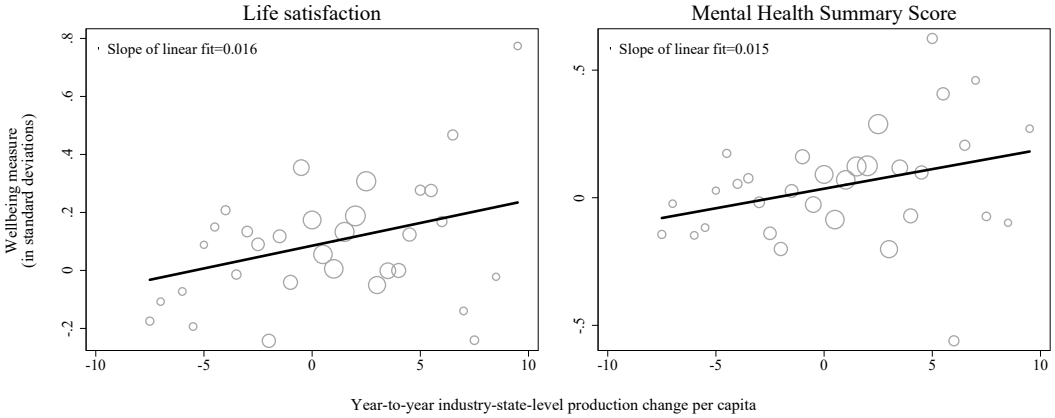
NOTE.— Own illustration based on data taken from the German Socioeconomic Panel (GSOEP) survey. The left plot gives life satisfaction on the 11-point Likert scale originally used in the GSOEP questionnaire. Life satisfaction enters the regression models standardized to mean 0 and standard deviation 1. The right plot gives the Mental Health Summary Score based on the SF12 questionnaire and standardized to mean 0 and standard deviation 1.

FIGURE 3.
Year-to-year changes in GDP per capita by industry



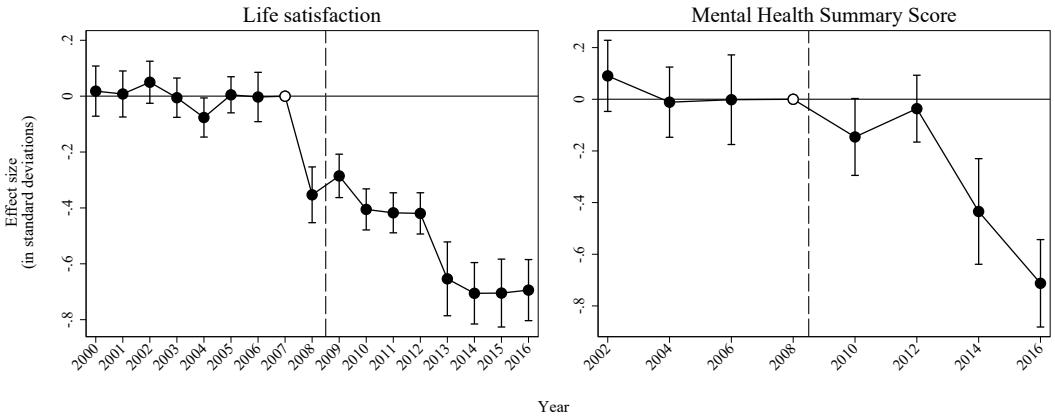
NOTE.— Own illustration based on data from the German Federal Statistical Office. The y-axes state the year-to-year production changes per capita by state in percent of the previous year's production. For state-level plots, see Figure A.3.

FIGURE 4.
Descriptive relationship between mental wellbeing and year-to-year industry–state-level GDP changes



NOTE.— Own illustration based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. Individual-level data on mental wellbeing was collapsed on industry–state–year level and linked to year-to-year GDP changes by industry and state. The outcomes were adjusted for individual-level control variables according to equation 3. Both outcome measures are standardized to mean 0 and standard deviation 1. The size of the circles indicates relative cell frequencies. The fitted lines and their slopes are based on OLS regressions.

