OXFORD BULLETIN OF ECONOMICS AND STATISTICS, 84, 5 (2022) 0305-9049
doi: 10.1111/obes.12508

Which factors were behind Germany's labour market upswing? A data-driven approach*

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Abstract

Germany has experienced a strong and sustained labour market upswing since the mid-2000s. While various studies have highlighted different specific reasons for this development, this study contributes to the debate by simultaneously considering a broad set of candidate factors for the upswing in a unified methodological framework and systematically weighing them against each other on an empirical basis. We develop a structural macroeconometric framework that leaves as many of the systematic interlinkages as possible for empirical determination while operating with a minimal set of restrictions in order to identify economically meaningful shocks. For this purpose, we combine short- and long-run restrictions based on established assumptions on labour force development, technological change, and search and matching in the labour market. Matching efficiency, the intensity of job creation, the growing labour force, and the declining propensity to separate explain most of the German labour market upswing.

I. Introduction

While labour markets in Europe and worldwide have struggled from the repercussions of the Great Recession and the European debt crisis for nearly a decade, Germany has embarked on a strong and sustained labour market upswing. By 2018, unemployment was more than halved compared with the peak in 2005, and employment has followed a steep and stable upward trend even in times of a weak economy. Consequently, debates in

JEL Classification numbers: C32, E24, J21.
*We are grateful to Hermann Gartner, Britta Gehrke, Christian Merkl, Thomas Rothe, Heiko Stüber, and to the participants of the IAB-FAU Macro-Labor Seminars 2018 and 2019, the IAB-UR Econometric Seminar 2019, the T2M conference 2019, the IAAE conference 2019, and the EEA conference 2019 for helpful suggestions and valuable input.

academics and politics have revolved around the question of the decisive reasons for this extraordinary development. These discussions are highly relevant far beyond the national context. For example, consideration is being given to whether and to what extent the German labour market reforms of the last decade should be replicated or whether the German success was based on a wage dumping policy compared with its trading partners.

These reforms may have contributed to the labour market upswing by increasing the institutional matching efficiency to improve the matching on the labour market, strengthening the incentives for firms to create jobs, increasing the willingness of workers to make concessions, and reducing the readiness to separate employment relationships. On the other hand, arguments are put forward that the key driving forces are exerted by large macro trends such as strong economic development, an increasing labour force, wage moderation, and a rising proportion of part-time workers. In this study, we explore the empirical relevance of this comprehensive set of potential factors and weigh them against each other on the basis of a large and well-identified structural macroeconometric model. In particular, we address shocks on matching efficiency, separation propensity, job creation intensity/deregulation, willingness to make concessions/wage determination, the labour force, and working time as well as a technology shock and an additional business cycle shock (with purely transitory effects).

This collection represents both a synopsis and an extension of the previous literature. For example, increased matching efficiency after severe labour market reforms has been documented (e.g. Launov and Wälde, 2016; Klinger and Weber, 2016; Hertweck and Sigrist, 2015), as well as lower separation rates (Hartung, Jung and Kuhn, 2018; Klinger and Weber, 2016). Some have argued that worsened outside options have increased the willingness of the unemployed to make concessions (Krebs and Scheffel, 2013) and have connected the social benefit reform to increased selection rates and vacancy postings (Hochmuth *et al.*, 2021). Others have pointed to a positive effect of moderate wages and flexible wage setting (Dustmann *et al.*, 2014). Moreover, an increase in labour supply could have boosted employment (Burda and Seele, 2020) just as generally lower and/or more flexible working hours (Burda and Hunt, 2011; Balleer *et al.*, 2016; Weber, 2015; Carrillo-Tudela, Launov and Robin, 2021).

The purpose of the underlying study is to learn about the relevance and timing of the different effects by systematically weighing the candidate reasons for the labour market upswing against each other on an empirical basis. The brief review outlined above demonstrates that the literature as a whole provides an extensive debate over the subject. Notwithstanding, the single studies have usually focused on specific points. While in the course of this discussion, many essential points are illuminated, an investigation comprising a broad set of factors in a unified methodological framework makes a crucial contribution.

The research concept comprises a flexible modelling approach. In particular, for an open approach, it is crucial to minimize the need to set assumptions a priori. That is, the less restrictive the econometric procedure is designed to be, the more the data will speak in the results. In this regard, a structural vector error correction (SVEC) framework has particular merits. By using this model class, we can leave as many of the systematic interlinkages as possible for empirical determination while operating with a minimal set of restrictions. At the same time, the model is inherently structural, identifying economically meaningful shocks and allowing for potential equilibrium effects.

We construct such a model for the German labour market development since reunification, which includes the stock variables of unemployment, vacancies, and employment and the flow variables of job finding rate and separation rate as well as wages, productivity, and working time. This set of variables reasonably captures the labour market and allows for various relevant mechanisms. We identify the eight structural shocks mentioned above via a combination of short- and long-run restrictions. These restrictions are based on cointegration properties, well-established assumptions about technological change and cyclical fluctuations, and search-and-matching theory of the labour market.

Thus, as a general contribution, our empirical model can serve as a blueprint for unravelling a very broad set of potential driving forces of the labour market. In particular, our identification scheme does not rely on country-specific settings. This contributes to the growing literature implementing labour market dynamics into macroeconometric applications (compare Hairaulta and Zhutova, 2018; Rahn and Weber, 2019; Nordmeier, Schmerer and Weber, 2016; Fujita, 2011; Ravn and Simonelli, 2007).

The main results based on historical decompositions are the following: The labour market upswing is driven by genuine labour market shocks themselves, while the cycle or technology shocks play no decisive role. Shocks that increased the efficiency of the matching process, shocks that increased job creation intensity, for example, from deregulating the labour market, and shocks that reduced the propensity of firms to separate from workers explain most of the German labour market upswing. This outcome suggests a clear role for the reforms, whereas wage moderation and especially economic development were less important. However, two further factors became crucial over time. Shocks that increased the labour force became decisive, just as a self-enforcing effect: While the declining separation rate was first driven by stochastic shocks, over time, it resulted increasingly systematically from a tightening labour market. The results point to a partial decoupling of the labour market from GDP or productivity development (Klinger and Weber, 2020).

The paper proceeds as follows. Section II documents facts about the labour market upswing, introduces the data, and discusses the variable selection. As part of a step-by-step procedure, section III presents a small stylized model as a starting point. Section IV presents our large, macroeconometric model, the technical identification, and the estimation procedure. Section V discusses the potential driving forces of the upswing and the concrete strategy of how to disentangle them. Section VI presents the results, and the final section concludes the study.

II. Data, facts, and figures

Data

For the small model presented in section III, we use the variables GDP growth, wage growth, and hours growth. All three variables are in quarterly frequency, seasonally adjusted, and range from 1992:q1 to 2017:q4 (104 observations). The data are publicly

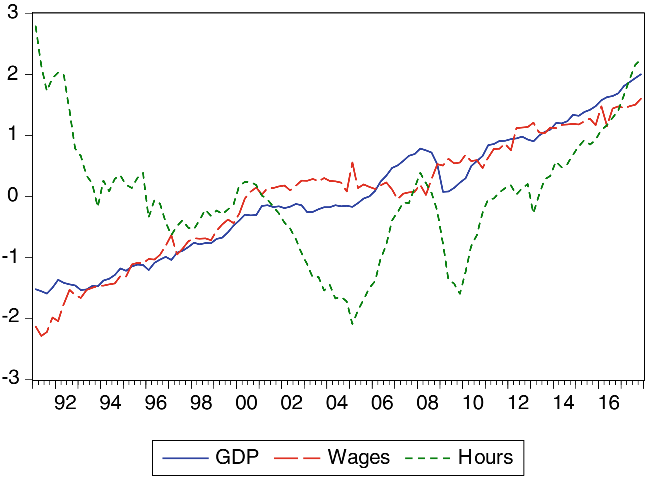

Figure 1. GDP, wages, and total hours, 1992–2017.
Notes: Seasonally adjusted data. For visual purposes, the time series in this figure are standardized to have mean 0 and variance 1 (normalized data) in order to put them on a common scale.
Source: Destatis.

accessible at the website of the German Federal Statistical Office. Figure 1 shows all three variables *in levels*. It documents the hours decline until approximately 2005 and the subsequent upswing, only temporarily interrupted by the Great Recession with a sharp decline of the GDP in 2008/2009. Furthermore, it shows the wage moderation during the 2000s.

