INSTITUTE FOR EMPLOYMENT RESEARCH

The Research Institute of the Federal Employment Agency

IAB-DISCUSSION PAPER

Articles on labour market issues

20|2019 Which Factors are behind Germany's Labour Market Upswing?

Christian Hutter, Sabine Klinger, Carsten Trenkler, Enzo Weber

ISSN 2195-2663

Which Factors are behind Germany's Labour Market Upswing?

Christian Hutter (IAB)

Sabine Klinger (IAB)

Enzo Weber (IAB, University of Regensburg)

Carsten Trenkler (University of Mannheim)

Contents

List of Figures

List of Tables

Abstract

The strong and sustained labour market upswing in Germany is widely recognized. In a developing literature, various relevant studies highlight different specific reasons. The underlying study, instead, simultaneously considers a broad set of factors in a unified methodological framework and systematically weighs the candidate reasons for the labour market upswing against each other on an empirical basis. The candidates are: shocks on (de)regulation of employment or job creation intensity, the efficiency of the matching process, wage determination, the separation propensity, the size of the labour force, technology, business cycle and working time. 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 search-and-matching theory and established assumptions on labour force development and technological change. Matching efficiency, job creation intensity, labour force, and separation propensity yield the largest contributions in explaining the German labour market upswing.

Zusammenfassung

Der starke und anhaltende Arbeitsmarktaufschwung in Deutschland ist allgemein anerkannt. In einer sich entwickelnden Literatur heben verschiedene relevante Studien unterschiedliche spezifische Gründe hervor. Die vorliegende Studie berücksichtigt stattdessen eine Vielzahl von Faktoren in einem einheitlichen methodischen Rahmen und wägt die potenziellen Gründe für den Arbeitsmarktaufschwung systematisch gegeneinander ab. Die Kandidaten sind: Schocks in Bezug auf die (De-) Regulierung der Beschäftigung oder die Intensität der Schaffung von Arbeitsplätzen, die Effizienz des Matching-Prozesses, die Lohnfindung, die Entlassungsneigung, das Arbeitsangebot, die Technologie, den Konjunkturzyklus und die Arbeitszeit. Wir entwickeln einen strukturellen makroökonometrischen Rahmen, der die Daten so frei wie möglich sprechen lässt und dabei mit einer minimalen Anzahl an Restriktionen arbeitet, um die wirtschaftlich bedeutsamen Schocks zu identifizieren. Zu diesem Zweck kombinieren wir kurz- und langfristige Restriktionen auf der Grundlage von Such- und Matchingtheorie und etablierten Annahmen zur Entwicklung des Arbeitsangebots und zum technologischen Wandel. Matching-Effizienz, Intensität der Schaffung von Arbeitsplätzen, Arbeitsangebot und Entlassungsneigung liefern die größten Beiträge zur Erklärung des deutschen Arbeitsmarktaufschwungs.

JEL

C32, E24, J21

Keywords

German labour market upswing, labour force, job creation, deregulation, efficiency, separation propensity

Acknowledgements

We are grateful to Thomas Rothe and to the participants of the IAB-FAU Macro-Labor Seminar 2018, 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.

1. Introduction

While labour markets in Europe and around the world have struggled from the repercussions of the great recession and the European debt crisis for nearly a decade, Germany embarked on a strong and sustained labour market upswing. By 2018, unemployment more than halved as compared to the peak in 2005, and employment follows a steep and stable upward trend even in times of weak economy. Consequently, debates in academics and politics revolve around the question of the decisive reasons for this extraordinary development. These discussions are of high relevance far beyond the national context, since, e.g., in Europe in particular it is considered in how far the German labour market reforms from the last decade should be replicated or whether the German success was based on wage dumping policies fuelling disequilibria in the EU.

In this study, we explore the empirical relevance of a 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 eight shocks, namely, shocks on the labour force, matching efficiency, separation propensity, job creation intensity / deregulation, wage determination, and working time as well as a technology shock and a business cycle shock. 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 et al., 2018; Klinger and Weber, 2016). Some argue that worsened outside options increased the willingness of the unemployed to make concessions (Krebs and Scheffel, 2013) and connect the social benefit reform to increased selection rates and vacancy posting (Hochmuth et al. (2019)). Others point 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, 2016) as well as generally lower and/or more flexible working hours (Burda and Hunt (2011), Balleer et al. (2016), Weber (2015), Carillo-Tudela et al. (2018)).

This brief review demonstrates that the literature as a whole provides an extensive debate on the subject. Notwithstanding, the single papers usually focus on specific points. While in the course of that many crucial points are illuminated, an investigation comprising a broad set of factors in a unified methodological framework makes a crucial contribution: By systematically weighing the candidate reasons for the labour market upswing against each other on an empirical basis, we learn about the relevance and timing of the different effects. This is the purpose of the underlying study.

This research concept makes the use of a flexible model approach a key issue. Particularly, it is crucial to choose an open approach that minimises the need of setting assumptions a priori. I.e., the less restrictive the econometric procedure is designed the more will the data speak in the results. Thereby, it is decisive that developments observed in the data are ascribed to the shocks *where they originate*. This means that the relevant shocks must be accurately filtered from the dataset, given a multitude of potential interlinkages between the variables and their complex and dynamic structure. This structure needs to be flexibly captured based on empirical measurement. In this regard, a structural vector error correction (SVEC) framework has particular merits. By use of 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. Moreover, it allows for incorporating equilibrium effects.

We construct such a model for the German labour market development between 1992 and 2017 comprising the stock variables unemployment, vacancies and employment, the flow variables 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 are based on cointegration properties, on well-established assumptions about technological change and cyclical fluctuations as well as on the search and matching theory of the labour market. In doing so, we demonstrate how to reconcile the theoretical search and matching framework with an empirical structural time series model with parsimonious restrictions. This adds to the growing literature that implements labour market dynamics into macro-econometric applications (compare Hairaulta and Zhutova, 2018; Rahn and Weber, 2017; Nordmeier et al., 2016; Fujita, 2011; Ravn and Simonelli, 2007). Having identified the shocks, we demonstrate their labour market impacts in an impulse response analysis. Then, in order to assess the relevance of the shocks for the German labour market upswing, we conduct a historical decomposition of employment and unemployment. This instrument allows tracing the labour market impact of the major driving forces through time. In this, we consider three subperiods which are particularly relevant for an understanding of the German labour market upswing. These are, first, the period between the labour market reforms and the onset of the great recession (2005-2008), second, the great recession itself and the recovery thereafter (2009-2011), third, the ongoing upswing (2012-2017).

The main message is: the labour market is driven by labour market shocks themselves. Shocks that increased job creation intensity, e.g. from deregulating the labour market, shocks that increased the labour force, shocks that raised the efficiency of the matching process, and shocks that reduced the propensity of firms to separate from workers yield the largest contributions in explaining the German labour market upswing. While the first three shocks revealed large impulse response coefficients, lower separations act via two channels: stochastically via large shocks and systematically as the separation rate declines if the labour market becomes tighter. All in all, the results clearly confirm a partial decoupling of the labour market from GDP or productivity development (Klinger and Weber, 2019). The cycle or technology shocks do not play a decisive role in the overall development of employment and unemployment.

The paper proceeds as follows. Section 2 documents facts on the labour market upswing, discusses the variable selection and introduces the data used in this paper. Section 3 discusses the potential driving forces of the upswing. Section 4 presents our macroeconomic model, the identification strategy and the estimation procedure. Section 5 presents the results and the final section concludes.

2. Data, facts, and figures

2.1. Data

We document the development of the German economy and labour market using eight variables: vacancies and unemployment, employment, working hours per employee and hourly wages, job finding rate and separation rate, as well as productivity per hour. Detailed information on the data and summary statistics are given in appendix A.1.

We follow the labour force concept to select the labour market stocks. Therein, employment is total employment and contains employees covered by social security, civil servants, marginally employed, and self-employed. Unemployment is defined following the ILO standard and is taken from the (European) labour force survey.

Vacancies are registered at the Federal Employment Agency (FEA). Though this number comprises about half of the total number of vacancies, the register data outperfom the German Job Vacancy Survey regarding length and frequency of the available time series data.

The worker flow rates are calculated from a 2 percent representative sample of the IAB Employment Biographies taken from the German social security and unemployment records. The data contains all individuals who are either (1) employed subject to social security, (2) marginally employed, (3) unemployment benefit recipients, (4) officially registered job-seekers, or (5) participants in labour market policy programmes. It covers more than 80 percent of the German labour force. To calculate the worker flows, we choose a cutoff-date each month and check for two subsequent months whether the employment status has changed. Employment-to-unemployment flows are divided by the number of employees in the previous month to get the separation rate. Unemployment-to-employment flows are divided by the number of unemployed workers in the previous month to get the job finding rate. This is consistent with the counting mechanism of the FEA: unemployment is counted in the mid of a month while flows from unemployment are counted between that date and the mid of the following month. Previous versions of that data have been used by Klinger and Weber (2016); Jung and Kuhn (2014); Nordmeier (2014).

Both wages and productivity are provided on an hourly basis by the system of national accounts of the German Federal Statistical Office. Wages contain gross wages including employers' social security contributions. They 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 survey as well as register-based source statistics to calculate 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 appendix A.1). All data are adjusted for seasonality. The sample ranges from January 1992 to December 2017. So the total number of observations amounts to 312.

The empirical methodology would be able to cope with stationary as well as non-stationary data. According to ADF tests, however, the null-hypothesis of non-stationarity cannot be rejected for any of the series while it can be rejected for the differenced series. Hence, all variables are integrated of order I(1).

2.2. The German labour market upswing

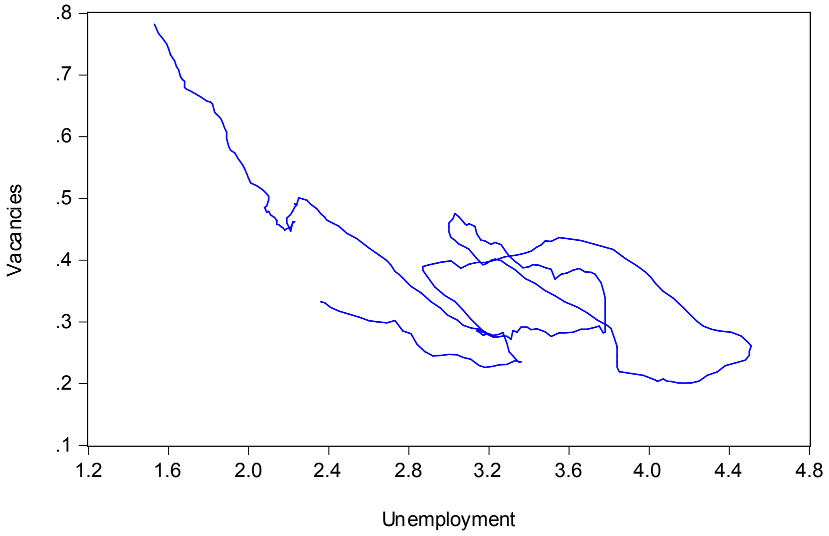
Figures 1 to 3 document the enormous and long-lasting labour market upswing in Germany.

Figure 1.: Employment, wages and productivity, 1992-2017

Notes: Normalized monthly data. Source: Destatis. Own interpolation of wages and productivity.

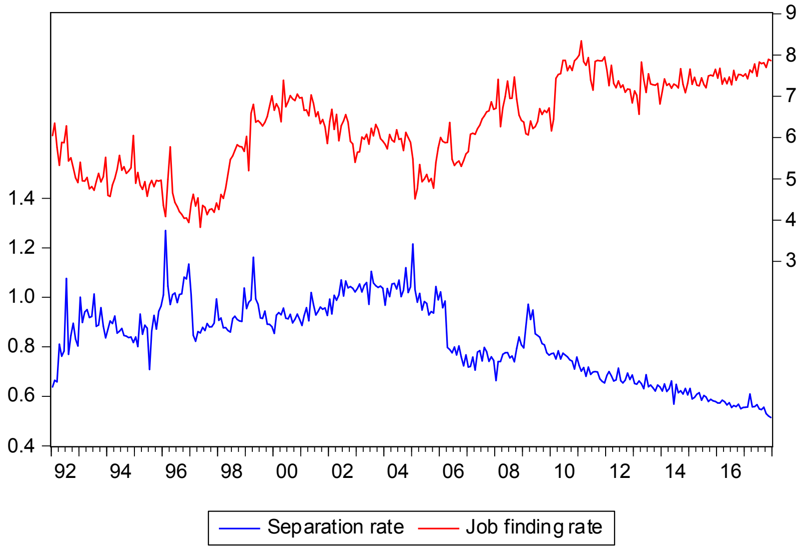
Figure 1 shows employment, wages and productivity. Obviously, the steep and sustained increase in employment starting in 2006 has been accompanied by a rather moderate increase in wages. In fact, the development of wages relative to productivity implies a decrease in the labour share making labour more profitable for firms than before. The behaviour of employment during the great recession in 2008 and 2009 has given food for debate in many developed economies. Despite the strongest decline 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 had

Figure 2.: The Beveridge curve: unemployment and vacancies, 1992-2017



Notes: The graph shows the Beveridge curve starting in January 1992 (lower left) and ending in December 2017 (upper left). Unit: 1 million. Source: Federal Employment Agency (vacancies), Eurostat (unemployment).