FIGURE 5.
Event study estimates of the impact of the 2008–09 financial crisis on mental wellbeing



NOTE.— Own illustration based on data taken from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. The markers refer to the γ coefficients in equation (10). The spikes give the 95 percent confidence interval. The standard errors are bootstrapped with 500 replications, clustered on state-level and bootstrap samples are stratified on year-level. For life satisfaction the p-value of a joint hypothesis test of $\gamma_{2000} = \gamma_{2001} = \gamma_{2002} = \gamma_{2003} = \gamma_{2004} = \gamma_{2005} = \gamma_{2006} = 0$ is 0.16, for bin-annually assessed mental health the p-value of a joint hypothesis test of $\gamma_{2002} = \gamma_{2004}\gamma_{2006} = 0$ is 0.87.

Appendix A Additional tables and figures

TABLE A.1.
Characteristics of GSOEP sample

	(1) All states	(2) West	(3) East
Baseline sample (with movers)			
Number of person–year observations	302,779	239,324	63,455
Number of persons	59,060	48,976	10,795
Average years in sample	9.7	9.5	10.6
Share of person–year observations with out-of-state move	1.0	1.1	0.9
Share of respondents that moved out of state	3.4	2.9	5.7
Sample without movers			
Number of person–year observations	283,475	224,628	58,847
Number of persons	57,056	47,107	9,949
Average years in sample	9.6	9.3	10.5

NOTE.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey, years 2000–2016. The number of observations in the upper panel refers to the sample with valid life satisfaction information. Individuals are classified as moving in row 4 if the state of residence in year $t-1$ differs from the state of residence in year t. Row 5 gives the share of respondents that have ever moved in the years they participated in the survey. If moving results in dropping out of the sample or leaving Germany, this is not classified as moving in this table. In the bottom panel, individuals that are observed to move (across states) are excluded from the reported sample.

TABLE A.2.
Industry classification

Industry sector	Businesses included
Manufacturing	Manufacture of motor vehicles and component parts; machinery for the reprocessing of metal, wood, rubber, and chemicals; consumer electronics and communication equipment, production of clothes and textiles; reprocessing of food and beverages
Finance	Financial services including insurance and private pension funding; buying, selling, and operating real estate; legal services; management and consultancy; advertising and market research
Trade	Wholesale and retail trade and repair of motor vehicles and motorcycles; transportation and storage; tourism including air transport and hotel services; food and beverage service activities including restaurants; information and communication including computer programming and consulting as well as broadcasting and publishing activities
Construction	Construction of buildings; civil engineering (roads and railways); electrical installation
Energy	Mining and extraction of crude petroleum and natural gas; electric power generation, transmission and distribution; municipal services including waterworks, waste management, and operation of sewer systems
Agriculture	Crop and animal production, hunting and related service activities; forestry and logging; fishing and aquaculture
Public services	Governmental and municipal administration, law enforcement, fire department, teachers, researchers at public universities and research institutes, defence, social work, public health services

NOTE.— Own representation. The industry sectors are defined through the Classification of Economic Activities, issue 2008 (WZ 2008) by the Statistical Offices of the Federation and the Länder, see Klassifikationsserver (2020). Agriculture is assessed through industries in sector A; mining, energy production, and municipality services are summarized in a joint category B, D, and E; manufacturing in C; construction in F; trade in G–J; finance in K–N; and public services in O–T.