In the larger model (section IV), we document the development of the German economy and labour market in a more comprehensive way using eight instead of three variables: vacancies, unemployment, employment, working hours per employee, hourly wages, job finding rate, separation rate, and productivity per hour. Detailed information about the data are given in section A in the Online Appendix.

The variable choice of the large model follows baseline search-and-matching models as presented in the Online Appendix. Working time is added in order to separately consider the hours dimension. Including employment and unemployment at the same time has the advantage that their sum can be used as a measure for the labour force. That is, by restricting the sum of their contemporaneous impulse responses to zero for the other shocks, we can identify a labour force shock (compare Table 2 in the Online Appendix). By including working time and employment, the inclusion of total hours is not necessary anymore because the latter is the product of the former two. Economic activity is captured by the productivity variable. We made this choice because productivity represents the activity variable used in the search-and-matching theory and in the large literature on technology shocks (e.g. Gali, 1999; Christiano et al. 2004). Furthermore, long-run restrictions (as in Table 2) for identification of technology shocks refer to reactions of productivity, and productivity is also part of potential cointegration relations, for example, with the wage. Our model contains both stock and flow variables. While stocks represent the standard labour market variables, the two flows job findings and separations allow for distinguishing the margins and thus identifying the channels of labour market shocks.

We follow the labour force concept to select the labour market stocks, which are measured in levels (i.e. the *number* of vacancies, unemployed, etc.), not in rates. Therein, employment is total employment and includes employees covered by social security, civil servants, the marginally employed, and the self-employed. Unemployment is defined following the ILO standard and is obtained from the (European) labour force survey. Vacancies are registered with the Federal Employment Agency (FEA). We take these register data because they outperform the German Job Vacancy Survey regarding the length and frequency of the available time series data.

The worker flow rates are calculated from a 2% representative sample of the IAB Employment Biographies (IEB), obtained from German social security and unemployment records. Unemployment-to-employment flows are divided by the number of unemployed workers in the previous month to obtain the job finding rate. This procedure is consistent with the counting mechanism of the FEA: Unemployment is counted in the middle of a month, while flows from unemployment are counted between this date and the middle of the subsequent month. Previous versions of the data have been used by Klinger and Weber (2016); Jung and Kuhn (2014); Nordmeier (2014); Gehrke and Weber (2018).

Both wages and productivity are provided on an hourly basis by the system of national accounts of the German Federal Statistical Office. Wages consist of gross wages, including employers' social security contributions, and are converted into real terms using the GDP deflator. The series on working time is drawn from the IAB working time calculations. This data set summarizes both survey- and register-based source statistics to calculate the average working time per employee.

Most of the data are available at a monthly frequency. Working hours, wages, and productivity, however, have to be interpolated from quarterly data. We follow Denton (1971) and use appropriate anchor variables for this procedure (see section A in the Online Appendix). All data are adjusted for seasonality. The sample ranges from January 1992 to December 2017, with 312 observations. Table 1 in the Online Appendix shows the summary statistics.

The German labour market upswing

Figures 2 to 4 document the enormous and long-lasting labour market upswing in Germany.

Figure 2 shows employment, wages, and productivity. The steep and sustained increase in employment starting in 2006 has been accompanied by a rather moderate increase in wages. In fact, the weak development of wages relative to productivity in the 2000s implies a decrease in the labour share, rendering labour more profitable for firms than before. The behaviour of employment during the Great Recession in 2008 and 2009 has provided food for debate in many developed economies. Despite the greatest decreases in GDP and productivity, Germany experienced an outstanding period of labour hoarding, and after the recession, the labour market started from the level of just 2007, while many other economies had to offset large employment losses first. However, the crisis left its footprint on the development of productivity, which has been sluggish since then; that is, the German labour market upswing has not been accompanied by a productivity upswing. Nonetheless, except for the phase of the Eurozone recession in 2011–13, GDP is on a stable growth path until the end of our sample.

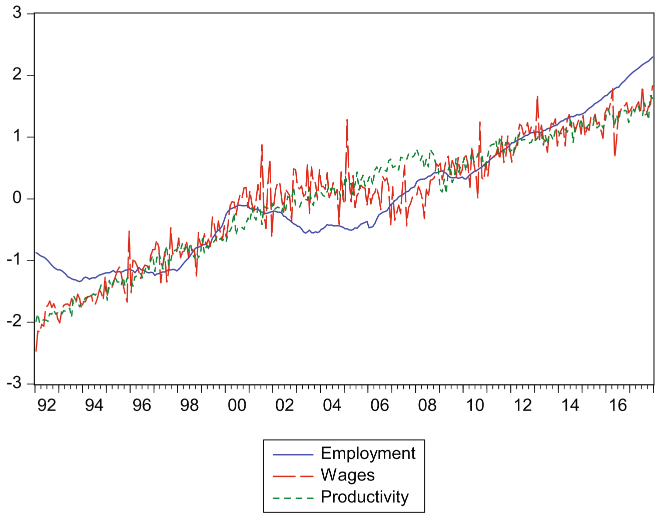

Figure 2. Employment, wages, and productivity, 1992–2017
Notes: Seasonally adjusted data. For visual purposes, the time series in this figure are standardized to have mean 0 and variance 1 (normalized data) in order to put them on a common scale.
Source: Destatis. Own interpolation of wages and productivity.

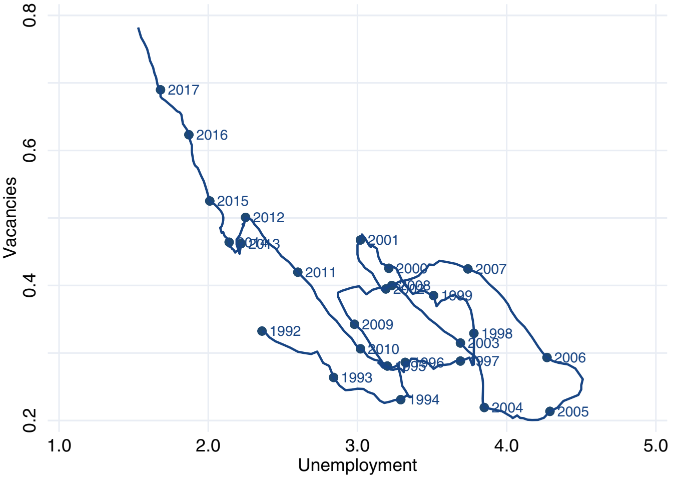

Figure 3. The Beveridge curve: unemployment and vacancies, 1992–2017
Notes: The graph shows the Beveridge curve from January 1992 to December 2017. Monthly data (seasonally adjusted). Unit: 1 million. The labelled dots represent the January observations of the respective years.
Source: Federal Employment Agency (vacancies), Eurostat (unemployment).