Figure 3.: Separation rate and job finding rate, 1992-2017



Notes: Unit: percent. Source: IAB Employment Biographies. Own calculations.

left its footprint on the development of productivity which has been sluggish since then. I.e., the German labour market upswing is not accompanied by a productivity upswing. Nonetheless, except for the phase of the Eurozone recession 2011-2013, GDP has been on a stable growth path until the end of our sample.

Figure 2 presents the Beveridge curve, the generally downward-sloping relation between vacancies and unemployment. The ratio of the two is interpreted as labour market tightness. The figure gives important insight into the nature of the upswing: following the Hartz reforms of the years 2003-2005, the curve shifted inwards – which has been exceptional also by international comparison (Bova et al., 2018). The inward shift indicates a better functioning of the labour market (compare Blanchard and Diamond, 1989) and has been connected to improved matching efficiency (Klinger and Weber, 2016; Launov and Wälde, 2016). Second, starting in 2010, the curve did not shift inwards remarkably anymore but 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. Unemployment is no longer reduced in the same way as the stock of vacancies increases.

The worker flow rates (Figure 3) give some intuition of why the labour market stocks improved so much. Remarkably, the job finding rate has increased stepwise after the Hartz reforms. This increase was shown to be of permanent, i.e., not cyclical, nature (Klinger and Weber, 2016). Even more strikingly, the separation rate has declined 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 alone, Germany ranked 6 among 35 OECD countries in 2017 – while it ranked 33 in 2005. It was not for nothing that Germany had used to be called ”sick man of Europe” (Siegele, 2004). 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 seems to be rational when explaining the reverse direction, too. Previous studies that investigated why the upswing occurred and, by the same token, whether it is replicable, typically focus on single or a very small set of shocks or institutions. Our approach is to comprise a reasonable number of driving forces in a unified empirical framework and let the data speak which had when an influential effect. Not only does this approach choose from a broader set of potential explanations, it also allows them to interact.

3. Driving forces

We explore a broad set of potential upswing drivers. The literature so far often focusses on the dynamic (labour market) outcomes following a (neutral or investment-specific) technology shock or a (fiscal or monetary) policy shock (e.g. Gali, 1999; Blanchard and Perotti, 2002; Christiano et al., 2005; Ravn and Simonelli, 2007; Rahn and Weber, 2017). Beyond their scope, however, labour market institutions themselves are highly informative for an explanation of the labour market upswing. This is even more true as the German labour market underwent many and deep institutional reforms. Thus, applying our econometric methodology on these kinds of labour market shocks has the main advantage that we extend the usual selection and comprise the essential issues discussed so far on our topic. In the following, we discuss the potential driving forces that are building blocks of our approach.

Labour force. A comparison of the changes in employment and unemployment during the past decade uncovers that the observed increase in employment cannot stem from the existing labour force only. Burda and Seele (2016) and Klinger and Weber (2019) argue in favour of a supply side effect. Indeed, while the demographic component of the German labour force is clearly negative, the labour force itself increased strongly due to record levels of net migration as well as higher participation. Thereby, legislative changes might have played a role. Regarding immigration, this involves the enlargement of the European Union (including free movement of workers) towards the east. Regarding participation, reforms of the pension system raised the legal retirement age and abolished early retirement subsidies. Thus, older workers' incentives to stay with their firm increased. Beyond legal changes, the labour force rose because of refugee immigration and because more and more mostly female workers decided to participate, albeit often in part-time jobs. All in all, net migration between 2006 and 2017 amounted to 3.8 million while the participation rate of those aged 15 to under 65 increased from 73.7 percent in 2005 to 78.2 percent in 2017.

Working time. Given the debate on whether hours worked and employment are substitutes or complements, the question whether working time changes contributed to the labour market upswing is an empirical one. In the data, two observations are specifically well documented: First, the part-time ratio – the share of part-timers in total dependent employment – rose from 34.0 percent in 2006 to 38.5 percent in 2017. Provided that this rise generated job-sharing in a significant manner, the reduction in working time can be interpreted as an influential factor for employment growth. Second, during the great recession in 2008/09, companies adjusted labour input along the intensive margin: in 2009, GDP shrank by 5.6 percent, per capita working hours by 3.2 percent, and productivity per hour by 2.6 percent. The extensive margin was kept untouched on aggregate. The labour hoarding effect of slimming working-time accounts or subsidized short-time work schemes were demonstrated by a large body of literature (Balleer et al., 2017, 2016; Weber, 2015; Herzog-Stein and Zapf, 2014; Burda and Hunt, 2011; Möller, 2010). This is likely to have strengthened employment.

Technology. Technological change is commonly connected to supply-side shocks that improve total factor productivity (compare, e.g. Gali, 1999; Uhlig, 2004; Ravn and Simonelli, 2007; Rahn and Weber, 2017). Through the lens of real business cycle theory (Kydland and Prescott (1982), Plosser (1989)), technology shocks can create economic fluctuations at business cycle frequencies. The exact pattern of effects of technology shocks on the labour market is subject to debate, however (Gali, 1999; Christiano et al., 2004).

Business cycle. In view of the criticism on 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. As such, we refer to rather demand-sided drivers of economic activity, for example government expenditure during the downturns. With regard to the German labour market upswing, arguments have been put forward that stress the enormous economic performance of China in the mid-2000s combined with the strong export-orientation of the German economy. However, during the period under consideration, the German economy experienced both stable and vivid performance as well as the great recession and the Eurozone recession. On average, GDP rose by an annual rate of 1.5 percent between 2005 and 2017. The recent economic upswing witnesses an unforeseen weakness in business investment. The investment-to-GDP ratio has come down to an average of 6.7 percent since 2009 while it was 7.7 percent before. This also points to a transitory impact rather than long-term changes in productivity or potential growth.

Wage determination. The potential influence of wage determination on labour market outcomes is straightforward. The sources and the mechanisms, however, may be manifold: First, consider the wage moderation after reunification when large parts of the Eastern German economy turned out to be unproductive and had to face new competitors form the Eastern European transition economies (Dustmann et al., 2014). Second, wage setting institutions have become more flexible. Collective bargaining coverage in Western Germany has decreased from 57 percent in 2006 to 49 percent in 2017 (IAB Establishment Panel). Opening clauses in collective bargaining contracts ease the adjustment process over the business cycle (also Dustmann et al., 2014). Wage concessions by workers were observed during the great recession (Heckmann et al., 2009). Third, with rising labour market tightness, wage concessions by firms have become more important as compared to the period before the upswing (German Job Vacancy Survey). Fourth, the introduction of a general minimum wage in 2015 increased reservation wages and made wage setting less flexible again. It affected about 10 percent of all employees (Bossler, 2017), but a diff-in-diff analysis revealed only limited short-run effects on employment (Caliendo et al., 2018). Fifth, workers' outside options worsened remarkably. The Hartz reform reduced the entitlement period to unemployment benefit. It introduced sanctions when unemployed did not meet the targeted search effort. It established a means-tested social assistance system that led to an immediate reduction of the net replacement rate by 11 percentage points between 2004 and 2005; between 2003 and 2011, the replacement rate even dropped by 20 percentage points. Worse outside options reduce reservation wages and bargaining power of workers. Hence, workers' willingness to make (wage) concessions had increased after the Hartz reforms (Krebs and Scheffel, 2013; Rebien and Kettner, 2011). In general, our term "wage determination" comprises both the wage setting process and the willingness to make concessions or increase search intensity according to the outside options. In subsection 5.3, we will separate these two ingredients.

Matching efficiency. Regarding the efficiency of the matching process we disentangle efficiency connected to search intensity and efficiency connected to the matching technology itself, i.e. the technological toolkit and institutional framework for unemployed, firms and the public employment service to form matches. Search intensity is already captured by wage determination (see outside options above). Regarding the matching technology itself, online job platforms, also introduced by the FEA, contributed to increased market transparency and improved matching. Furthermore, the FEA and its local branches underwent a severe restructuring of its organisation and tasks in the course of the Hartz reforms. Since 2004, the FEA has been providing measures of active labour market policy according to the principles of effectiveness and efficiency. Social benefit recipients were included in the labour market policy efforts. Furthermore, it introduced case managers and a customer segmentation to tailor treatment properly and established specific service departments for firms. All this targeted at reducing mismatch and imperfect information. Indeed, an increase of matching efficiency after the reforms has been documented by, e.g., Launov and Wälde (2016); Klinger and Weber (2016); Stops (2016); Hertweck and Sigrist (2015); Klinger and Rothe (2012); Fahr and Sunde (2009). Nonetheless, the worse the searcher profiles become in the course of a strong reduction in unemployment, the harder it is to maintain or even further increase matching efficiency.

Separation propensity. The role of separations in explaining the labour market upswing in Germany has been addressed by Klinger and Weber (2019, 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. The most relevant source of changes in firing costs are changes in the employment protection legislation (EPL). Indeed, the OECD indicator on the strictness of employment protection in temporary contracts shrank from 3.25 at the beginning of the 1990s to 1.13 since 2013. In the course of the Hartz reforms, negotiation of fixed-term contracts was made easier and the minimum firm size for which the standard EPL applies was raised. Relaxing EPL (or allowing fixed-term contracts) typically increases job creation and labour market flows but has hardly any effect on employment and unemployment (Kahn, 2010; Cahuc and Postel-Vinay, 2002). As regards the second aspect, 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 are firm's firing strategies.

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) isolate such a measure of job creation intensity from systematic vacancy posting explained by the factors mentioned above. This is equivalent to the efficiency parameter in a matching or production function. Notably, labour market deregulation enters job creation intensity because it lowers the costs to obey legal restrictions in employment contracts. In Germany, temporary agency work as well as marginal employment accounted for a substantial part of the labour market dynamics after they had been deregulated by the Hartz reforms. Regarding temporary agency work, the government abolished limits of assignment duration, made it easier to rehire, and allowed for own collective bargaining instead of equal pay (in 2018, some of these elements were removed). The share of temporary agency workers in total employment covered by social security has more than doubled from 1.2 percent in 2004 to 2.7 percent in 2017. The share in total incoming vacancies increased from 21.3 percent in 2005 to 34.4 percent in 2017 (earlier comparable data is not available). Regarding marginal employment, the tax and social contribution burden was lowered and the working time limit was abolished. (Nonetheless, marginal employment contains not even 30 percent of a full-time contract on average). Within the first four years after the reform, the number of marginally employed rose by more than 10 percent. Since then, it has been declining.

In the next section, we present the econometric model to explore when and how much the diverse driving forces affected the German labour market.

4. Methodology

4.1. Model

As a precondition of reliable impulse responses and a 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. Second, it captures very general dynamics and interaction of the variables without imposing strong structural assumptions a priori. In fact, the task of the model structure is to provide a suitable econometric frame to let the data speak. Thus, we start with a vector autoregressive process of order q, VAR(q):

$$y_t = \sum_{i=1}^{q} A_i y_{t-i} + \mu D_t + u_t, \quad t = 1, 2, \dots, T, \tag{4.1}$$

where $y_t = (y_{1t}, \dots, y_{Kt})'$ is a K-dimensional random vector, A_i are 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 asymptotic validity of our inference procedures we assume that u_t is a K-dimension iid process with E$(u_t) = 0$, E$(u_t u_t') = \Sigma_u$, Σ_u being nonsingular, and, for some finite constant c, E$|u_{it}u_{jt}u_{kt}u_{mt}| < c$ for $i, j, k, m = 1, \dots, K$, and all t. Finally, the initial values $y_0, \dots, y_{-q+1}$ are assumed to be fixed.

In our case, y_t contains 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 of variables reflects the unified economic framework of labour market stock and flow variables necessary to investigate our research questions.