Table A.3.
First-stage results of the IV approach

	(1)	(2)
	Sample for	
	Life satisfaction	Mental Health Summary Score
First stage of the IV		
$\Delta \hat{P}^{Z}_{rt}$	0.8980***	0.8750***
	(0.0680)	(0.1090)
Number of observations	302,779	138,941
Number of state–year cells	272	128
First-stage F-statistic	40.5	24.4

Note.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar year and federal state. The cell in the first column gives the estimated effect of shift-share adjusted production change on production change using the sample for that we observed life satisfaction. The second column repeats the analysis for the sample for that we observed bi-annually assessed Mental health Summary Score. The F-statistic stated at the bottom of the table refers to instrument. Observations are weighted by the number of individuals making up each cell. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

Table A.4.
Estimation results leaving years 2007–10 out

	(1)	(2)
	Dependent variable	
	Life satisfaction	Mental Health Summary Score
Aggregated OLS		
ΔP_{rt}	0.0675***	0.0731*
	(0.0163)	(0.0329)
Shift-share IV		
$\Delta \hat{P}_{rt}$	0.1121***	0.0935***
	(0.0189)	(0.0166)
Number of observations	302,779	138,941
Number of state–year cells	208	96
First-stage F-statistic	37.8	27.1

Note.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. The table follows the same structure as Table 3. We drop the years around the finical crisis 2007–10. As the production measures are relative to the year 2000, the values of relative production changes and the shift-share adjusted production changes we use as instrument are unaffected by donut hole around the crisis years. The F-statistic stated at the bottom of the table refers to instrument in the first stage of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

TABLE A.5.
Estimation results for using 1991 as baseline year

	(1)	(2)
	Dependent variable	
	Life satisfaction	Mental Health Summary Score
Aggregated OLS		
ΔP_{rt}	0.0638***	0.0752*
	(0.0177)	(0.0304)
Shift-share IV		
$\Delta \hat{P}_{rt}$	0.1305***	0.0939***
	(0.0247)	(0.0202)
Number of observations	302,779	138,941
Number of state–year cells	256	128
First-stage F-statistic	27	19.9

NOTE.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. The table follows the same structure as Table 3. Unlike Table A.8, here we use year 1991 (the earliest with available data for all German states) as baseline period of the industry shares weights in equation (8) when calculating the shift-share adjusted production for the IV approach. The production changes are still calculated relative to year 2000 in order to get the same scaling as in the baseline results. Accordingly, the OLS estimations in the first row are unchanged, but for rounding errors. The F-statistic stated at the bottom of the table refers to instrument in the first stage of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

TABLE A.6.
Estimation results without out-of-state movers

	(1)	(2)
	Dependent variable	
	Life satisfaction	Mental Health Summary Score
Aggregated OLS		
ΔP_{rt}	0.0790***	0.0686***
	(0.0109)	(0.0196)
Shift-share IV		
$\Delta \hat{P}_{rt}$	0.1097***	0.0787***
	(0.0109)	(0.0124)
Observations	283,475	129,964
Number of cells	272	128
First-stage F-statistic	196.5	84.6

NOTE.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. The table follows the same structure as Table 3. Compared to Table A.8 we drop respondents who move out of the state we originally observe them in while being part of the GSOEP. Therefore, the resulting new sample is somewhat smaller than our original estimation sample. The auxiliary regression is, again, conducted for the new sample according to equation (3). The F-statistic stated at the bottom of the table refers to instrument in the first stage of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

Table A.7.
Estimated effect of current and one-year lagged GDP per capita change on mental wellbeing

	(1)	(2)
	Dependent variable	
	Life satisfaction	Mental Health Summary Score
Aggregated OLS		
ΔP_{rt}	0.0408***	0.0985***
	(0.0090)	(0.0237)
$\Delta P_{r,t-1}$	0.0426***	−0.0227
	(0.0098)	(0.0164)
Shift-share IV		
$\Delta \hat{P}_{rt}$	0.0595***	0.1249***
	(0.0122)	(0.0260)
$\Delta \hat{P}_{r,t-1}$	0.0625***	−0.0365*
	(0.0071)	(0.0166)
Number of state–year cells	240	128
First-stage F-statistic for ΔP_{rt}	73.9	123.0
First-stage F-statistic for $\Delta P_{r,t-1}$	119.8	72.1