Figure 3 presents the Beveridge curve, which is the generally downward-sloping relationship between vacancies and unemployment. The ratio of the two is interpreted as labour market tightness. The figure provides important insights into the nature of the upswing: Following the Hartz reforms of 2003–06, the curve shifted inwards – which was also exceptional by international comparison (Bova, Jalles and Kolerus, 2018). The inward shift indicates better functioning of the labour market (compare Blanchard and Diamond, 1989) and has been connected to improved matching efficiency (Klinger

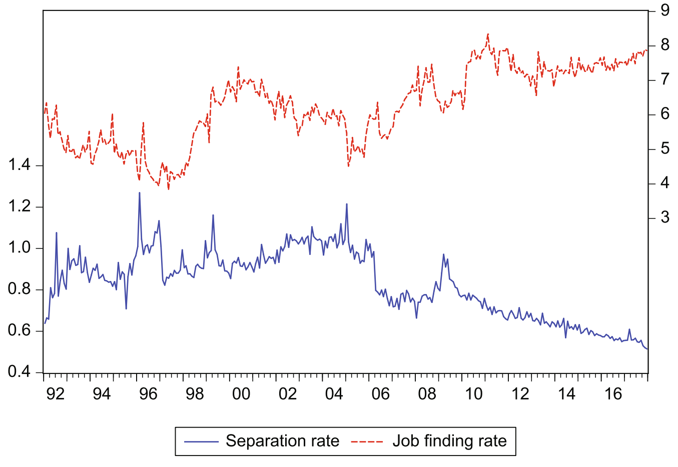

Figure 4. Separation rate and job finding rate, 1992–2017
Notes: Seasonally adjusted data. Unit: percent.
Source: IAB Employment Biographies. Own calculations.

and Weber, 2016; Launov and Wälde, 2016). We also note that because the trajectory during the inward shift is relatively flat, it is likely that, in parallel, positive effects on vacancies occurred. Second, starting in 2010, we observe a strongly upward moving limb: The number of vacancies relative to the unemployed has been rising extraordinarily. The labour market has become unusually tight (Klinger and Weber, 2020).

The worker flow rates (Figure 4) give some insight into why labour market stocks improved so much. Remarkably, the job finding rate increased stepwise after the Hartz reforms. This increase was shown to be of a permanent, that is, not cyclical, nature (Klinger and Weber, 2016). Even more strikingly, the separation rate has decreased for years. By the end of our sample, it had reached the lowest value since reunification. As the separation rate was found to be more influential for the dynamics of German unemployment than job findings (e.g. Jung and Kuhn, 2014; Hertweck and Sigrist, 2015; Klinger and Weber, 2016), this outstanding development also points to a potential source of the remarkable increase in employment and decrease in unemployment.

Undoubtedly, the figures mirror an extraordinary labour market development. Regarding OECD harmonized unemployment rates, Germany ranked 33 among 35 OECD countries in 2005 – having been called the ''sick man of Europe'' (Siegele, 2004) – while after extraordinary development, it ranked 6 in 2017. The interaction of aggregate shocks and institutions (Blanchard and Wolfers, 2000) has been found to be a plausible reason for the long-lasting aggravation. Hence, a similar approach also seems to be rational when explaining the reverse direction. Previous studies that investigated why the upswing occurred and, by the same token, whether it is replicable have typically focused on single or only few shocks or institutions.

III. A small stylized model

As a starting point, we construct a small stylized model including the (logarithmised) variables GDP, wages, and hours. While our ultimate goal is to distinguish the influence of a broad set of shocks simultaneously, we use the small model as part of a step-by-step approach. Particularly, in this stylized framework, we shed light on the role of aggregate activity, wage and employment shocks.

To capture very general dynamic interactions of the three variables, we start with a reduced-form VAR model. Augmented Dickey–Fuller (ADF) tests confirm that our variables should be treated as non-stationary. We run the so-called trace test (see Johansen, 1995) and find one cointegration relation. Since cointegration relations generalize a VAR in first differences, we estimate a vector error correction model (VECM). We use Johansen's maximum likelihood (ML) approach to estimate the reduced-form VECM parameters. We apply a sequential elimination procedure based on a restricted feasible GLS (FGLS) estimator to find a parsimonious subset model (compare Lütkepohl, 2005, Sects. 5.2 and 7.3). A lag length of 2 quarters ensures no serial correlation is left in the VECM residuals according to Portmanteau tests.

The correlated reduced-form residuals are not economically interpretable but are usually specified as linear combinations of structural shocks. In our small model, these structural shocks are defined as technology shocks, wage shocks, and employment shocks. Under the standard assumption of zero cross-correlations between the different structural shocks, three restrictions are needed to identify the structural form. For this purpose, we make use of a combination of short- and long-run restrictions:

1. We follow the standards in the growth literature stating that the long-term driver of productivity is given by technology shocks. Since productivity is defined as GDP over hours, this assumption means that the GDP reactions to the other two shocks equal the respective hours reactions in the long run (thereby ensuring a zero long-run effect on productivity).
2. Disentangling the wage shock from the employment shock requires only the weak assumption that the potential triggering of wage reactions to employment shocks does not pass off within a single quarter. Hence, we assume that the contemporaneous reaction of wages to employment shocks is zero.

After obtaining the dynamics of the model from the reduced form, the structural form is estimated by ML given the restrictions described above. The resulting impulse responses mirroring the relevance of the shocks are shown in Figure 5. The most relevant hours reaction is found in the case of the employment shock (+0.79%), followed by the technology shock (+0,59%) and the wage shock (−0.25%).

So far, we have used total hours of all employed. Since the strong increase in part-time employment during the sample means that the hours upswing was less pronounced for full-time employment, special attention is warranted in our analysis. When total hours of full-time workers (instead of total hours of all employed) are included in the model, the relative importance of the impulse responses of hours to the three shocks remains unchanged. The long-run response to employment shocks is still the largest (+0.81%), followed by the technology shock (+0.55%) and the wage shock (−0.35%).

In this small model, the exact reasons behind the strong role of the labour market remain unknown. The model just summarizes them under the column ''employment shock''. Potential candidates could be, among others, increasing labour force and increasing

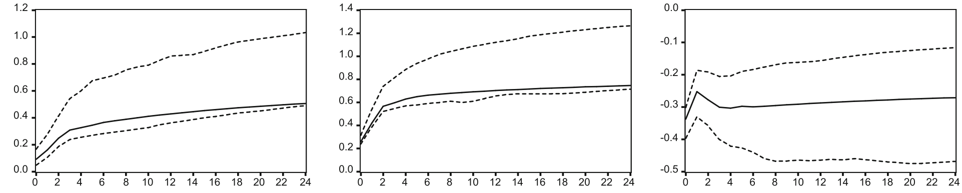

Figure 5. Small stylized model: Impulse responses of hours
Notes: The solid lines show the responses of total hours to positive technology shocks (left panel), wage shocks (middle panel), and employment shocks (right panel) for up to 24 quarters. The dotted lines denote 2/3 confidence intervals. Unit of shocks: All shocks are normalized to have a variance of 1. Unit of responses: percent.
Source: Own calculations.

matching efficiency. This emphasizes that more than just three variables are warranted so that we have a more comprehensive set of potential driving forces at hand (see section V). For this purpose, the next section will develop a larger model.

IV. Methodology

Model

It is decisive that the developments observed in the data be ascribed to the shocks *where they originate*. Logically, the relevant shocks must be accurately filtered from the data set, given a multitude of potential interlinkages between the variables and their complex and dynamic structure. This structure must be flexibly captured based on empirical measurement.

As a precondition of reliable impulse responses and meaningful historical decomposition, our model combines two properties: First, it is structural in that economically meaningful shocks are identified, and equilibrium effects can be considered; and second, it captures very general dynamics and interactions of the variables without imposing strong structural assumptions a priori. The model separates a systematic part, comprising dynamics, interactions, and deterministics, from a stochastic part. From the latter, the structural shocks will be identified. For instance, if a working time reduction is observed, this may be due to an exogenous innovation or working time may react endogenously to other developments, for example, in the business cycle. In fact, the task of the model structure is to provide a suitable econometric frame to allow the data to speak.