Augmented Dickey-Fuller (ADF) tests confirm that our variables should be treated as non-stationary, i.e., the VAR process is assumed to be integrated of order 1. This 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 may represent equilibrium effects in the model economy. Therefore, we re-write the VAR (4.1) into a vector error correction model (VECM) that explicitly incorporates the cointegration relationships as preferred by the data. The considered VECM reads as

$$\Delta y_t = \nu + \alpha\beta'(y_{t-1} - \rho_1(t-1)) + \sum_{i=1}^{q-1} \Gamma_i \Delta y_{t-i} + u_t, \tag{4.2}$$

where $\Gamma_i = -\sum_{j=i+1}^{q} A_j$, $i = 1, \dots, q-1$, and $\Pi = -(I_K - A_1 - \dots - A_q)$ with $0 \leq$ 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 (4.2) 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

$$u_t = B\epsilon_t, \tag{4.3}$$

where B is a nonsingular $(K \times K)$ 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 above.

By inserting (4.3) into (4.2) we obtain the structural VECM (SVECM). From this SVECM, we obtain under appropriate assumptions, compare Johansen (1995: Theorem 4.2), the following structural moving average (MA) representation for y_t

$$y_t = C\sum_{i=1}^{t}(B\epsilon_i + \mu D_t) + C(L)(B\epsilon_t + \mu D_t) + A, \tag{4.4}$$

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, $i = 0, 1, 2, ...$, 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 so-called 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 $r > 0$.

4.2. Identification

4.2.1. Technical identification

As is well known, the initial impact matrix B, i.e., the SVECM, is 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 labeled 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, i.e., 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 shock on wages, efficiency shock on the job finding rate, cycle shock and technology shock on productivity[1], separation propensity shock on the separation rate, working time shock on hours.

In order to identify these economically meaningful shocks, we eventually apply an identification scheme that distinguishes the shocks by when, how, and how long they hit the model economy. Our econometric framework has the advantage of leaving the dynamics completely unrestricted and introducing constraints on the immediate and/or the long-run impact only to the extent that is necessary and economically justifiable. Thereby, the short- and long-run restrictions are based on well-established assumptions on technological change or the business cycle as well as on the search and matching theory of the labour market. In the following, the latter is laid out in a baseline model version on which we can draw when detailing the identification.

4.2.2. Search and matching theory

The search and matching approach (Diamond, 1982; Mortensen and Pissarides, 1994) contains the following main features: We explicitly consider two labour market states, employed E_t and unemployed U_t. The respective shares in the labour force L_t would add to 1.

$$\frac{U_t}{L_t} = 1 - \frac{E_t}{L_t} \tag{4.5}$$

In addition, a third state, out of the (domestic) labour force, is taken into account as the labour force (employment plus unemployment) is allowed to be time-varying.

Either state evolves through the law of motion. The change in employment, for example, originates

[1] The cycle shock loads positively also on other variables such as employment or hours, so that the choice of normalisation has no effect here.

from separations S_t and matches M_t:

$$\Delta E_t = M_t - S_t \tag{4.6}$$

Search for a job or a worker, respectively, is costly and time-consuming. Search frictions arise from asymmetric information, mismatch, and the lack of a central market place. Matches are formed out of vacancies V_t and unemployed U_t according to a matching function, i.e. the production function of matches (in this case, with constant returns to scale).

$$M_t = \mu_t V_{t-1}^{1-\alpha} U_{t-1}^{\alpha} \tag{4.7}$$

Matching efficiency μ_t represents the productivity measure of that function. It depends on determinants such as the institutional quality of employment services, search intensity, willingness to take up work, or mismatch (compare Launov and Wälde, 2016; Klinger and Weber, 2016; Davis et al., 2013).

The structure of job seekers could be further controlled for by inserting exogenous variables into a vector X_t that account for the shares of, among others, the long-term unemployed or the low-qualified in total unemployment (e.g. Gehrke and Weber (2018)).

$$\mu_t = \mu_t^* + X_t \beta \tag{4.8}$$

The stock variables enter the matching function with one lag, which accounts for the expenditure of time that the whole search and recruiting process takes and is consistent with the counting mechanism of the FEA (see section 2.1). Regarding monthly data, the time aggregation bias is negligibly small (Nordmeier, 2014). As a consequence of this timing, the job finding rate will react on impact only to shocks that directly affect matching efficiency but not to shocks that change only unemployment and vacancies in the first round.

The job finding rate jfr_t and the worker finding rate wfr_t relate matches to the lagged stocks of unemployment and vacancies, respectively. With labour market tightness defined as $\theta_t = V_t/U_t$, they read as:

$$jfr_t = \frac{M_t}{U_{t-1}} = \mu_t \theta_{t-1}^{1-\alpha} \tag{4.9}$$

$$wfr_t = \frac{M_t}{V_{t-1}} = \mu_t \theta_{t-1}^{-\alpha} \tag{4.10}$$

Free entry of firms is ensured. This yields a job creation curve of the form:

$$\frac{\kappa^V}{wfr_t} = p_t - w_t + \delta(1 - s_t)\frac{\kappa^V}{wfr_{t+1}}, \tag{4.11}$$

where κ^V is named vacancy posting costs and comprises all sorts of costs that affect the value of a (vacant or filled) job, such as recruitment costs or legal obligations connected to the job. p_t and w_t are productivity gained from and wages paid for the match. s_t equals the total separation rate and comprises exogenous as well as endogenous separations.

A match of a vacancy and an unemployed person creates a surplus. For workers, the resulting wage exceeds the value of outside options like unemployment benefit or home production b while for firms, the profit from the productive match exceeds the value of a vacant job. The surplus is shared in wage negotiations according to a Nash bargaining rule where bargaining power γ of either party and reservation wages become relevant.

$$w_t = \gamma(p_t + \theta_{t-1}\kappa^V) + (1 - \gamma)b \tag{4.12}$$

Separations consist of a group of exogenous dismissals or quits and a group of endogenously dismissed workers (compare Fujita and Ramey, 2012). Exogenous separations occur with separation rate s_t^{ex} (which is time-varying because it may be subject to shocks). Endogenous separations occur because i) a worker's productivity is hit by an idiosyncratic shock with arrival rate λ that leads to a new productivity below reservation productivity with probability $G(R)$ or ii) reservation productivity changes such that a fraction of workers $E_{t-1}(R_t)/E_{t-1}$ is affected even if they do not face a productivity shock (expressed by the complementary probability $(1 - \lambda)E_{t-1}$).

$$S_t = s_t^{ex}E_{t-1} + (1 - s_t^{ex})(\lambda G(R_t)E_{t-1} + (1 - \lambda)E_{t-1}(R_t)) \tag{4.13}$$

Reservation productivity is derived from the endogenous job destruction condition (Pissarides (2000)). A job is destroyed if its value is zero, i.e. if its return (productivity minus wages) is too low:

$$0 = pR - w(R) + \frac{\lambda}{\delta + \lambda}\int_R^1 [p(n - R) - (w(n) - w(R))]\, dG(n) \tag{4.14}$$

Conclusively, the theory postulates relations between variables none of which is restricted in the model, not even on impact. The details which effects we may restrict are given below. Table 1 presents an overview.

Table 1.: Identifying assumptions in the matrices of short- and long-run effects

response \ shock	lf	wt	tech	cyc	wd	eff	sep	jci
				Short run				
vacancies	$\theta_{V,lf}$	$\theta_{V,wt}$	$\theta_{V,tech}$	$\theta_{V,cyc}$	$\theta_{V,wd}$	$\theta_{V,eff}$	$\theta_{V,sep}$	$\theta_{V,jci}$
unemployment	$\theta_{U,lf}$	$\theta_{U,wt}$	$\theta_{U,tech}$	$\theta_{U,cyc}$	$\theta_{U,wd}$	$\theta_{U,eff}$	$\theta_{U,sep}$	0
employment	$\theta_{E,lf}$	$-\theta_{U,wt}$	$-\theta_{U,tech}$	$-\theta_{U,cyc}$	$\theta_{E,wd}$	$-\theta_{U,eff}$	$-\theta_{U,sep}$	$-\theta_{U,jci}$
job finding rate	0	$\theta_{F,wt}$	$\theta_{F,tech}$	$\theta_{F,cyc}$	$\theta_{F,wd}$	$\theta_{F,eff}$	0	0
wage	$\theta_{W,lf}$	$\theta_{W,wt}$	$\theta_{W,tech}$	$\theta_{W,cyc}$	$\theta_{W,wd}$	0	$\theta_{W,sep}$	$\theta_{W,jci}$
productivity	$\theta_{P,lf}$	$\theta_{P,wt}$	$\theta_{P,tech}$	$\theta_{P,cyc}$	$\theta_{P,wd}$	$\theta_{P,eff}$	$\theta_{P,sep}$	$\theta_{P,jci}$
separation rate	$\theta_{S,lf}$	$\theta_{S,wt}$	$\theta_{S,tech}$	$\theta_{S,cyc}$	$\theta_{S,wd}$	0	$\theta_{S,sep}$	0
working time	0	$\theta_{H,wt}$	$\theta_{H,tech}$	$\theta_{H,cyc}$	$\theta_{H,wd}$	0	0	0
				Long run				
vacancies	$\xi_{V,lf}$	$\xi_{V,wt}$	$\xi_{V,tech}$	0	$\xi_{V,wd}$	$\xi_{V,eff}$	$\xi_{V,sep}$	$\xi_{V,jci}$
unemployment	$\xi_{U,lf}$	$\xi_{U,wt}$	$\xi_{U,tech}$	(0)	$\xi_{U,wd}$	$\xi_{U,eff}$	$\xi_{U,sep}$	$\xi_{U,jci}$
employment	$\xi_{E,lf}$	$\xi_{E,wt}$	$\xi_{E,tech}$	(0)	$\xi_{E,wd}$	$\xi_{E,eff}$	$\xi_{E,sep}$	$\xi_{E,jci}$
job finding rate	$\xi_{F,lf}$	$\xi_{F,wt}$	$\xi_{F,tech}$	0	$\xi_{F,wd}$	$\xi_{F,eff}$	$\xi_{F,sep}$	$\xi_{F,jci}$
wage	$\xi_{W,lf}$	$\xi_{W,wt}$	$\xi_{W,tech}$	0	$\xi_{W,wd}$	$\xi_{W,eff}$	$\xi_{W,sep}$	$\xi_{W,jci}$
productivity	$\xi_{P,lf}$	0	$\xi_{P,tech}$	0	0	0	0	0
separation rate	$\xi_{S,lf}$	$\xi_{S,wt}$	$\xi_{S,tech}$	0	$\xi_{S,wd}$	$\xi_{S,eff}$	$\xi_{S,sep}$	$\xi_{S,jci}$
working time	$\xi_{H,lf}$	$\xi_{H,wt}$	$\xi_{H,tech}$	0	$\xi_{H,wd}$	$\xi_{H,eff}$	$\xi_{H,sep}$	$\xi_{H,jci}$

Notes: The table shows the identifying assumptions regarding the short- and long-run effects in our structural macroeconometric model. lf: labour force, wt: working time, tech: technology, cyc: business cycle, wd: wage determination, eff: matching efficiency, sep: separation propensity, jci: job creation intensity. $\theta_{k,j}$ and $\xi_{k,j}$ are defined as the contemporaneous and long-term reactions of the kth variable to the jth structural shock, respectively. (0): Two of the eight cycle shock zeroes are no additional binding restrictions, but zeroes that follow from the cointegration properties.

4.2.3. Application to the SVECM

Labour force shock. Once workers have entered the labour force, they are either employed or unemployed (equation 4.5). Then, changes to employment are equivalent to changes in unemployment with opposite sign, at least on impact. The labour force shock – e.g. higher immigration or participation – changes the size of the work force. It is the only one that can immediately affect the labour force and may thus move both employment and unemployment into the same direction (for exceptions see below). The labour force shock may make additional persons enter unemployment, but since matches by definition of the matching function would appear only from the following month onwards (equation 4.7), there is no contemporaneous effect on the job finding rate. In the long run, one could think of the labour force 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 restrict the long-run responses of wages and productivity, too. Since these restrictions are not necessary for full identification and would considerably decrease the likelihood, we leave these effects unconstrained. This allows for heterogeneity in the composition of the additional labour force and also has the advantage of not a priori excluding specific results from the migration literature (e.g., Ottaviano and Peri, 2012). However, appendix A.3 shows that the results do not hinge on this exception.

Working time shock. This shock – for example variations in the part-time ratio or the facilitation of short-time work during the great recession – is the only one to change working hours per employee immediately (for exceptions see below). Note that a shock refers to an innovation that goes beyond endogenous reactions. If, for example, working time decreases in a recession in just the usual way, the cause is not a working time shock itself but a shock to economic activity.