Note.— Own calculations based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. Following the suggestion of Jaeger *et al.* (2018) we include lagged instruments to account for general equilibrium adjustment dynamics. This results in an IV approach with two first stages, one for the current and one for the one-year lagged production change as dependent variables. The instruments, current and one-year lagged shift-share adjusted production enter both first-stage regressions. All regressions include a linear time trend and federal state fixed effects. The F-statistics refer to both instruments in each of the first-stage regressions of the IV approach. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

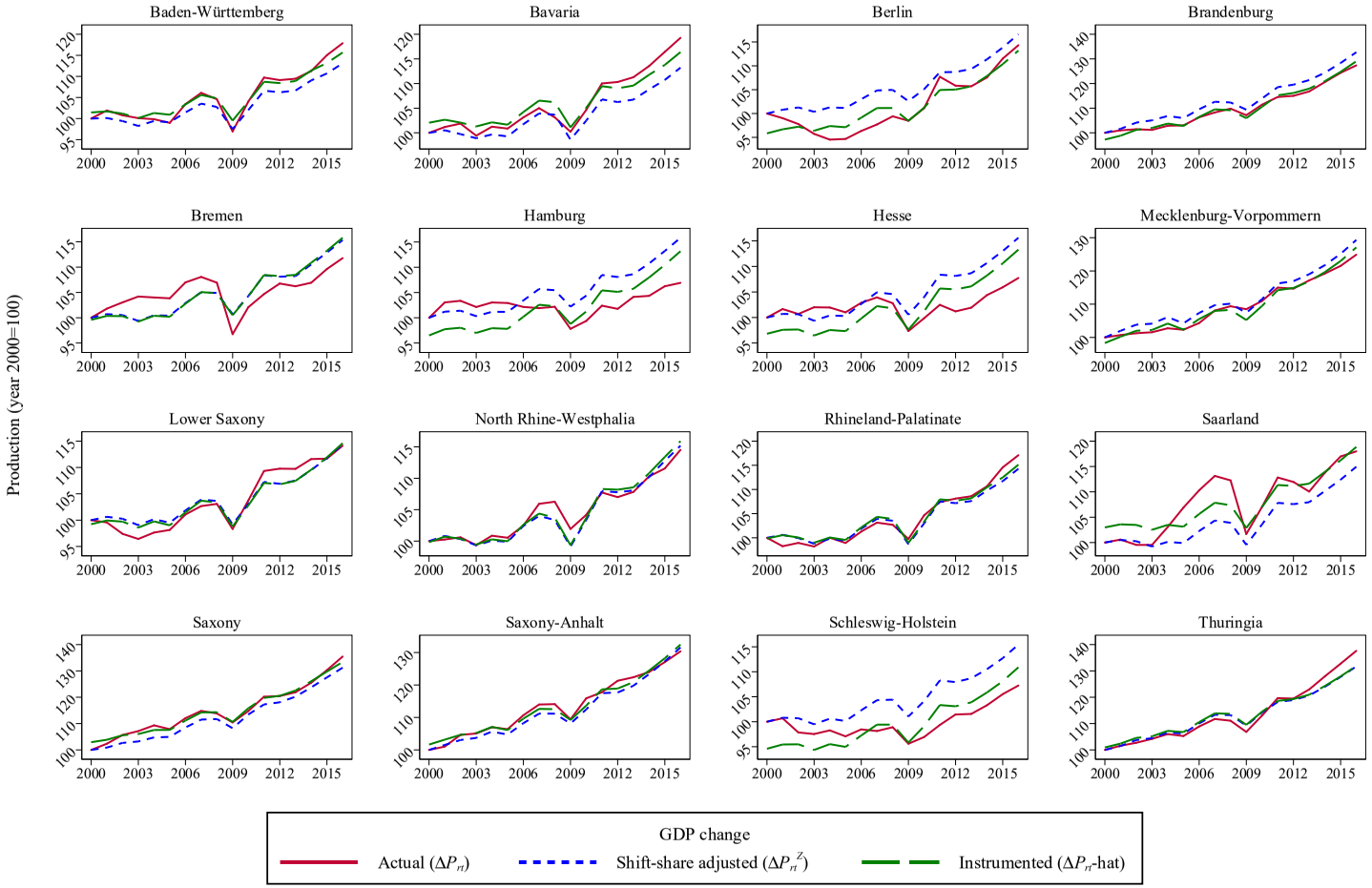
Table A.8.
Estimated effect of GDP per capita change on potential effect channels—original scale