Thus, we start with a vector autoregressive process of order q, VAR(q):

$$y_t = \sum_{i=1}^{q} A_i y_{t-i} + \mu D_t + u_t, \quad t = 1, 2, \ldots, T, \tag{1}$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a K-dimensional random vector, A_i represents fixed $(K \times K)$ coefficient matrices, and $D_t = (1, t)'$ collects the deterministic terms with associated fixed coefficients $\mu = (\mu_0, \mu_1)$, where μ_i, $i = 0, 1$ is of dimension $K \times 1$. To ensure the asymptotic validity of our inference procedures, we assume that u_t is a K-dimensional iid process with $\mathrm{E}(u_t) = 0$, $\mathrm{E}(u_t u_t') = \Sigma_u$, Σ_u being non-singular and that, for some finite constant c, $\mathrm{E}|u_{it}u_{jt}u_{kt}u_{mt}| < c$ for $i, j, k, m = 1, \ldots, K$, and all t. Finally, the initial values $y_0, \ldots, y_{-q+1}$ are assumed to be fixed.

In our large model, y_t consists of the $K = 8$ endogenous variables vacancies (V), unemployment (U), employment (E), job finding rate (F), wages (W), productivity (P), separation rate (S), and working time per employee (H). This choice reflects a set of labour market stock and flow variables immanent to the unified economic framework for investigating our research questions.

ADF tests confirm that our variables should be treated as non-stationary. This treatment implies, first, the existence of non-zero long-run effects of the shocks and, second, the potential presence of cointegration relationships among the variables. These relationships could represent equilibrium effects in the model economy. Therefore, we re-write the VAR (1) into a VECM, which explicitly incorporates the cointegration relationships as preferred by the data. The considered VECM reads as

$$\Delta y_t = \nu + \alpha\beta'(y_{t-1} - \rho_1(t-1)) + \sum_{i=1}^{q-1}\Gamma_i \Delta y_{t-i} + u_t, \tag{2}$$

where $\Gamma_i = -\sum_{j=i+1}^{q} A_j$, $i = 1, \ldots, q-1$, and $\Pi = -(I_K - A_1 - \cdots - A_q)$ with $0 \leq \mathrm{rk}(\Pi) = r < K$ such that $\Pi = \alpha\beta'$ with α and β being full column rank $(K \times r)$ matrices for $0 < r < K$. Note that r is equal to the number of linearly independent cointegration relations given by $\beta' y_{t-1}$. We have assumed that $\mu_1 = -\alpha\beta'\rho_1$ for some deterministic $K \times 1$ vector ρ_1. Hence, the linear trend can be restricted to the cointegration relations such that the VAR process does not allow for a quadratic trend; compare Johansen (1995, sect. 5.7). It follows that $\nu = \mu_0 - \alpha\beta'\rho_1$.

The VECM in (2) represents the reduced form of an underlying structural system. In particular, the contemporaneously correlated residuals in u_t do not represent economically interpretable innovations. Instead, they are usually specified as linear combinations of unique structural shocks. Formally, this can be expressed as

$$u_t = B\epsilon_t, \tag{3}$$

where B is a non-singular $(K \times K)$ coefficient matrix such that $\Sigma_u = BB'$, and ϵ_t represents the vector of structural shocks. Our approach connects these shocks to the driving forces discussed in section V.

The structural VECM (SVECM) follows from inserting (3) into (2). From this SVECM, we obtain under appropriate assumptions (compare Johansen, 1995, theorem 4.2) the structural moving average (MA) representation for y_t

$$y_t = C\sum_{i=1}^{t}(B\epsilon_i + \mu D_t) + C(L)(B\epsilon_t + \mu D_t) + A, \tag{4}$$

where A depends on initial values such that $\beta' A = 0$, $C = \beta_\perp(\alpha'_\perp(I_k - \sum_{i=1}^{q-1}\Gamma_i)\beta_\perp)^{-1}\alpha'_\perp$ with $\alpha_\perp$ and $\beta_\perp$ being $(K \times K - r)$ matrices of full column rank such that $\alpha'\alpha_\perp = 0$ and $\beta'\beta_\perp = 0$, respectively. Moreover, $C(L)B\epsilon_t = \sum_{i=0}^{\infty} C_i u_{t-i}$ is an $I(0)$ process.

The coefficient matrices C_i, $i = 0, 1, 2, \ldots$ depend on the VECM parameters, and it holds that $C_i \to 0$ as $i \to \infty$.

Hence, the long-run effects of the structural shocks on the model variables in y_t are given by the long-run impact matrix CB. Moreover, $(C + C_i)B$ represents the structural impulse responses at any finite horizon i with $C + C_0 = I_K$ such that B contains the impact effects of the shocks. Finally, note that CB is of reduced rank $K - r$. Thus, the long-run impulse responses of the variables are not linearly independent if $r > 0$.

Technical identification

The initial impact matrix B and thus the SVECM as a whole are not identified without imposing restrictions. Assuming $E[\epsilon_t \epsilon_t'] = I_K$ by convention, we need to impose at least $K(K-1)/2 = 28$ (linearly) independent restrictions on B and CB to achieve identification; see Lütkepohl (2005, sect. 9.2). Restrictions on B will be called short-run restrictions, while restrictions on CB are labelled as long-run restrictions. As CB is of reduced rank in case of cointegration, one has to be careful when determining the number of independent restrictions. For example, a zero column in CB only counts for $K - r$ independent restrictions; for a discussion, see Lütkepohl (2005, sect. 9.2).

In our empirical model set-up, we impose exactly 28 linear restrictions. Based on our estimates, the rank criterion of Lütkepohl (2005, proposition 9.4) indicates local identification of the SVECM, that is, the existence of a locally unique solution for B. Identification is only local as B enters $\Sigma_u = BB'$ in ''squared form''. Hence, identification is only up to column signs, as multiplying a column of B with -1 will still recover Σ_u. To obtain a globally unique matrix B, we follow Lütkepohl (2005, sect. 9.1.2) and normalize one element in each column of B to be non-negative. In detail, we apply the following sign normalizations with respect to the structural shocks described below: job creation intensity shock on vacancies, labour force shock on the sum of employment and unemployment, wage determination shock on wages, matching efficiency shock on the job finding rate, cycle shock on vacancies[1], technology shock on productivity, separation propensity shock on the separation rate, and working time shock on per capita working hours.

Specification, estimation, and inference

We consider a VAR order of $q = 7$, even though the information criteria (Akaike, Bayesian) would have preferred fewer lags. We do so in order to avoid serial correlation in the reduced-form residuals and thus to ensure that we capture any relevant dynamics in the data.

Based on the VAR(7), we run the trace test and find $r = 2$ cointegration relations. While economically, one could think of different relations, such as the Beveridge curve or the job creation curve, restricting the cointegration space to specific relationships is not necessary for our purposes. Allowing for $r = 2$, we use Johansen's ML approach to estimate the reduced-form VECM parameters in (2), including the cointegration matrix β.

[1]The cycle shock also loads positively on other variables, such as working time or job finding rate, so the choice of normalization has no effect here.

To account for equation (8) in the Online Appendix and control for shifts in μ_t due to a changing composition of the unemployed, we add as exogenous variables the following five shares with respect to all unemployed persons to the equation for the job finding rate in our VECM: low-skilled (no completed degree), long-term (>1 year), older (aged 55+), foreign, female.

As in the small model, we search for a parsimonious subset VECM. To be precise, we sequentially exclude the short-run dynamics parameters in Γ_i, $i = 1, \ldots, q-1$, which do not satisfy an absolute t-value of at least 1.645. This threshold value is consistent with a 10% significance level based on the standard normal distribution. The adjusted Portmanteau test (see, for instance, Lütkepohl, 2005, Sect. 8.4.1) cannot reject the null hypothesis of no serial correlation in the residuals of the resulting subset VECM up to a lag of 24, even at the 10% significance level.