Technology shock. 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, only the restriction of a congruent development of employment and unemployment applies (equation 4.5). In particular, we allow a free estimate of the responses of working hours on impact as well as in the long run (this is an exception to the identifying rule of the working time shock). Given the discordant literature on how technology shocks affect total hours worked (e.g. Uhlig, 2004; Canova et al., 2010), an unrestricted empirical strategy seems reasonable. Accordingly, the reaction of employment is unrestricted, which follows directly from the job creation and job destruction equations (4.11), (4.13) and (4.14). However, we show in appendix A.3 that the results are robust to this exception.

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 only counts for $K - r$ independent restrictions as r of the zero entries are an implicit consequence of the cointegration properties as 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 in order to accommodate results that demand shocks are mitigated along the intensive margin (e.g. Panovska (2017), Herzog-Stein and Zapf (2014)).

Wage determination shock. The wage determination shock is the only one that immediately affects all variables. This generous identification scheme is rationalized as the shock summarizes several sources why wages initially change (see section 3), among them wage bargaining, wage concessions, minimum wage reforms, outside options and reservation wages. This collection is justified by the Nash bargaining rule of the search and matching model (equation 4.12): Wages are negotiated to optimally share the surplus from the match between workers and firms. They depend on the bargaining power and the outside options of workers (as well as productivity and tightness which refer to other shocks of our model). However, the collection demands a strict scheme where to impose a zero restriction. Wage concessions may influence firms' separation decisions (equation 4.14). Besides the extensive margin of labour demand (E), our baseline model also allows for contemporaneous effects on the intensive margin (H). Outside options and reservation wages impact job findings immediately via matching efficiency, if a (low-paid) job is more quickly accepted (equation 4.8). Moreover, wage shocks following changes to labour market institutions do not solely enforce adjustments within the labour force but may even prompt agents to enter or leave the labour force (Rothe and Wälde, 2017; Fuchs, 2014). Besides this broad definition of a wage determination shock, subsection 5.3 provides the results of an alternative identification strategy allowing us to separate the pure wage setting channel and the willingness channel of this shock.

Matching efficiency shock. The matching efficiency shock refers to the functioning of the labour market beyond job search intensity and includes, for example, changes to the transparency and institutions of the matching process. The efficiency shock affects the matching technology (equation 4.7) – immediately moving the job finding rate, employment and vacancies (equations 4.9 and 4.6 and 4.11). We refrain from immediate impacts of the efficiency shock on wages and the separation rate, as matches do not show up contemporaneously in the wage equation (4.12) nor in the job destruction equations (4.13) and (4.14). The restrictions hold even if we assumed that efficiency affects hiring costs which might imply a short-run effect on wages and separations. But empirical studies find hiring costs to be low (Carbonero and Gartner, 2017), 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, see equation 4.14) would not be changed considerably.

Separation propensity shock. A separation propensity shock – for example changes in firing costs – moves the separation rate irrespective of other endogenous factors such as labour market tightness. The slow-down of the separation rate due to increased labour scarcity would be found in the systematic reactions of the model to changes in vacancies and unemployment. As regards the stochastic separations propensity shock, it changes the option value of a job in case of splitup. Via job creation (equation 4.11), tightness reacts. But matching efficiency is unaffected, so the effect on the job finding rate is zero on impact (equation 4.7). Furthermore, the rules identifying the labour force and the working time shocks are binding. 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, and this effect is left unrestricted (equation 4.12).

Job creation intensity shock. A job creation intensity shock increases vacancy posting beyond the influence of standard factors such as wages and productivity. The relevant shifting parameter in the job creation equation (4.11), named vacancy posting costs, comprises recruitment costs as well as costs connected to any legal regulations for, e.g., temporary agency work. 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 which increases vacancies and tightness and raises the job finding rate (equation 4.9), but – according to the matching function (4.7) – only with delay. There might be an increase in matching efficiency, because for given tightness, the share of vacancies for temps with comparatively low duration rises. This increases the average worker finding rate and, consequently, the job finding rate – but also with delay as this kind of vacancies has to be created, and filled, first. 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 job finding rate and separation rate being constant on impact, the law of motion (4.6) implies a zero effect for unemployment, too.

4.3. Specification, Estimation, and Inference

In order to avoid serial correlation in the reduced form residuals, we consider a VAR order of $q = 7$, even though the information criteria (Akaike, Bayesian) would have preferred fewer lags.

Based on the VAR(7) we run the so-called trace test, see Johansen (1995), and find $r = 2$ cointegration relations. Cointegrations relations generalize a VAR in first differences. Thus, in the first place, we specify these two cointegration relations to bring the model as close to the data as possible. Beyond that, the search and matching theory gives rise to believe that such long-run relations economically exist (think, for instance, of the Beveridge curve or the job creation curve). However, restricting the cointegration space to specific relationships is not necessary for our purposes. Allowing for $r = 2$, we use Johansen's maximum likelihood (ML) approach to estimate the reduced form VECM parameters in (4.2) including the cointegration matrix β.

In order to take into account equation (4.8) 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), old (aged 55+), foreign, female.

We apply a sequential elimination procedure based on a restricted feasible GLS (FGLS) estimator, see Lütkepohl (2005: Sects. 5.2 and 7.3), to find a parsimonious subset VECM. To be precise, we sequentially exclude the short-run dynamics parameters in $\Gamma_i, i = 1, \ldots, q-1$, that do not satisfy an absolute t-value of at least 1.645. This threshold value is consistent with a 10 percent significance level based on the standard normal distribution. The adjusted Portmanteau test, see, e.g., 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 lag 24 even at the 10 percent significance level.

Following Lütkepohl (2005: Sect. 9.1), the structural form is estimated using a non-linear maximum likelihood approach employing the restrictions introduced in section 4.2. Inference on the impulse responses shown in the next section is based on a semiparametric bootstrap approach that delivers the displayed pointwise confidence intervals. We describe our specification, estimation, and bootstrap approaches in more detail in Appendix A.2.

5. Results

5.1. Impulse Responses: What if a shock occurs?

Having identified the structural shocks, we demonstrate their labour market impacts in an impulse response analysis. Impulse responses have the character of a hypothetical simulation: They show the reactions of the model variables over time *if* a specific shock occurs. We present the results with respect to employment and unemployment as the two key variables of the labour market upswing.[2] They are given in Figures 4 and 5 together with 2/3 bootstrapped confidence intervals that are calculated following Hall (1992). The impulse responses are comparable in size since all shocks are normalised to have a variance of 1. The scale unit in the figures is 1 million.

Both employment and unemployment increase significantly following a unit **labour force shock**. The effect on unemployment is comparatively small and becomes insignificant within the first year. This result resembles the finding in the macro-econometric study by Weber and Weigand (2018) who conclude that immigration to Germany did not raise unemployment.[3] Employment, by contrast, reacts rather quickly and reaches a significant total effect of about 60,000 workers. The quick reaction of employment to labour force shocks is in line with Blanchard (2006). We argue that when the labour force increases due to later retirement age, for instance, unemployment is not affected at all. With increasing employment and stable unemployment, the unemployment rate will shrink in the long run due to a positive labour force shock.

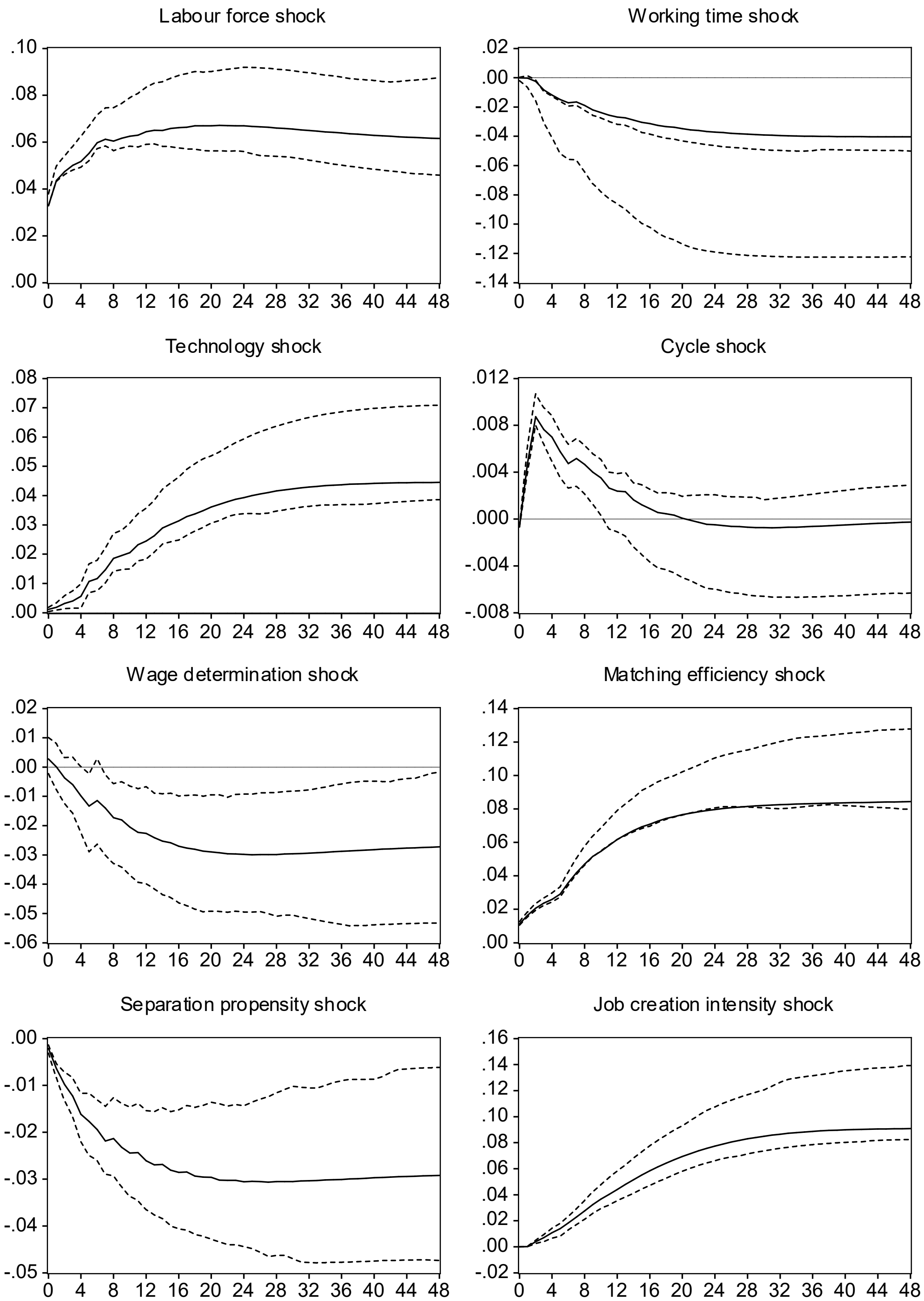
A positive **working time shock** by one unit decreases employment by 40,000 and increases unemployment by more than 20,000 people in the long run. Both effects are significant. From the macroeconomic point of view, working hours and workers are substitutes. Thus, working time reductions during the great recession via working time accounts or publicly subsidized short-time work could have helped to hoard labour. The reaction is sluggish, however, possibly because it takes more time to adjust workers than to adjust working hours. Furthermore, if the short-time work scheme had not existed during the great recession, firms would have dismissed more workers – but certainly not at once but distributed over several months.

In the short-run, the **technology shock** has only a small impact on unemployment and employment. Over time, however, the effects lead to significant increases in employment and reductions in unemployment by about 40,000 people. This pattern accounts for a remarkable adjustment process where technological progress creates new job opportunities in the long-run.