	(1)	(2)	(3)	(4)
	Dependent variable			
	Employment		Income	
	Have employment	No worries: job loss	Labor income	No worries: own econ. situation
Aggregated OLS				
ΔP_{rt}	−0.0002	0.0048***	0.0065***	0.0034**
	(0.0001)	(0.0010)	(0.0015)	(0.0011)
Shift-share IV				
$\Delta \hat{P}_{rt}$	−0.0003	0.0086***	0.0097***	0.0056***
	(0.0002)	(0.0018)	(0.0019)	(0.0015)
Number of observations	184,255	184,255	164,480	164,480
Number of state–year cells	272	272	272	272
First-stage F-statistic	40.5	40.5	40.5	40.5

Note.— Own estimation based on data from the German Socioeconomic Panel (GSOEP) survey and the German Federal Statistical Office. All regressions include fixed effects for calendar years and federal states. Outcome variables are adjusted for individual-level characteristics according to equation (3). Outcome variables are on their original scales before standardization: employment is binary (employed=1) as well as no worries about job loss and no worries about own economic situation (some or little worries=1). Changes are interpreted in percentage points. Monthly gross labor income is in logs and changes are interpreted in percent. Observations are weighted by the number of individuals making up each cell. State-clustered standard errors in parentheses with significance: *p<0.10, **p<0.05, ***p<0.01.

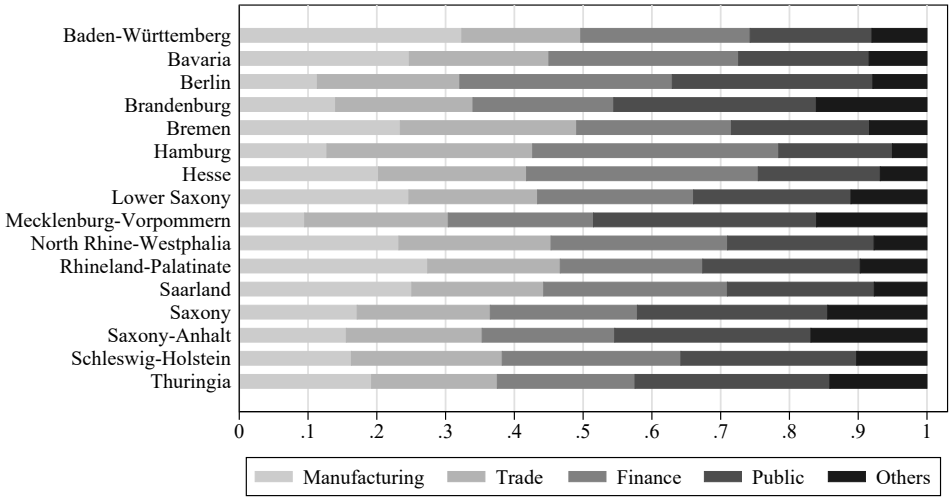
FIGURE A.1.