Following Lütkepohl (2005, Sect. 9.1), the structural form is estimated using a nonlinear ML approach employing the restrictions introduced in section V (see also Table 2 in the Online Appendix). Our specification, estimation, and bootstrap approaches are described in more detail in section D in the Online Appendix.

V. Identifying driving forces

To identify economically meaningful shocks to the driving forces, we eventually apply an identification scheme that distinguishes the shocks by when, how, and for how long they affect the model economy. Our econometric framework leaves the dynamics completely unrestricted and introduces constraints on the immediate and/or the long-run impact only to the extent that is necessary and economically justifiable.

For the foundation of the short- and long-run restrictions, we draw on established macroeconomic concepts. This includes theories of technological change as well as the business cycle for the part of the macroeconomy. Thereby, we exploit results on technology shocks as drivers of long-run productivity and on the transitory character of cyclical shocks. For the labour market, we build on search-and-matching theory to inform the identification scheme. Particularly, we ensure that all relationships suggested by the theory are left unrestricted and are thus reflected in our generalized structural econometric setting. We give a brief outline of a baseline search-and-matching model version in the Online Appendix so that formal reference can be made when detailing the identification of the structural shocks.

Key ingredients are a matching function, a job creation curve, a wage bargaining rule, and reservation productivity. We allow for a time-varying labour force and thus cover three labour market states: employed, unemployed, and out of the labour force. Regarding the matching function, the stock variables enter with one lag, which accounts for the expenditure of time that the whole search and recruiting process requires and is consistent with the counting mechanism of the FEA (see Subsection II). Regarding monthly data, the time aggregation bias is negligibly small (Nordmeier, 2014). As a consequence of this timing, the job finding rate will react contemporaneously only to shocks that directly affect matching efficiency but not to shocks that change solely unemployment and vacancies in the first round.

An overview of the identification scheme is shown in Table 2 in the Online Appendix. In the following, we discuss the potential driving forces that are building blocks of our approach as well as the shock identification.

Labour force: A comparison of the changes in employment and unemployment over the past decade shows that the observed increase in employment could not stem from the existing labour force only. Burda and Seele (2020) and Klinger and Weber (2020) argued in favour of a supply-side effect. Once workers have entered the labour force, they are either employed or unemployed (as in equation (5) in the Online Appendix). The labour force shock – for example, higher immigration or participation – changes the size of the workforce. In principle, this shock is the only thing that can affect the labour force *on impact* and might thus move both employment and unemployment in the same direction (for exceptions, see below); note that additional labour force can enter the labour market not only via unemployment but also directly via employment (e.g. migrants entering with a job offer, older workers postponing retirement), so we make no assumptions about the distribution between the two states. Beyond the initial month, our modelling approach allows the labour force to be changed by any of the structural shocks. The labour force shock can lead to additional persons entering unemployment, but since matches would appear only from the following month onwards (equation (7) in the Online Appendix), there is no contemporaneous effect on the job finding rate. In the long run, one could think of the shock as a pure blow-up of the labour force, corresponding to a blow-up in vacancies leaving labour market tightness and the job finding *rate*, as well as the separation *rate*, unaffected. By the same token, one might also restrict the long-run responses of wages and productivity. Since these restrictions are not necessary for full identification and would considerably decrease the likelihood, we leave these effects unconstrained. This procedure has the advantage of not a priori excluding specific results from the migration literature (e.g. Ottaviano and Peri, 2012). However, section G in the Online Appendix shows that the results do not hinge on this exception.

Working time: Given the debate over whether hours worked and employment are substitutes or complements, the question of whether working time changes contributed to the labour market upswing is an empirical one. In our model, the working time shock is the only one to change working hours per employee immediately (for exceptions, see below). In this context, note that a shock refers to an innovation that goes beyond endogenous reactions. If, for example, working time decreases in a recession only following the usual system dynamics, the cause would not be a working time shock itself but a shock to economic activity. A shock would occur, however, if working time changes deviate from the standard pattern. These shocks could represent institutional changes, such as in short-term work or maternity leave policies, as well as variations in the working time preferences of the labour force (whereas the labour force shock itself was modelled as a pure size shock at the extensive margin).

Technology: The technology shock is the only one to affect labour productivity in the long run, following the standard assumption by Gali (1999) and many others. The only exception is the labour force shock, as explained above. With respect to the short run, in particular, both employment and working time can be affected by the technology shock (the latter of which is an exception to the identifying rule of the working time shock). These two reactions make up for the initial impact on total hours worked. Given the discordant literature on how technology shocks affect total hours worked (e.g. Uhlig, 2004; Canova, Lopez-Salido and Michelacci, 2010), an unrestricted empirical strategy seems reasonable. This is also the case in view of the role of productivity for job creation and job destruction decisions (as in conditions (11), (13), and (14) in the Online Appendix). We show in section G in the Online Appendix that the results are robust to the exception concerning $\theta_{H,tech}$.

Business cycle: In view of the criticism of the idea that technology shocks are the only source of cyclical fluctuations (e.g. Summers, 1986), we offer a further source as an explicit cycle shock. The cycle shock is allowed to produce economic fluctuations at business cycle frequencies but does not affect the economy in the long run. Hence, the column in the matrix of long-run effects CB, referring to the cycle shock, is set to zero. This zero column counts for $K - r$ independent restrictions because r of the zero entries are implicit consequences of the cointegration properties discussed above. On impact, the cycle shock is exempted from the identifying rule of the working time shock. Instead, an immediate reaction of working time is allowed to accommodate results in which demand shocks are mitigated along the intensive margin (e.g. Panovska, 2017; Herzog-Stein and Zapf, 2014).

Wage determination: The influence of wage determination on labour market outcomes can have manifold sources and mechanisms. First, consider the wage moderation after reunification. Second, wage setting institutions have become more flexible. Third, with rising labour market tightness, wage concessions by firms have become more important than during the period before the upswing (according to the German Job Vacancy Survey). Fourth, the introduction of a general minimum wage in 2015 increased reservation wages and made wage setting less flexible again. Fifth, workers' outside options worsened remarkably after the Hartz reforms in 2006, reducing reservation wages and the bargaining power of workers. Hence, workers' willingness to make (wage) concessions increased (Krebs and Scheffel, 2013; Rebien and Kettner, 2011). In general, these examples make it evident that our term ''wage determination'' comprises both the wage setting process and the willingness to make concessions or increase search intensity according to outside options. In section F of the Online Appendix, we will separate these two ingredients using an alternative identification strategy. It follows from the fact that the wage determination shock summarizes several sources for why wages initially change, that it is the only shock that can immediately affect all variables.

Matching efficiency: Regarding the efficiency of the matching process, we disentangle efficiency connected to search intensity – as already captured by wage determination and outside options above – and efficiency connected to the matching technology itself, that is, the technological toolkit and institutional framework for the unemployed, firms, and the public employment service to form matches. Our approach implies that search intensity is part of the willingness (i.e. wage determination) shock that can immediately move the wage, in contrast to the matching efficiency shock. Intuitively, more intensive search at a given wage would be equivalent to constant search at a lower wage. Thus, higher search intensity corresponds to lower reservation wages. By the same token, higher search intensity would also imply additional persons entering the labour market, thus affecting the labour force. In contrast, the efficiency shock affects the matching technology (in equation (7) in the Online Appendix) – immediately moving the job finding rate, employment, and vacancies (equations (9), (6), and (11) in the Online Appendix). We refrain from the immediate impacts of the efficiency shock on wages and the separation rate because matches do not appear contemporaneously in either the wage bargaining rule (equation (12) in the Online Appendix) or the job destruction conditions (equations (13) and (14) in the Online Appendix). We argue that the restrictions hold even if one assumes that matching efficiency affects hiring costs. Empirical studies have found hiring costs to be low (Carbonero and Gartner, 2022), so their changes would be of a size of secondary importance. Moreover, the share passed to workers through wage renegotiations is likely to be limited, and the effect on the average wage level of all employees is negligible. By the same token, the option value of labour hoarding in the reservation productivity (the cut-off point for separations in the job destruction condition; equation (14) in the Online Appendix) would not be changed considerably.