A positive one unit **cycle shock** represents an economic expansion. It has a positive impact on productivity but not as strong as the technology shock. Consequently, the "cyclical" reactions are

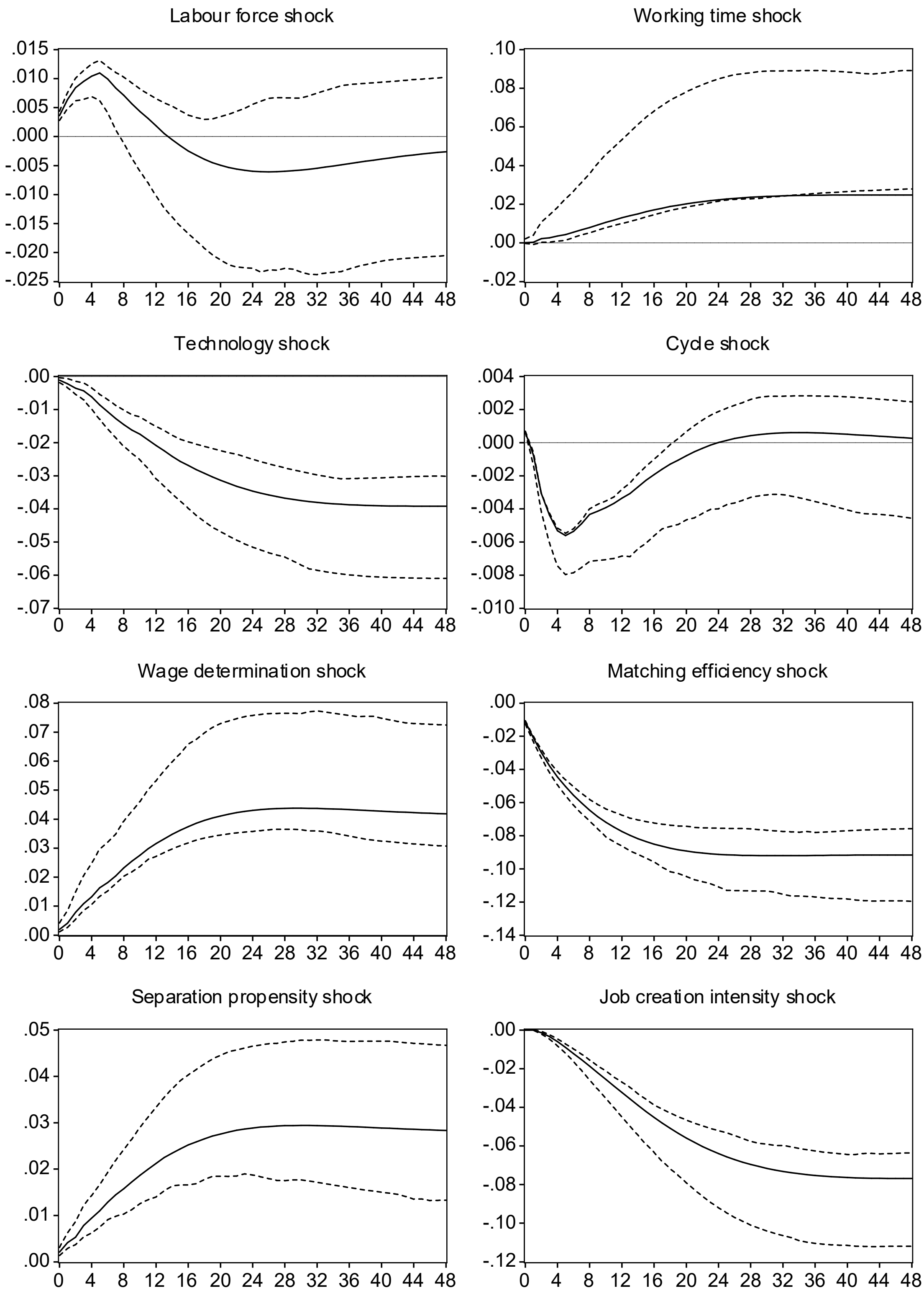
[2] The impulse responses of the other variables have been checked for plausibility and are available upon request.
[3] Our labour force shock does not only include immigration, but also participation and demographics.

Figure 4.: Impulse responses of employment



Notes: The solid lines show the responses of employment to 1 unit shocks up to 48 months. The dotted lines denote Hall (1992)'s 2/3 bootstrapped confidence intervals. Unit: 1 million. Source: Own calculations.

Figure 5.: Impulse responses of unemployment



Notes: The solid lines show the responses of unemployment to 1 unit shocks up to 48 months. The dotted lines denote Hall (1992)'s 2/3 bootstrapped confidence intervals. Unit: 1 million Source: Own calculations.

small (just as documented by Klinger and Weber (2019) on the decoupling of employment growth from the business cycle). In the long-run, both effects turn to zero by restriction. These impulse responses have the following implications: First, persistent changes in employment and unemployment are assigned to the technology shock. Second, it needs large shocks for the cycle to be a potential driver of the labour market upswing. However, the small effects might turn out advantageous if the great recession is classified as a negative cycle shock (see next section).

The impulse responses of the **wage determination shock** show significant harmful effects following wage increases. Unemployment continuously rises up to a long-run effect of about 40,000 people. Employment slightly rises on impact but then turns negative until it reaches a long-run effect of about 30,000 workers less. Furthermore, higher wages reduce the number of vacancies and the job finding rate. Vice versa, *negative* wage shocks may well have contributed to the labour market upswing.

Highly significant and economically relevant effects are visible following a unit **matching efficiency shock**: Unemployment and employment are affected similarly. They steadily decline/rise until the long-run effect of approximately 90,000 people less in unemployment and 80,000 people more in work is reached. Matching efficiency amounts to one of the largest single effects in this impulse-response analysis, rationalising the assumption that the parts of the Hartz reforms that increased matching efficiency were an influential driver of the labour market upswing. One reason for its strong effects ist that higher matching efficiency also raises the number of vacancies and the job finding rate while it decreases the separation rate.

A positive **separation propensity shock**, as initiated by a decrease in employment protection (another issue of the Hartz reforms), worsens labour market stocks significantly by about 30,000 in the long-run. In line with the EPL literature, labour market dynamics rise, though the job finding rate only temporarily. Vice versa, a negative separation propensity shock increases employment via fewer exits and reduces unemployment via fewer entries.

Finally, a **job creation intensity shock** has large positive effects on the labour market. Accompanied by increases in vacancies and the job finding rate, employment rises following a positive job creation intensity shock by about 90,000 workers in the long-run, while unemployment decreases by about 80,000 persons.

To summarize the impulse response analysis: The effects on the stocks of unemployment and employment are in line with the theoretical expectations. The largest effects are obtained from the job creation intensity shock, the matching efficiency shock, and the labour force shock. After these prominent candidates to explain the German labour market upswing, there are some potential drivers such as separation propensity, wage determination, technology or working time that exert medium-sized effect on the labour market once they occur. Ranking last in terms of response size, the cycle would require considerable shocks to (temporarily) leave a substantial mark on the labour market. We investigate in the next subsection, when the single shocks occurred, how large they were and how much they contributed to the record increase in employment and reduction in unemployment.

5.2. Historical decompositions: What did the shocks effect over time?

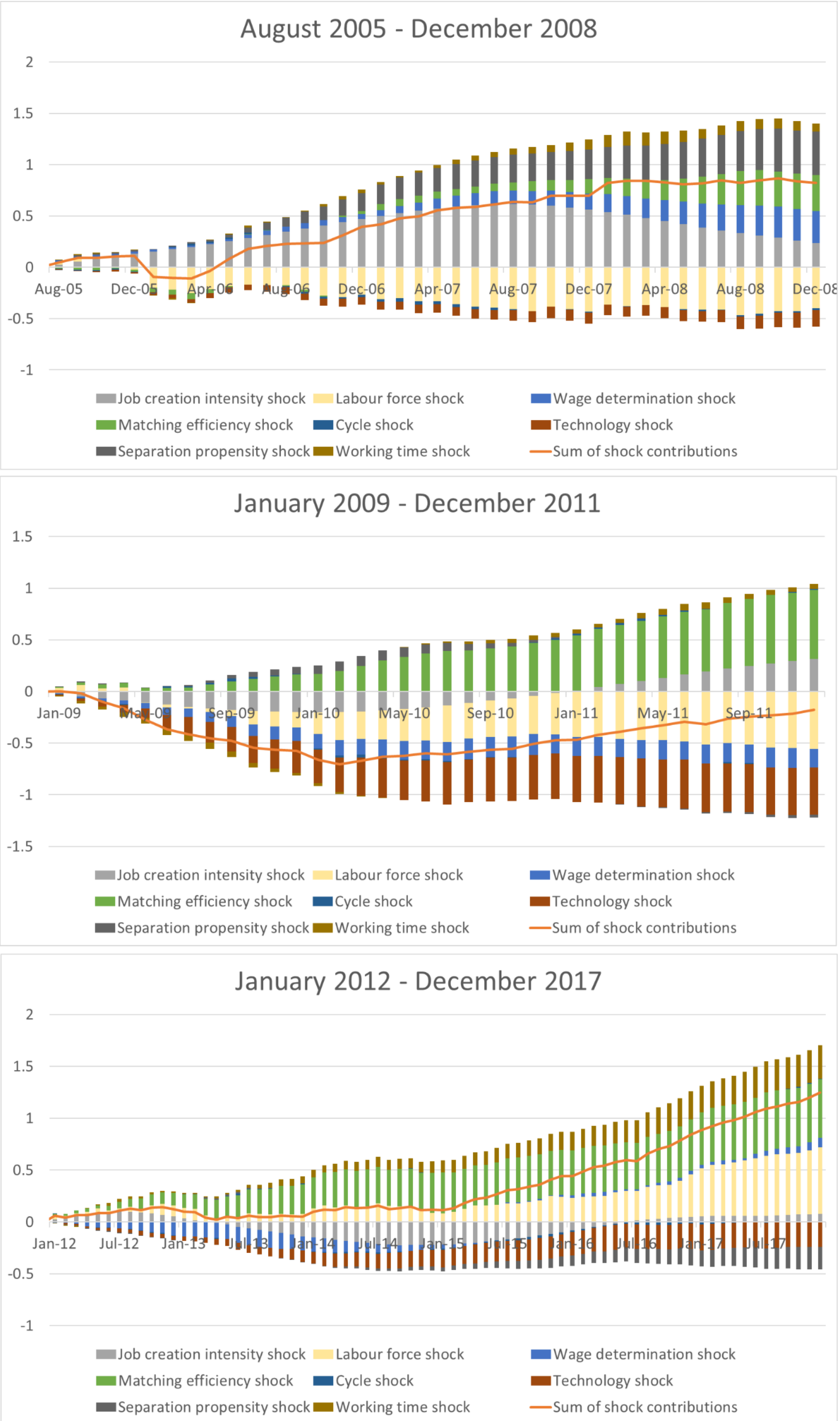
Historical decompositions quantify "how much a given structural shock explains the historically observed fluctuations" of the variables in y_t, Kilian and Lütkepohl (2017: Sect. 4.3). To be precise, in our set-up of $I(1)$ variables, we compute how the different structural shocks that effectively occurred over time have contributed to the actual changes of the variables over certain interesting subperiods. The historical decompositions can be obtained from the structural MA representation of y_t (for details, see Appendix A.2).

Note that the decompositions refer only to the variables' development that is driven by the shocks, not by deterministics such as the remarkable linear trend. Between 2005 and 2017, about 81 percent of the decrease in unemployment by 2.98 million and 36 percent of the increase in employment by 5.26 million can be explained by the structural innovations. Figures 6 and 7 show the accumulated non-deterministic changes of the two stocks since the beginning of each of three considered subperiods as well as the contributions of the different structural shocks.

The first subperiod covers the time span between August 2005 when unemployment started to shrink and December 2008 (just before the great recession hit the labour market). This phase was stamped by a strong economic upswing. However, neither the technology nor the cycle shock show a substantial influence on the 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 shocks, the latter only until mid-2007. The labour market reforms of 2003 to 2005 had been implemented to deregulate the labour market regarding flexible types of employment, for example. Their effects seem to be distributed over some time. However, especially temporary agency work as well as marginal employment grew above average in those years. The relevance of the matching efficiency shock and the wage determination shock has built up mainly after mid-2007 and over the year 2008, more and more 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 to 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 that time.