Comparison of actual, shift-share-adjusted, and shift-share-instrumented GDP development over time



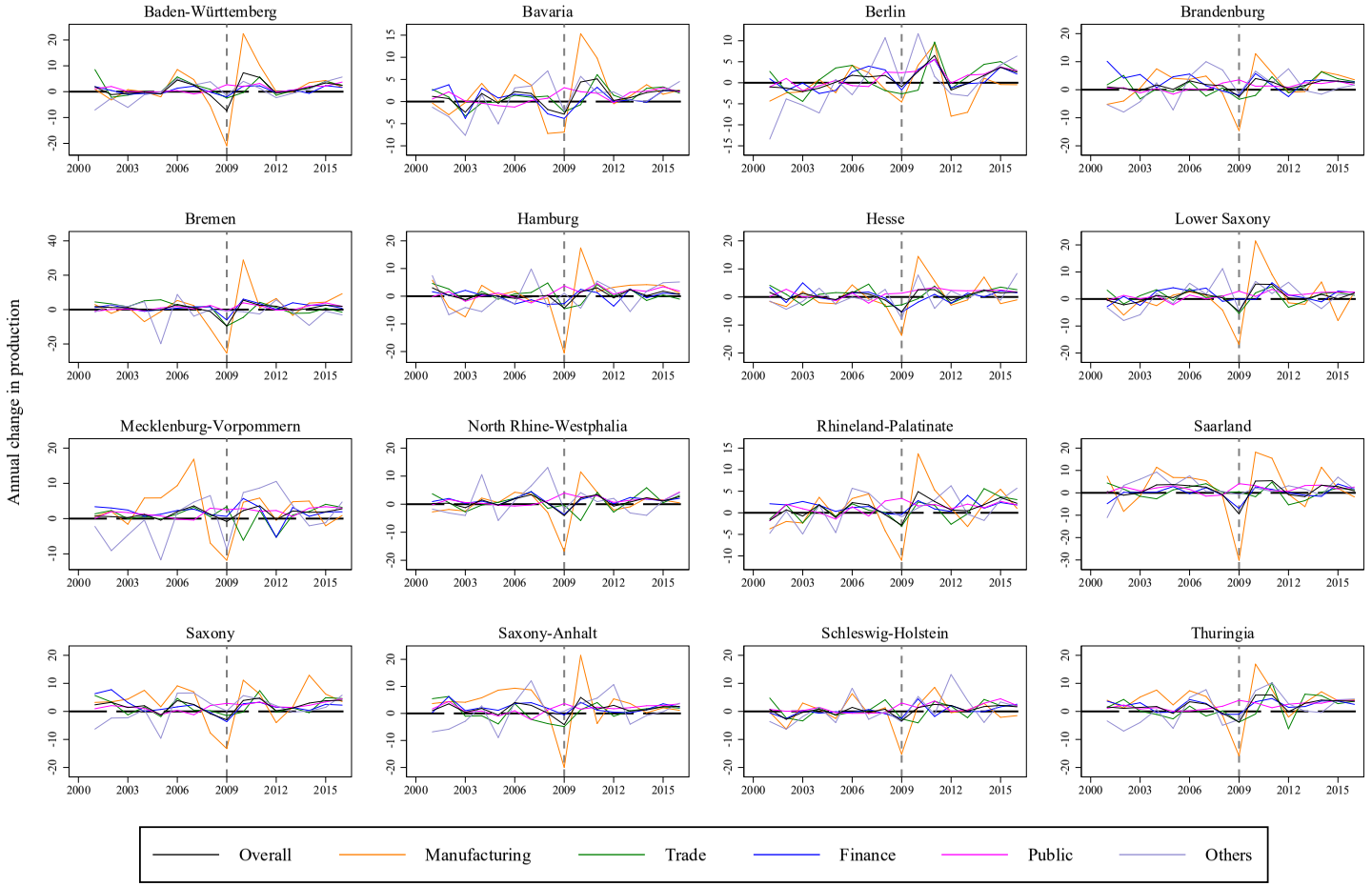
NOTE.— Own illustration based on data from the German Federal Statistical Office. This figure plots the development of actual production change, shift-share adjusted production change (that is, our instrument), and instrumented production change over time. All figures are per capita. The baseline period is year 2000 and actual production is set to 100 in year 2000.