Separation propensity: The role of separations in explaining the labour market upswing in Germany has been addressed by Klinger and Weber (2020); Klinger and Weber (2016) and Hartung *et al.* (2018). The propensity of firms to dismiss workers depends on firing costs on the one hand and on the opportunity costs of firing and rehiring on the other hand. A decisive source of changes in firing costs is provided by employment protection legislation (EPL). Relaxing EPL (or allowing fixed-term contracts) typically increases job creation and labour market flows but has fewer effects on employment and unemployment (Kahn, 2010; Cahuc and Postel-Vinay, 2002). Regarding the second aspect, the opportunity costs of firing and rehiring are affected by labour market tightness. The more costly and time-consuming the hiring process is, the more cautious the firm's firing strategies tend to be. Endogenous separations (as in equation (13) in the Online Appendix), for example, due to variations in productivity or tightness, are driven by the systematic model part. In contrast, a separation propensity shock – for example, changes in firing costs – moves the separation rate irrespective of other endogenous factors. The shock changes the option value of a job in cases of split-ups. Via job creation (equation (11) in the Online Appendix), tightness reacts, but the matching efficiency (in the matching function (7) in the Online Appendix) is unaffected, so the effect on the job finding rate is zero on impact. As the bargaining power of workers is affected by the readiness for dismissals (depending on employment protection, fixed-term contracts, rehiring costs, etc.), wages may well be renegotiated (as in the bargaining rule (12) in the Online Appendix), and this effect is left unrestricted. Note that a slowdown of the separation rate that stems from hiring difficulties due to increasing labour scarcity (compare Klinger and Weber, 2020) would be found in the systematic reactions of the model to changes in vacancies and unemployment, but not in the shock.

Job creation intensity: Job creation intensity determines vacancy posting beyond the scope that standard fundamental factors of a job creation curve – such as productivity, wage costs, and matching rate – account for. For instance, Gehrke and Weber (2018) isolated such a measure of job creation intensity from systematic vacancy posting explained by these factors. Job creation intensity is a shifting parameter of the job creation condition, just as it is the case with matching efficiency in the matching function. Notably, labour market deregulation enters job creation intensity because it lowers the costs to obey legal restrictions in employment contracts. A job creation intensity shock increases vacancy postings beyond the influence of standard factors such as wages and productivity. The relevant shifting parameter in the job creation curve (equation (11) in the Online Appendix), called vacancy posting costs, comprises recruitment costs as well as costs connected to any legal regulations. Thus, such a shock could change the flexibility of employment contracts on the brink of the labour market by deregulation, for example. It affects the value of (such) jobs for firms, increasing vacancies and tightness and raising the job finding rate, but – according to the matching function (equation (7) in the Online Appendix) – only with delays. By the same token, the separation rate cannot react immediately: Vacancies have to be created and filled before the new match can be separated. With the job finding rate and separation rate being constant on impact, a law of motion (equation (6) in the Online Appendix) also implies a zero effect for unemployment.

VI. Results

Having identified the structural shocks, their labour market impacts can be demonstrated in an impulse response analysis and in historical decompositions. Impulse responses (see section E in the Online Appendix) show the reactions of the model variables over time *if* one specific shock occurs. By contrast, historical decompositions quantify ''how much a given structural shock explains the historically observed fluctuations'' of the variables of interest (Kilian and Lütkepohl, 2017, sect. 4.3).

In our set-up of $I(1)$ variables, we compute how the different structural shocks that effectively occurred over time have contributed to the cumulative changes in the variables over certain interesting subperiods. Thus, our decompositions show how much the single shocks contributed to the record increase in employment and reduction in unemployment. The historical decompositions can be obtained from the structural MA representation of Δy_t (for details, see section D in the Online Appendix), where the decompositions refer only to the variables' development that is driven by the shocks, not by deterministics. Figures 6 and 7 show the accumulated non-deterministic changes in the two stocks since the beginning of each of the considered subperiods as well as the contributions of the different structural shocks. For the sake of comparison, we also added a preupswing subperiod to shed light on what factors were a drag on the labour market before 2005.

The first subperiod covers the time span before the upswing, that is, between January 2001 and July 2005. It shows that almost all factors contributed to the sclerotic condition the labour market was in before the year 2005. During these more than four years alone, shock-driven employment fell by more than 2 million, while unemployment rose by approximately the same amount. Especially low matching efficiency and job creation intensity were a drag on both variables. The only relevant exception is the technology shock, which showed positive effects but only until 2002. This is in line with Hutter and Weber (2021) who document that the secular productivity flattening occurred around this time.

The second subperiod covers the time span between August 2005, when unemployment started to shrink, and December 2008 (just before the Great Recession affected the labour market). This phase was stamped by a strong economic upswing. However, neither the technology nor the cycle shock shows a substantial influence on labour market stocks. Instead, employment was mainly supported by negative separation propensity and wage determination shocks as well as positive matching efficiency and job creation intensity

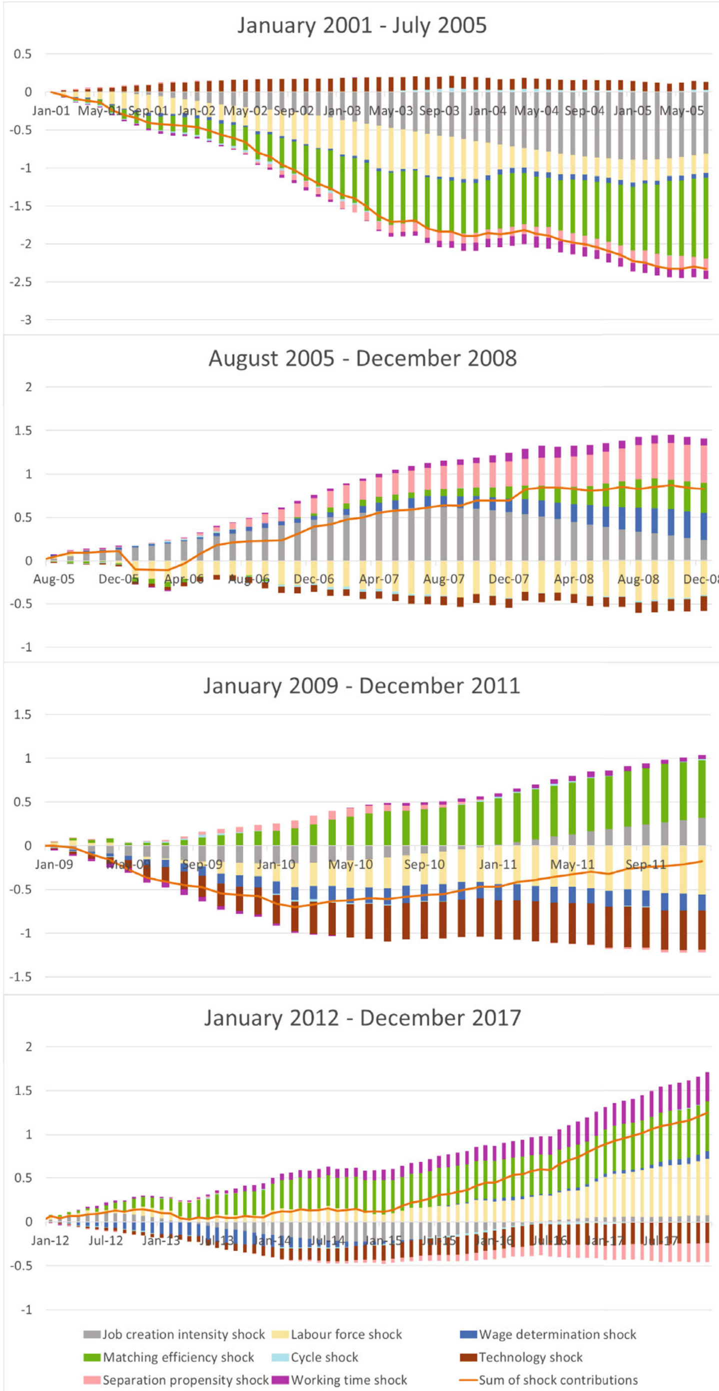

Figure 6. Historical decomposition of employment
Notes: The figure shows the accumulated shock-driven changes in employment as well as the contributions of the different structural shocks. Unit: 1 million.
Source: Own calculations.