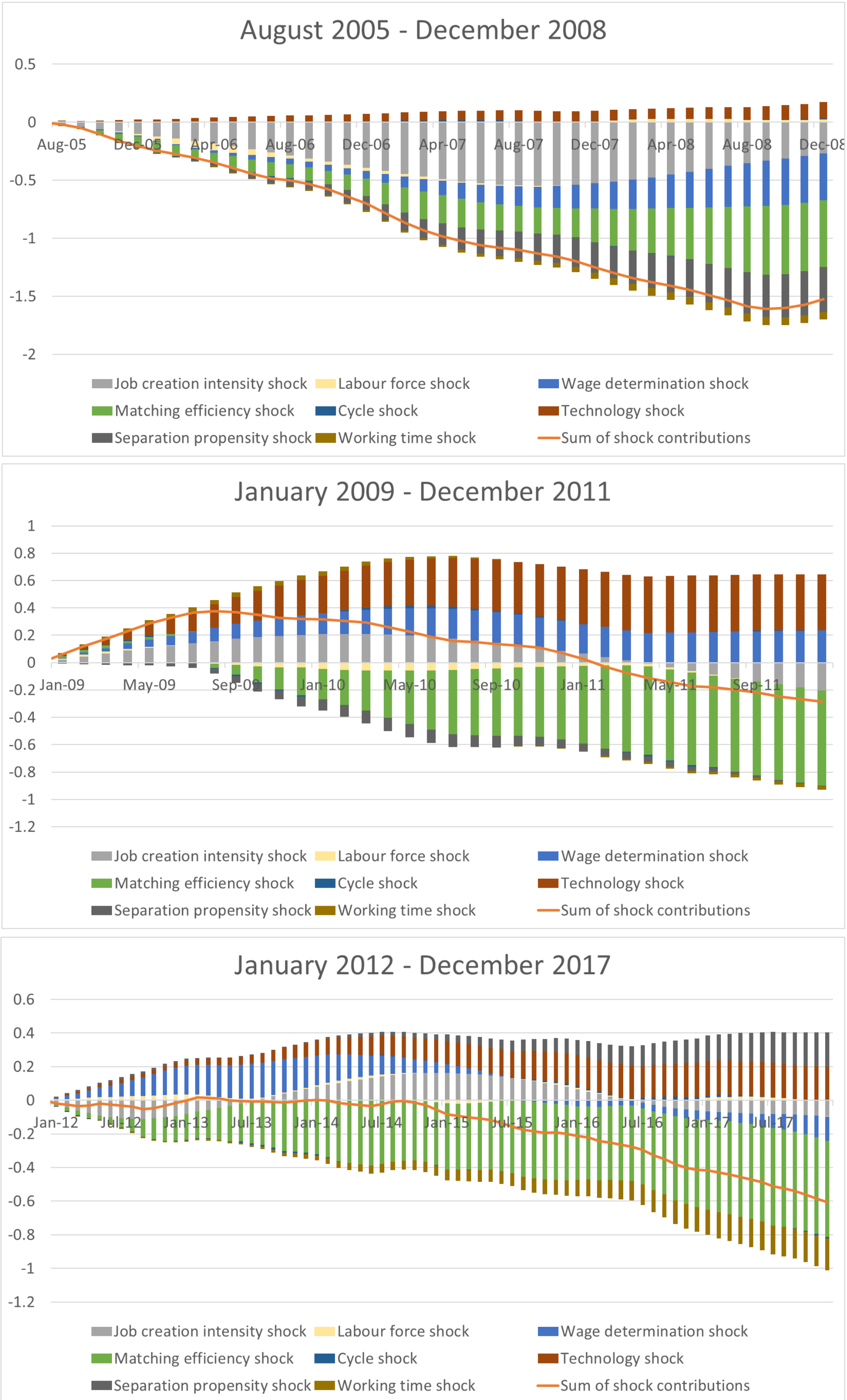
The same drivers that supported employment contributed to the substantial reduction of unemployment, the non-deterministic part of which amounts to 1.5 million during the first subperiod. The most important influence stems from the matching efficiency shock. Its increase after the

Figure 6.: Historical decomposition of employment



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

Hartz reforms clearly contributed to the reduction in unemployment. Note that increased search intensity due to reductions in unemployment benefit or a shorter entitlement period is captured in the wage determination shock. This one also played a substantial role in reducing unemployment in that period. Until mid-2007, the role of the job creation intensity shock has been larger than at the end of the period. The increase in the flexible (and often low-pay) types of employment at that time raised job findings for an otherwise hard-to-place group of unemployed. Another helpful driving force was the separation propensity shock: Avoided layoffs – for example as a consequence of a higher readiness of employees to make concessions regarding the qualification profile of their workplace – did not result in unemployment.

The second subperiod covers the great recession and the recovery thereafter (January 2009 to December 2011). Over the year 2009, shock-driven employment shrank by about 700,000 workers and took another two years to recover. In comparison to the observed series it becomes obvious that the strong deterministic upward trend masked the reaction of the labour market to the variety of shocks during the great recession to some extent: actual employment recovered faster than the non-deterministic part. As net migration was close to zero during the subperiod, negative labour force shocks hampered employment. What is 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 technology shock with long-run impacts instead of a just cyclical downturn. This is reasonable given the general slow-down of productivity growth after the recession and underlines the importance of studies in its sustainable effects (e.g. Yagan, 2019; Klinger and Weber, 2019). In addition, since wages did not mirror the drastic productivity decline during economic crisis, ceteris paribus they were a drag on the employment development. Instead, the recovery just to the pre-crisis level resulted from a diverse mix of structural shocks: better matching efficiency and increased incentives to create new jobs were the main drivers. Beyond them, working time shocks do not play but a minor role. Notwithstanding, flexible working time arrangements helped to safeguard jobs. But working time during the crisis did not primarily fall due to specific idiosyncratic shocks but due to a systematic endogenous reaction to the 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 has even decreased by 280,000 people. Still, the main drivers resemble the situation of employment: the bad impact of negative technology shocks and positive wage determination shocks were overcompensated 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 an obstacle to employment development again, they had only limited relevance for unemployment. Hence, transitions from unemployment into retirement do not seem to be an influential argument.

The third 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 that period, the shock-driven part of employment rose by 1.25 million. Contrary to the earlier subperiods, the labour force shock is the most important driver this time, reflecting the quick labour market integration of immigrants as well as longer working lives of older people. However, while the labour force shock was found to be an important driver of employment, it had hardly any relevance for unemployment. Hence, transitions from unemployment into retirement do not seem to be an influential argument. Again, the matching efficiency shock was a major driving force of the employment upswing. Thereby, higher recruitment intensity of firms as well as higher readiness to accept a certain mismatch of worker profiles are likely to have played a role (e.g., Bossler et al. (2018)). Furthermore, due to the decreasing working time even in the face of strong labour market development, negative working time shocks gained some importance during this subperiod.

Starting in mid 2013, wage determination became again a driver of the employment upswing, turning a negative contribution into a positive one by the end of 2017. This is due to the fact that productivity growth caught up again with wage growth during that time. Job creation intensity has also contributed to employment growth in this subperiod, but only since the beginning of 2015. During that time, vacancies themselves rose enormously. However, only a small amount of this increase is due to inflows of vacancies. The main reason is the strongly increasing vacancy duration. Hence, 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 3) reflecting labour market hoarding of firms due to increasing labour market tightness are not reflected in the separation propensity shocks of our model, and hence do not appear as supportive driving force in our historical decomposition. This is due to the fact that labour market tightness as such is a function of vacancies and unemployment and hence captured in the systematic part of our model. Indeed, the increase of vacancies and decrease of unemployment within our last subperiod show that the labour market became extremely tight (see also Figure 2). Furthermore, we find the long-run impact multipliers of S in equation (4.1) to be negative with respect to V and positive with respect to U, which supports our reasoning that increasing tightness indeed substantially lowered the separation rate and hence contributed to the employment upswing (compare Klinger and Weber (2019)).

The development of unemployment only slowed-down temporarily in the last subperiod. However, after 2015, the decrease continued and amounted to 600,000 by the end of 2017. Although this is a remarkable figure, it still falls short of the shock-driven plus of employment of 1.25 during the same subsample. This again clarifies that different sources than unemployment must have boosted employment, namely entrants from out of the labour force as well as workers staying longer in their jobs. Beyond that, the drivers are laterally reversed with matching efficiency, working time, wage determination and job creation intensity being the contributors to unemployment reduction.

The overall message of the historical decomposition is: The three high potential candidates following the impulse response analysis (matching efficiency, job creation intensity, labour force), plus separation propensity yield the largest contributions in explaining the German labour market upswing, albeit they did so in different subperiods. This result is in line with the finding in Klinger and Weber (2019) that labour market and GDP decoupled to some extent. At least, the related cycle or technology shocks do not play a decisive role in the overall development. Instead, the labour market is driven by labour market shocks themselves.

5.3. Separating the effects of wage setting and willingness

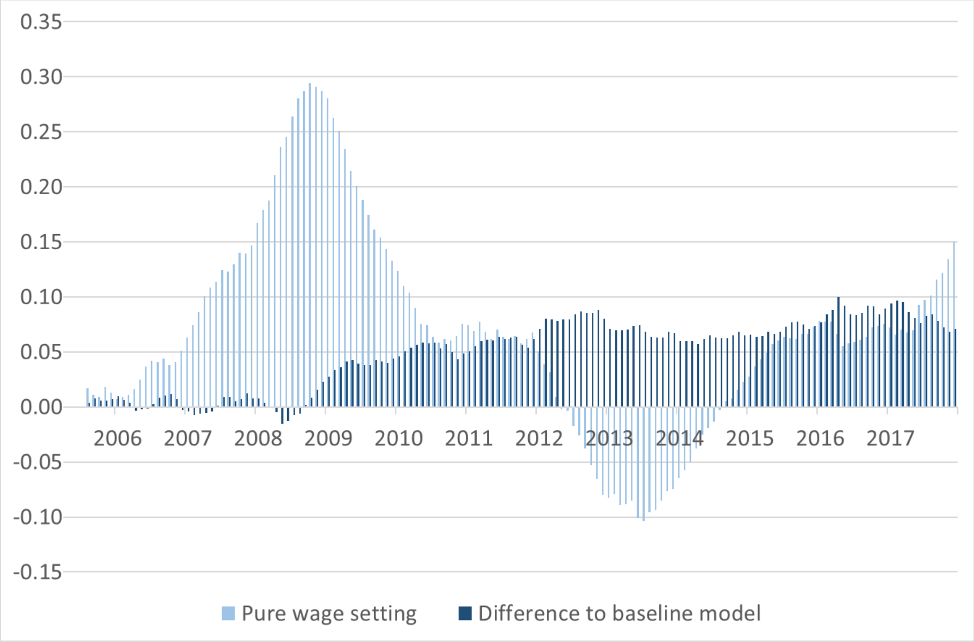
The discussion in subsection 4.2 revealed that the wage determination shock comprises a variety of potential driving forces all of which come along with changing wages. They can be summarized into two channels: first, the wage setting process, and second, the willingness to make concessions or increase search intensity according to the outside options. In order to check their relative importance, we present a different identification strategy that limits this shock to a pure wage setting shock and hence allows to deduce the importance of the willingness channel, too.

While in the baseline model all responses to the wage determination shock were unrestricted on impact, on the pure wage setting shock, here we place short-run restrictions on the labour force and the job finding rate ($\theta_{E,wd} = -\theta_{U,wd}$ and $\theta_{F,wd} = 0$, compare Table 1). A pure wage setting shock changes the value of a filled vacancy and leads to an increase in vacancies according to the job creation condition (equation 4.11). This increase yields more matches and a higher job finding rate, but only with delay, as matching efficiency is unaffected (equations 4.7 and 4.9). Furthermore, a pure wage setting shock does not contain the willingness component that captures first and foremost a change in the search and participation behaviour due to a change in outside options (e.g. Rothe and Wälde, 2017). In order to exclude this channel from the pure wage setting shock, the exception of the identifying rule of the labour force shock is lifted.

The difference between the historical contributions of a pure wage setting shock and the overall wage determination shock of our baseline model can be interpreted as the effects of the willingness component. Figures 8 and 9 show the respective contributions to employment and unemployment.

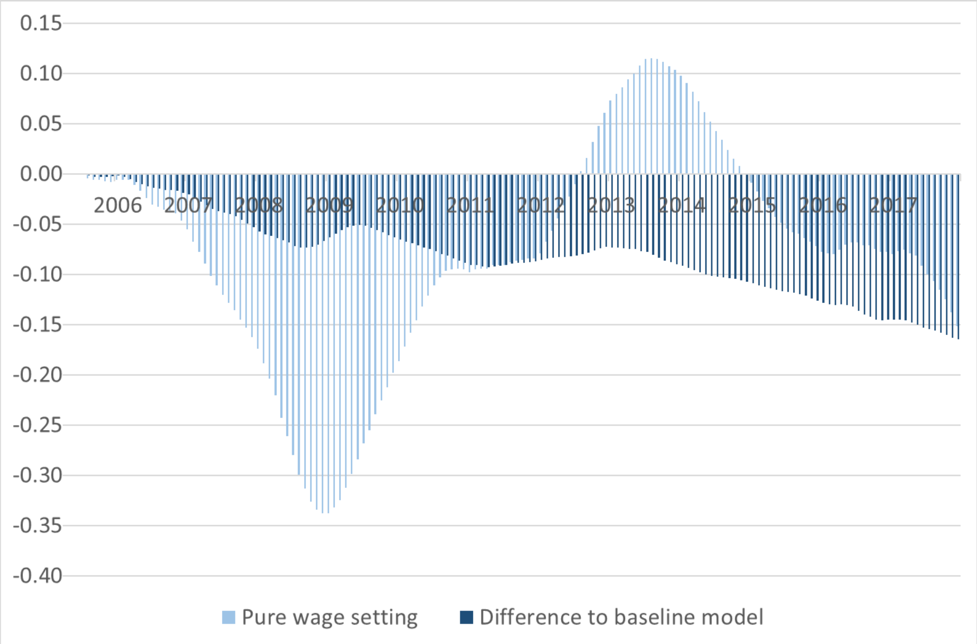
The figures show that, due to the wage moderation, the wage setting shock contributed in the second half of the 2000s to decreasing unemployment and increasing employment. However, from 2009 onwards it dampened the labour market, because wages did not mirror the drastic productivity decline. The willingness shock has improved the labour market development since 2004, the time of the Hartz reforms. This continued in 2015 and 2016, where the favourable effects of the wage setting shock ceased potentially due to the minimum wage introduction. Over the whole period between 2005 and 2017, pure wage setting shocks explain a minus of 150,000 unemployed,

Figure 8.: Historical decomposition of employment: pure wage setting shock and difference to the wage determination shock of the baseline model



Notes: The figure shows the historical contributions to employment of a pure wage setting shock and the difference to the wage determination shock of the baseline model. Unit: 1 million. Source: Own calculations.