FIGURE A.2.
Industry shares on GDP by state in year 2000 (baseline period)



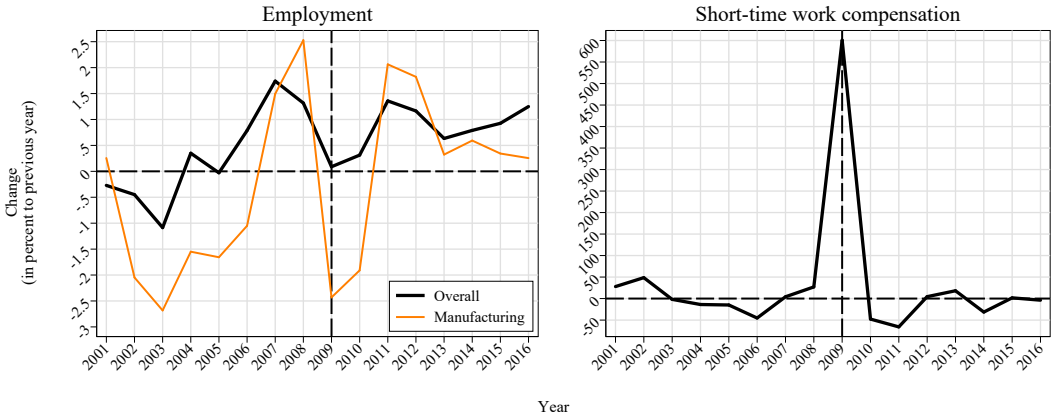
NOTE.— Own illustration based on data from the German Federal Statistical Office. Industry shares by state refer to the baseline period, year 2000.

FIGURE A.3.
Year-to-year changes in GDP per capita by industry and state



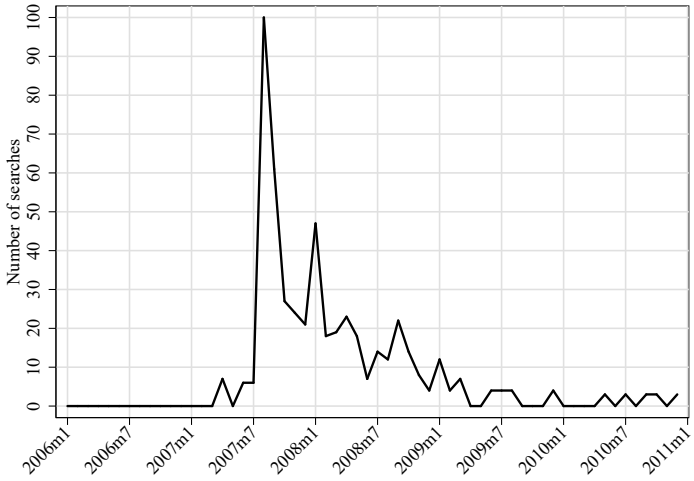
NOTE.— Own illustration based on data from the German Federal Statistical Office. The y-axes state the year-to-year production changes per capita by state in percent of the previous year's production. For a nationally aggregated plot, see Figure 3.

FIGURE A.4.
Changes in employment and short-time work compensation over time



NOTE.— Own illustration. Employment data are taken from DeStatis (2018b). Data on short-time work compensation are taken from BA (2020). The left panel gives the year-to-year change (in percent) in the number of employment persons (incl. self-employed) overall and for the manufacturing sector. The right panel gives the year-to-year change (in percent) in full-time equivalent employees under short-time work compensation.

FIGURE A.5.
Google searches for "mortgage crisis"



NOTE.— Own illustration based on data from Google Trends (2020) for "mortgage crisis" searches (German *Hypothekenkrise*). The x-axis gives the time horizon from January 2006 to December 2010. The y-axis gives Google's search intensity, measured between 0 and 100; the higher the value, the more often the term was searched.

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