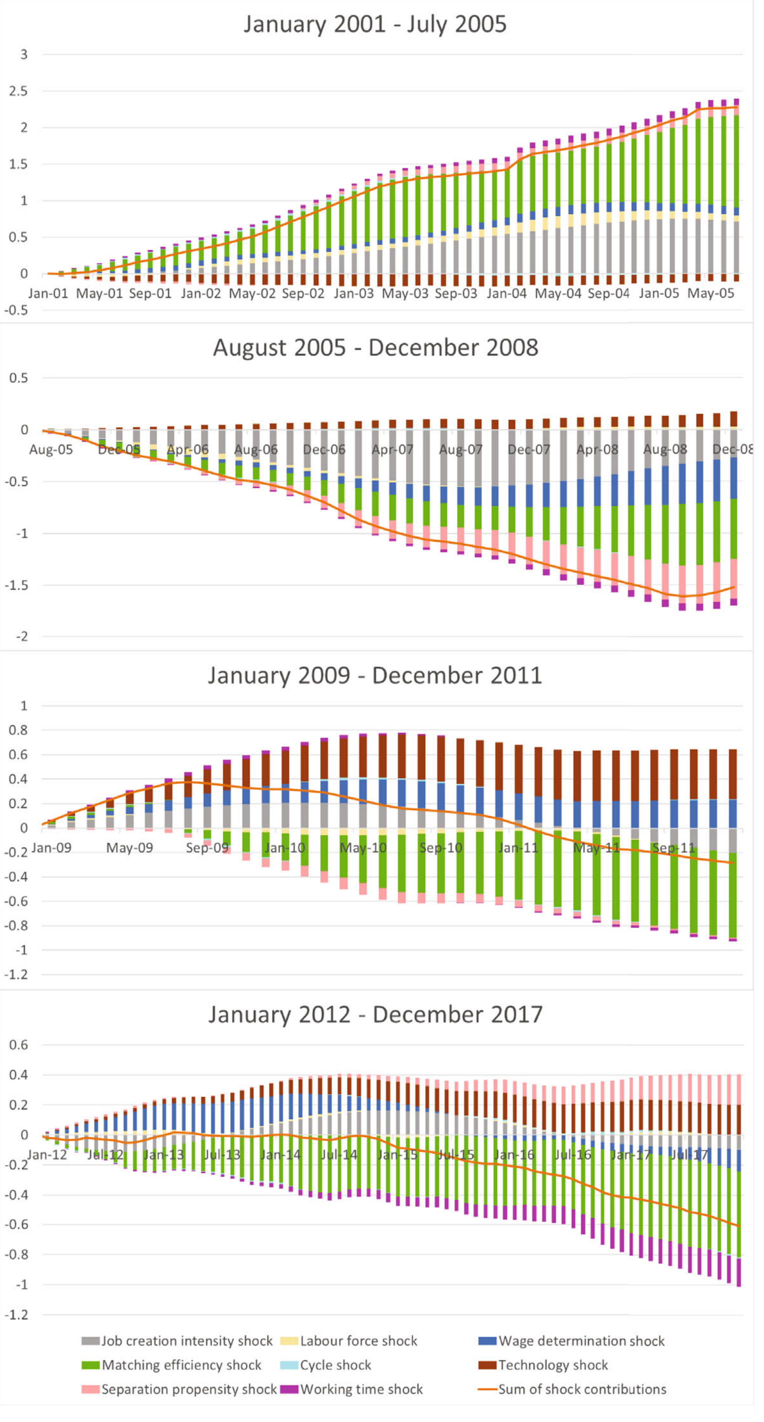

Figure 7. Historical decomposition of unemployment
Notes: The figure shows the accumulated shock-driven changes in unemployment as well as the contributions of the different structural shocks. Unit: 1 million.
Source: Own calculations.

shocks, with the last item only until mid-2007. The labour market reforms of 2003–06 were implemented to deregulate the labour market regarding flexible types of employment, for example. Their effects appear to be distributed over some time. However, in particular, temporary agency work as well as marginal employment had above-average growth in those years. The relevance of the matching efficiency shock and the wage determination shock increased mainly after mid-2007 and over 2008, increasingly substituting the impact of the job creation intensity shock. With respect to the Hartz reforms, even employed workers were found to be ready to make concessions regarding wages or working time to safeguard their jobs and not become unemployed (compare Krebs and Scheffel, 2013; Rebien and Kettner, 2011). By contrast, negative labour force shocks were an obstacle to an even stronger rise in employment. Indeed, the migration balance was comparatively low to negative at the time.

The same drivers that supported employment contributed to the substantial reduction of unemployment, the non-deterministic part of which amounted to 1.5 million during the second subperiod. The most important influence stemmed from the matching efficiency shock. Its increase after the Hartz reforms clearly contributed to the reduction in unemployment that was affected from the very beginning. Note that increased search intensity due to reductions in unemployment benefits or a shorter entitlement period is captured in the wage determination shock. The latter also played a substantial role in reducing unemployment during this period. Until mid-2007, the role of the job creation intensity shock was larger than at the end of the period. The increase in the flexible (and often low-paying) types of employment at the time increased job findings for an otherwise hard-to-place group of unemployed persons. Another helpful driving force was the separation propensity shock: Avoided layoffs – for example, as a consequence of greater readiness of employees to make concessions regarding the qualification profiles of their workplaces – did not result in unemployment.

The third subperiod covers the Great Recession and the recovery thereafter (January 2009–December 2011). Over 2009, shock-driven employment shrank by approximately 700,000 workers and recovered thereafter. As net migration was close to zero during the subperiod, negative labour force shocks hampered employment. More striking, however, is the large and increasing negative contribution of technology shocks. In other words, the Great Recession is classified by the data as a shock with long-run impacts, instead of just a cyclical downturn. This conclusion is reasonable given the general slowdown of productivity growth also after the recession and underscores the evidence from studies of its sustainable effects (e.g. Yagan, 2019; Klinger and Weber, 2020). In addition, since wages did not mirror the drastic productivity decline during the economic crisis, ceteris paribus, they were a drag on employment development (compare also Figure 2). Instead, the recovery just to the precrisis level resulted from a diverse mix of structural shocks: Better matching efficiency and increased incentives to create new jobs were the main drivers. Beyond those drivers, working time shocks only played a minor role. Notwithstanding, flexible working time arrangements helped to safeguard jobs, but working time during the crisis primarily fell not due to specific idiosyncratic shocks but due to a systematic endogenous reaction to the – very deep – recession. Thus, working time operates as a *channel* through which the effects of the recessionary shocks on the labour market are dampened, but not predominantly as a *source* of discretionary shocks.

The shock-driven part of unemployment rose for a shorter period and to a smaller extent (+380,000 people until mid-2009) during the economic downturn. By the end of 2011, unemployment had even decreased by 280,000 people. Nevertheless, the main drivers resemble the situation of employment: The adverse impacts of negative technology shocks and positive wage determination shocks were overcompensated for by positive matching efficiency and job creation intensity shocks after the crisis and – to a smaller extent – by negative separation propensity and working time shocks. While negative labour force shocks were again an obstacle to employment development, they had only limited relevance to unemployment.