Figure 9.: Historical decomposition of unemployment: pure wage setting shock and difference to the wage determination shock of the baseline model



Notes: The figure shows the historical contributions to unemployment of a pure wage setting shock and the difference to the wage determination shock of the baseline model. Unit: 1 million. Source: Own calculations.

which amounts to 48 percent of the unemployment decrease explained by overall wage determination shocks in our baseline model. This leaves a substantial amount of historical explanatory power to the willingness component. Also with respect to employment, an increase of 150,000 (68 percent of the total wage determination effect) can be attributed to the pure wage setting shock.

In sum, we can state that both the wage setting and the willingness channel contributed to the labour market upswing, but with different patterns. Our results also suggest that by far not the whole wage moderation – and its impact on labour demand – can be attributed to changes in wage setting, but that also the Hartz reforms and their effects on willingness played an important role.

6. Conclusion

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

The underlying 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 identification of a set of key economic and labour market shocks while limiting restrictive a-priori assumptions to a minimum. This provides a framework for letting the data speak on the sources of the remarkable labour market upswing. As candidates we consider shocks to job creation intensity, labour force, wage determination, matching efficiency, technology, the business cycle, separation propensity and working time.

Our approach allows us to measure the dynamic effects on employment and unemployment if such a shock occurs, i.e., impulse responses. Comparing the effect sizes reveals that job creation intensity shocks as well as shocks on the labour force and on matching efficiency have a specifically high potential of being drivers of the upswing. In order 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 make use of historical decompositions. We find that the candidate driving forces mentioned above plus the separation propensity shock indeed yield the largest contributions in explaining the German labour market upswing, but in different subperiods. The business cycle and technology shocks do not play a decisive role. This result is in line with the finding in Klinger and Weber (2019) that labour market and GDP decoupled to some extent. Instead, the labour market is driven by labour market shocks themselves.

Our results suggest a clear role of the Hartz reforms for the upswing, via increasing matching efficiency, fostering job creation and strengthening search intensity. However, also further developments such as the expanding labour force played a role. The wage moderation had more limited impacts, which also were in part initiated by the reforms via increasing the willingness to take up jobs. While the reforms spurred the labour market upswing, they also came along with critical effects such as intensifying downward wage pressure (compare Gartner et al. (2019)).

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

References

Amisano, G. and C. Giannini (1997). *Topics in Structural VAR Econometrics* (2nd ed.). Springer-Verlag.

Antoni, M., A. Ganzer, and P. vom Berge (2016). Sample of integrated labour market biographies (SIAB) 1975-2014. FDZ Datenreport 4/2016, Institute for Employment Research (IAB), Nuremberg.

Balleer, A., B. Gehrke, W. Lechthaler, and C. Merkl (2016). Does short-time work save jobs? A business cycle analysis. *European Economic Review 84*, 99–122.

Balleer, A., B. Gehrke, and C. Merkl (2017). Some surprising facts about working time accounts and the business cycle in Germany. *International Journal of Manpower 98*(7), 940–953.

Blanchard, O. (2006). European unemployment: the evolution of facts and ideas. *Economic Policy 21*(45), 5–59.

Blanchard, O. and P. Diamond (1989). The Beveridge Curve. *Brookings Papers on Economic Activity 1*.

Blanchard, O. and R. Perotti (2002). An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output. *The Quarterly Journal of Economics 117*(4), 1329–1368.

Blanchard, O. and J. Wolfers (2000). The role of shocks and institutions in the rise of European unemployment: the aggregate evidence. *The Economic Journal 110*(462), 1–33.

Bossler, M. (2017). Employment expectations and uncertainties ahead of the new German minimum wage. *Scottish Journal of Political Economy 64*(4), 327–348.

Bossler, M., N. Gürtzgen, A. Kubis, and A. Moczall (2018). Lowest number of unemployed per vacancy over the last 25 years. IAB Kurzbericht 23/2018, Institute for Employment Research (IAB), Nuremberg.

Bova, E., J. T. Jalles, and C. Kolerus (2018). Shifting the Beveridge curve: What affects labour market matching? *International Labour Review 157*(2), 267–306.

Burda, M. and J. Hunt (2011). What Explains the German Labor Market Miracle in the Great Recession. *Brookings Papers on Economic Activity 42*, 273–335.

Burda, M. and S. Seele (2016). No Role for the Hartz Reforms? Demand and Supply Factors in the German Labor Market, 1993-2014. SFB 649 Discussion Paper 2016-010, Humboldt-Universität, Berlin.

Cahuc, P. and F. Postel-Vinay (2002). Temporary jobs, employment protection and labor market performance. *Labour Economics 9*, 63–91.

Caliendo, M., A. Fedorets, M. Preuss, C. Schröder, and L. Wittbrodt (2018). The short-run employment effects of the German minimum wage reform. *Labour Economics 53*, 46–63.

Canova, F., D. Lopez-Salido, and C. Michelacci (2010). The effects of technology shocks on hours and output: a robustness analysis. *Journal of Applied Econometrics 25*, 755–773.

Carbonero, F. and H. Gartner (2017). Inspecting the relation of search cost and search duration for new hires. Discussion papers in economics 21, Friedrich Alexander University (FAU).

Carillo-Tudela, C., A. Launov, and J.-M. Robin (2018). The Fall in German Unemployment: A Flow Analysis. *IZA Discussion Paper No. 11442*.

Cavaliere, G., R. A. Taylor, and C. Trenkler (2013). Bootstrap co-integration rank testing: the role of deterministic variables and initial values in the bootstrap recursion. *Econometric Reviews 32*, 814–847.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy 113*(1), 1–45.

Christiano, L. J., M. Eichenbaum, and R. J. Vigfusson (2004). The Response of Hours to a Technology Shock: Evidence Based on Direct Measures of Technology. *Journal of the European Economic Association 2*(2-3), 381–395.

Davis, S., R. J. Faberman, and J. C. Haltiwanger (2013). The Establishment-Level Behavior of Vacancies and Hiring. *The Quarterly Journal of Economics 128*(2), 581–622.

Denton, F. T. (1971). Adjustment of Monthly or Quarterly Series to Annual Totals: An Approach Based on Quadratic Minimization. *Journal of the American Statistical Society 66*(333), 99–102.

Diamond, P. A. (1982). Aggregate demand management in search equilibrium. *Journal of Political Economy 90*(5), 881–894.

Dustmann, C., B. Fitzenberger, U. Schönberg, and A. Spitz-Oener (2014). From Sick Man of Europe to Economic Superstar: Germany’s Resurgent Economy. *Journal of Economic Perspectives 28*, 167–188.

Fahr, R. and U. Sunde (2009). Did the Hartz Reforms Speed-Up the Matching Process? A Macro-Evaluation Using Empirical Matching Functions. *German Economic Review 10*, 284–316.

Fuchs, J. (2014). Der Einfluss von Hartz IV auf die westdeutsche Stille Reserve – Ergebnisse auf Basis unterschiedlicher methodischer Ansätze. *AStA Wirtschafts- und Sozialstatistisches Archiv 8*(1), 33–48.

Fujita, S. (2011). Dynamics of worker flows and vacancies: Evidence from the sign restriction approach. *Journal of Applied Econometrics 26*(1), 89–121.

Fujita, S. and G. Ramey (2012). Exogenous versus endogenous separation. *American Economic Journal: Macroeconomics 4*(4), 68–93.

Gali, J. (1999). Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *The American Economic Review 89*(1), 249–271.

Gartner, H. (2005). The imputation of wages above the contribution limit with the German IAB employment sample. FDZ Methodenreport, No. 02/2015, Institute for Employment Research, Nuremberg.

Gartner, H., T. Rothe, and E. Weber (2019). The Quality-Weighted Matching Function: Did the German labour market reforms trade off efficiency against job quality? IAB-Discussion Paper 24/2019, Institute for Employment Research (IAB), Nuremberg.

Gehrke, B. and E. Weber (2018). Identifying asymmetric effects of labor market reforms. *European Economic Review 110*, 18–40.

Hairaulta, J.-O. and A. Zhutova (2018). The cyclicality of labor-market flows: A multiple-shock approach. *European Economic Review 103*, 150–172.

Hall, P. (1992). *The Bootstrap and Edgeworth Expansion*. Springer, New York.

Hartmann, M. and T. Riede (2005). Erwerbslosigkeit nach dem Labour-Force-Konzept – Arbeitslosigkeit nach dem Sozialgesetzbuch: Gemeinsamkeiten und Unterschiede. *Wirtschaft und Statistik* (4), 303–310.

Hartung, B., P. Jung, and M. Kuhn (2018). What hides behind the German labor market miracle? Unemployment insurance reforms and labor market dynamics . Discussion Paper 13328, Center for Economic Policy Research.

Heckmann, M., A. Kettner, S. Pausch, J. Szameitat, and K. Vogler-Ludwig (2009). Wie Betriebe in der Krise Beschäftigung stützen. IAB Kurzbericht 18, Institute for Employment Research (IAB), Nuremberg.

Hertweck, M. and O. Sigrist (2015). The ins and outs of German unemployment: a transatlantic perspective. *Oxford Economic Papers 67*, 1078–1095.

Herzog-Stein, A. and I. Zapf (2014). Navigating the great recession: the impact of working-time accounts in Germany. *ILR Review 67*(3), 891–925.

Hochmuth, B., B. Kohlbrecher, C. Merkl, and H. Gartner (2019). Hartz IV and the Decline of German Unemployment: A Macroeconomic Evaluation. *IZA Discussion Paper No. 12260*.

Johansen, S. (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

Jung, P. and M. Kuhn (2014). Labour market institutions and worker flows: Comparing Germany and the US. *The Economic Journal 124*(581), 1317–1338.

Kahn, L. M. (2010). Employment protection reforms, employment and the incidence of temporary jobs in Europe: 1996-2001. *Labour Economics 17*, 1–15.

Kilian, L. and H. Lütkepohl (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

Klinger, S. and T. Rothe (2012). The impact of labour market reforms and economic performance on the matching of the short-term and the long-term unemployed. *Scottish Journal of Political Economy 59*, 90–114.

Klinger, S. and E. Weber (2016). Decomposing Beveridge Curve Dynamics by Correlated Unobserved Components. *Oxford Bulletin of Economics and Statistics 78*(6), 877–894.

Klinger, S. and E. Weber (2019). GDP-Employment decoupling and the slow-down of productivity growth in Germany. IAB-Discussion Paper 12/2019, Nuremberg.

Krebs, T. and M. Scheffel (2013). Macroeconomic Evaluation of Labor Market Reform in Germany. *IMF Economic Review 61*, 664–701.

Kydland, F. E. and E. C. Prescott (1982). Time to build and aggregate fluctuations. *Econometrica 50*(6), 1345–1370.

Launov, A. and K. Wälde (2016). The employment effect of reforming a public employment agency. *European Economic Review 84*, 140–164.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Berlin: Springer.

Möller, J. (2010). Germany's job miracle in the world recession. Shock-absorbing institutions in the manufacturing sector. In *The Economy, Crises, and the Labor Market. Can Institutions Serve as a Protective Shield for Employment? (Applied Economics Quarterly Supplement)*, Volume 56, pp. 9–28. Klaus F. Zimmermann and Christian Wey (Publisher).

Mortensen, D. T. and C. A. Pissarides (1994). Job Creation and Job Destruction in the Theory of Unemployment. *Review of Economic Studies 61*, 397–415.