The fourth subperiod comprises the last 5 years of our sample – a phase of mostly stable economic development and a strong labour market boom despite the Eurozone recession. During this period, the shock-driven part of employment considerably increased. In contrast to the earlier subperiods, the labour force shock is the most important driver during this time, reflecting the quick labour market integration of immigrants as well as the longer working lives of older people. However, while the labour force shock was found to be an important driver of employment, it had barely any relevance for unemployment. Until approximately 2014, the matching efficiency shock was again a major driving force of the employment upswing. In this way, a higher recruitment intensity of firms as well as greater readiness to accept a certain mismatch of worker profiles was likely to have played a role (e.g. Bossler *et al.*, 2018). Furthermore, the development of online job search technologies proceeded (Faberman and Kudlyak, 2016; Kuhn and Mansour, 2014), allowing for an increasing transparency and thus facilitating a quicker and more efficient matching. Due to decreasing working time, even in the face of strong labour market development, negative working time shocks gained some importance during this subperiod. For instance, new rules for paid parental leave favoured the acceptance of part-time employment (Zimmert and Zimmert, 2020). Job creation intensity weakened slightly in the beginning, for example, following moderately stricter regulation of temporary employment agency work in December 2011 and EPL in 2013.

Starting in mid-2013, wage determination again became a driver of the employment upswing, turning a negative contribution into a positive contribution by the end of 2017. The reason is that productivity growth caught up again with wage growth, which remained relatively moderate even in times of increasing labour market tightness. The wage determination shock shows no negative contributions at the time of the introduction of the minimum wage. While this is in general in line with micro evaluations (e.g. Bossler and Gerner, 2019) finding no substantial employment effects, we analyse wage shocks in more detail in section F in the Online Appendix. The job creation intensity also contributed to employment growth in this subperiod but only since the beginning of 2015. During that time, the number of vacancies themselves increased enormously. However, only a limited amount of this increase was due to inflows of vacancies. The main reason was the strong increase of vacancy duration. In this regard, the increase in vacancies cannot be interpreted as an increase in labour demand fuelling employment growth but as an increase in labour scarcity. By the same token, the historically low levels of the separation rate (see Figure 4), signalling labour market hoarding of firms due to increasing labour market tightness (see also Figure 3), are not reflected in the separation propensity shocks of our model and hence do not appear as a supportive driving force in our historical decomposition. The reason is that labour market tightness as such is a function of vacancies and unemployment and hence is captured in the systematic part of our model. Indeed, we find the long-run impact multipliers of S in equation (1) to be negative with respect to V and positive with respect to U, supporting our reasoning that increasing tightness indeed substantially lowered the separation rate and thus contributed to the employment upswing (compare Klinger and Weber, 2020).

The development of unemployment only slowed temporarily in the last subperiod. After 2015, the decrease continued and amounted to 600,000 by the end of 2017. Although this is a remarkable figure, it still clearly falls short of the employment plus during the same subsample. This result again clarifies that different sources than unemployment must have boosted employment, namely, entrants from outside the labour force as well as workers staying longer in their jobs. Beyond these factors, the drivers are laterally reversed, with the matching efficiency, working time, wage determination, and job creation intensity being contributors to unemployment reduction.

As an overall message, matching efficiency, job creation intensity, and labour force shocks yield the largest contributions in explaining the German labour market upswing. While the positive impact of labour force shocks on employment is concentrated in recent years, the matching efficiency and job creation intensity had already increased after the labour market reforms. Indeed, during that time, both an inward shift and an upward movement along the Beveridge curve (Figure 3) can be observed. Regarding the important role of matching efficiency shocks, an established literature (including Launov and Wälde, 2016; Klinger and Weber, 2016; Stops, 2016; Hertweck and Sigrist, 2015; Klinger and Rothe, 2012; Fahr and Sunde, 2009; Gehrke and Weber, 2018) finds a strongly increased matching efficiency in the German labour market upswing. These studies usually build on a matching function, that is, with job findings on the left-hand side and unemployed and vacancies on the right-hand side. Our approach includes the same and even generalizes the matching function: The fourth VECM equation models the job finding rate, with lags of unemployment, vacancies, and the further system variables on the right-hand side. Furthermore, recall that this equation was controlled for the structure of the pool of unemployed. While this stipulation allows for an appropriate assessment of efficiency changes, the observed job finding rate (Figure 4) does not mirror the full improvement in the recent decade: The structure considerably worsened again (which might be expected for a strong labour market upswing) after it had improved during the Great Recession, when people with rather good risks had entered the pool due to the weak economy (Hutter and Weber, 2017). Indeed, following our estimates, the job finding rate would have increased by one percentage point more had the structure remained stable since 2005. Gehrke and Weber (2018) elaborate on the unemployment composition, too. The cycle or technology shocks play no decisive role in the overall development (section G in the Online Appendix presents an alternative specification as a robustness check). Instead, the labour market is driven by genuine labour market shocks themselves, leading to a certain decoupling of GDP and employment, as discussed above.

VII. Conclusion

Germany has experienced an outstanding labour market upswing since the mid-2000s. Intense discussions about its sources continue until today, especially in view of the controversial Hartz reforms and the fact that many other European countries experienced a labour market slack during the same period. Various studies have analysed specific factors regarding their role in German labour market development.

The foregoing paper contributes to this literature by investigating a broad set of candidate driving forces simultaneously based on an empirical macroeconomic approach. For this purpose, we construct a structural macroeconometric model that enables unravelling a set of key economic and labour market shocks while limiting restrictive a priori assumptions to a minimum. This approach provides a framework for letting the data speak on the sources of the remarkable labour market upswing. For candidates, we consider the following shocks: job creation intensity, labour force, wage determination, matching efficiency, technology, the business cycle, separation propensity, and working time.

To pin down the contributions of the different shocks to the labour market development in specific periods, especially since the beginning of the upswing in 2005, we use historical decompositions. We find that the matching efficiency shock and the job creation intensity shock, plus the labour force shock in recent years, yield the largest contributions in explaining the German labour market upswing. Wage determination (consisting of the two components of wage setting and willingness to make concessions/search efforts), working time, and separation propensity shocks had further influence. The business cycle and technology shocks do not play decisive roles. This result is in line with the finding in Klinger and Weber (2020) that labour market and GDP decoupled to some extent. Instead, the labour market is driven by genuine labour market shocks themselves.

We find that increased matching efficiency, stronger job creation, and higher search intensity were influential for the upswing. This suggests that the Hartz reforms played a relevant role because these factors can be connected to important elements of the reforms. However, further developments such as the expanding labour force also played a role. Wage moderation had more limited impacts, which also were in part initiated by the reforms by increasing the willingness to accept jobs. Moreover, while the reforms spurred the labour market upswing, our results and further evidence imply that they also came along with critical effects such as intensifying downward wage pressure (compare Gartner, Rothe and Weber, 2019).

With respect to discussions about how far replicating the German labour market reforms in other countries would be desirable, our results suggest that a closer look at the specific parts of the reforms is warranted. On the one hand, there are driving forces, such as increasing matching efficiency, that yield sizeable and long-lasting positive outcomes. On the other hand, as mentioned above, some driving forces are accompanied by negative side effects, such as intensified wage pressure. While these effects have to be weighed against the advantages, diminishing wage costs have not been found to be among the most decisive factors for the labour market upswing.

On the methodological side, the general construction of the econometric framework enables empirical measurement in a theoretical macro-labour setting. This paves the way for further labour market analyses identifying structural shocks in a data-driven model environment.

Final Manuscript Received: September 2020

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1 Supporting Information