Nordmeier, D. (2014). Worker flows in Germany: Inspecting the time aggregation bias. *Labour Economics 28*, 70–83.

Nordmeier, D., H.-J. Schmerer, and E. Weber (2016). Trade and labor market dynamics: What do we learn from the data? *Economics Letters 145*, 206–209.

Ottaviano, G. and G. Peri (2012). Rethinking the effects of immigration on wages. *Journal of the European Economic Association 10*(1), 152–197.

Panovska, I. B. (2017). What explains the recent jobless recoveries? *Macroeconomic Dynamics 21*(3), 708–732.

Pissarides, C. A. (2000). *Equilibrium Unemployment Theory, 2nd Edition*. MIT Press Books, The MIT Press.

Plosser, C. I. (1989). Understanding real business cycles. *Journal of Economic Perspectives 3*(3), 51–77.

Rahn, D. and E. Weber (2017). Patterns of unemployment dynamics in Germany. *Macroeconomic Dynamics 23*, 322–357.

Ravn, M. O. and S. Simonelli (2007). Labor market dynamics and the business cycle: Structural evidence for the United States. *Scandinavian Journal of Economics 109*(4), 743–777.

Rebien, M. and A. Kettner (2011). Die Konzessionsbereitschaft von arbeitslosen Bewerbern und Beschäftigten nach den Hartz-Reformen. *WSI-Mitteilungen 64*(5), 218–225.

Rothe, T. and K. Wälde (2017). Where did all the unemployed go? Discussion Paper 18/2017, Institute for Employment Research (IAB), Nuremberg.

Siegele, L. (2004). Germany on the mend. *The Economist, accessed 03 May 2019, https://www.economist.com/news/2004/11/17/germany-on-the-mend*.

Stops, M. (2016). Revisiting German labour market reform effects - a panel data analysis for occupational labour markets. *IZA Journal of European Labor Studies 5*, 43 pages.

Summers, L. H. (1986). Some skeptical observations on real business cycle theory. *Federal Reserve Bank of Minneapolis Quarterly Review 10*(4), 23–27.

Uhlig, H. (2004). Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association 2*(2-3), 361–371.

Weber, E. (2015). The labour market in Germany: reforms, recession and robustness. *De Economist 163*(4), 461–472.

Weber, E. and R. Weigand (2018). Identifying macroeconomic effects of refugee migration to Germany. *Economics Bulletin 38*(2), 852–862.

Yagan, D. (2019). Employment Hysteresis from the Great Recession. *Journal of Political Economy 127*(5), 2505–2558.

A. Appendix

A.1. Details on Data

This section provides additional details on the data sources and methods used for data preparation.

Labour market stocks. The data on employment and unemployment correspond to the labour force concept. This ensures the same data gathering method and avoids any overlap of the two groups. The data are provided by the German Federal Statistical Office, based on the (European) Labour Force Survey. Registered unemployment would be available for a longer horizon but does not comprise the above mentioned advantages. In 2017, ILO unemployment was about 64 percent of registered unemployment. The intersecting set is also approximately 60 percent (Hartmann and Riede, 2005). Employment is total employment and contains employees covered by social security, civil servants, marginally employed, and self-employed.

Vacancies are registered vacancies provided by the FEA. We accounted for a structural break in 2000 when the definition changed and vacancies for the second labour market, for example, were excluded. According to the German Job Vacancy Survey, the reporting rate was 51 percent. However, the survey data are not suitable for our analysis as they are available at quarterly frequency (which still had to be interpolated to monthly) as from 2006.

Job finding rate and separation rate. To calculate the hazard rates, we stick to register data based on the micro database of the FEA. We use a 2 percent random sample of the Integrated Employment Biographies (IEB V13.01.00). An available draw from the IEB covers the years until 2014 and is provided as scientific use-file by the Research Data Center of the Institute for Employment Research (IAB) via remote data access after on-site use. Antoni et al. (2016) contains the latest data description. According data has been used to consider ins and outs of German unemployment and the time aggregation bias (Jung and Kuhn, 2014; Nordmeier, 2014). The IEB consist of all individuals in Germany, which are characterized by at least one of the following labour market status: (1) employment subject to social security, (2) marginal part-time employment, (3) benefit receipt according to the German Social Code III or II, (4) officially registered as job-seeking at the FEA, (5) participation in programs of active labour market policies. However, the data set does neither contain a well-defined status of inactivity nor self-employment. A stock of inactive persons is not available. Each labour market status is represented on a daily basis. Thus, we can see the status of each person at a certain point in time and define a change in the status as transition. For every person in our data set aged between 15 and 74 years we define the labour market status at the 15th of each month. We use the monthly status to calculate aggregated stocks. If the status of a person changes, we count this transition as an exit from one status and an entry into the other status. This procedure delivers gross worker flows. The according hazard rates can be interpreted as transition probabilities: The exit rate is calculated as the number of exits in period t devided by the source stock in period $t-1$. Concretely, the job finding rate is the ratio of transitions from unemployment into employment and the unemployment stock in the preceding month. Similarly, the entry rate is calculated as the number of entries in period t devided by the source stock of period $t-1$. Thus, the separation rate is the fraction of employed workers of period $t-1$ that registered as unemployed during the following month t. To model these transitions, a non-intersecting data set is required for each person. However, persons may exert more than one status at one and the same point of time. For instance, they may be unemployed, receive benefit and earn money from a mini-job within the legal restrictions. Among such concurrent states, we have to select the most important one. This is done using a priority list where unemployment dominates employment and participation in measures of active labour market policy. The status of employment includes employment subject to social security, vocational training, marginal and subsidized employment as well as job creation schemes. The data may lack the status information for single periods, e.g. because of measurement error or because unemployed do not receive benefit for 90 days if they quit the job themselves. To account for this we allow gaps of 30 days between unemployment and employment and 90 days between employment and unemployment. Gaps between two unemployment spells or training measures not exceeding 42 days are defined as unemployment.

Wages, productivity, and working time. The anchor variable for wages comprises the dependent workers' nominal gross hourly wages and salaries plus the employers' social security contributions. The time series is converted to real terms through the GDP deflator. Wage cost and GDP deflator are taken from the German Federal Statistical Office (Destatis) at quarterly frequency. Monthly dynamics must be imputed through a second variable. Therefore, we use the wage information in the 2 percent sample of the Integrated Employment Biographies (IEB), the same data set as for the hazard rates. This data set provides wage data with high quality and precision compared to survey data. We rely on information of full-time workers because part-time wages cannot be pinpointed due to a lack of information about the hours worked. In case of multiple employment, only reports of the main job are included. The key advantage is that the large data set comprises a high number of intra-year observations. Usually, an employer reports the individual worker's data relevant for the social security system once per year (annual report). In this case, the reported wage reflects the total payment received by the worker during the calendar year. However, the timing of individual wage changes due to promotion or tariff changes within a year is not reflected in annual reports, which – if not addressed – would lead to an underestimation of the intra-year wage dynamics. However, this problem can be addressed if a worker changes his or her job after January or before December or if there is an intra-year switching of, for instance, the health insurance company. These or similar events affecting the social security system require additional reports from which information on the *true* wage dynamics within a calendar year can be deduced. As a consequence, we only use wage information stemming from reports that cover employment episodes of less than a full year. Wages above the social security contribution ceiling are imputed following Gartner (2005). The monthly mean wage is converted to real terms through the CPI as published by the OECD. Following Denton (1971), our final variable of monthly wages is generated using both the quarterly real wage cost from the Statistical Office and the monthly real wages from the micro data. The first variable serves as anchor variable to capture the correct level and trend, while the second provides the monthly dynamics to fill the gaps.

The same interpolation methodology is used for productivty and working time. As regards productivity, the anchor variable is the quarterly index from the Federal Statistical Office (Destatis). It refers to real GDP per hour worked by the whole working population. To capture the monthly dynamics, we use the production index (including mining, manufacturing and production of goods, power supply, and construction) from the Federal Statistical Office.

For working time, we use a quarterly time series of total hours divided by the number of gainfully employed persons from the Institute for Employment Research (IAB) as anchor variable.[1] The monthly dynamics is imputed using a seasonally and working-day-adjusted time series of total hours divided by the number of workers in the manufacturing and mining industries. It is provided by the Federal Statistical Office.

All series were adjusted for seasonality using the X12-ARIMA procedure. Occasionally, we control for singular outliers if the technical adjustment did not capture seasonal irregularities.

A.2. VECM: Specification, Estimation, and Inference

In this appendix, we describe how the baseline model has been specified and estimated. Furthermore, we present the applied inference procedures, i.e., impulse response analysis and historical decompositions.

A.2.1. Specification and Estimation

The VAR order selection is initially based on the Akaike and Bayesian information criteria, see Lütkepohl (2005: Sect. 4.3). As the residuals of the suggested models still exhibit significant residual autocorrelation we have increased the VAR lag order to 7. The trace test of Johansen (1995: Sect. 6.3) is applied to the resulting VAR to determine the number of cointegration relations. We have evidence for $r = 2$ cointegration relations with respect to our 8-dimensional baseline model. The trace test version for a VECM with a linear trend restricted to the error correction term has been applied. The VECM with a restricted linear trend is used throughout. For convenience, we introduced the notation $\beta^+ = (\beta' : \tau_1)'$ with $\tau_1 = \beta' \rho_1$, where the $(K + 1 \times r)$-dimensional matrix β^+ extends the cointegration matrix by the coefficients associated with the restricted linear trend. Therefore, we also label β^+ as cointegration matrix in the following. In order to identify β^+ we

[1] In order to capture the correct level for a monthly analysis, the time series is divided by 3.

set its $(r \times r)$ upper block equal to the identity matrix I_r. The latter ensures identification of the cointegration matrix β^+.

Due to the large number of parameters by which our VECM is characterized, we have specified a parsimonious subset VECM with zero constraints imposed on the short-run dynamics parameters in Γ_i, $i = 1, \ldots, q-1$. To this end, a sequential elimination procedure has been applied. The procedure works as follows:[2]

In a first step, the full VECM has been estimated by using the reduced rank ML estimator in connection with the normal density, see Johansen (1995: Sect. 6.1 and 6.2). Thereby, we obtain the estimator $\hat{\beta}^+$ of the cointegration matrix. We condition on this estimator $\hat{\beta}^+$ for the subsequent steps of the procedure. This approach is justified as $\hat{\beta}^+$ converges with a higher rate than $\sqrt{T}$ under our assumptions, i.e., it is superconsistent. As a consequence, we can treat β^+ as known with respect to the estimators of the remaining (subset) VECM parameters. Indeed, the asymptotic distribution of these latter estimators is the same as when conditioning on the true cointegration matrix β, see Lütkepohl (2005: Sect. 7.2).

In the second step, we identify the unconstrained coefficient in the matrices $\Gamma_1, \ldots, \Gamma_{q-1}$ that is associated with the smallest absolute t-ratio. If this absolute t-ratio is below the threshold 1.645, corresponding to a 10 percent significance level, then the coefficient is set to zero. Otherwise, the procedure stops. In the former case, the remaining free parameters in $\Gamma_i, i = 1, \ldots, q-1$ as well as α are estimated by applying the restricted FGLS estimator of Lütkepohl (2005: Sect. 7.3, eq. (7.3.6)). Note again that $\hat{\beta}^+$ has been fixed and will not be re-estimated.

Third, the second step is repeated until all of the absolute t-ratios referring to the non-constrained coefficients are above the threshold of 1.645. For further details on the sequential elimination procedure see Lütkepohl (2005: Sect. 5.2).

We have eventually tested for residual autocorrelation with respect to the resulting subset VECM using the adjusted Portmanteau test whose degrees of freedom take account of the cointegration rank and the number of zero constraints underlying the corresponding subset VECM, see Lütkepohl (2005: Sect. 8.4).

The structural VECM employing the constraints described in section 4.2 is estimated by non-linear ML, see Lütkepohl (2005: Sect. 9.3). To this end, the long-run restrictions imposed on CB are re-written with respect to the structural impact matrix B. As input for estimation we use the residual variance matrix estimator $\hat{\Sigma}_u = T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$ with $\hat{u}_t$, $t = 1, \ldots, T$, being the residual vectors obtained from the restricted FGLS estimation. The ML approach delivers the estimator $\hat{B}$ that maximizes the log-likelihood function such that $\hat{\Sigma}_u = \hat{B}\hat{B}'$ in our case of exact identification. From $\hat{B}$ the structural impulse response coefficients can be computed as described below.

[2] All steps of the following procedure that are applied to the matrices $\Gamma_1, \ldots, \Gamma_{q-1}$ are applied analogously to the matrices holding the coefficients of the exogenous variables described in 4.3.

We implement non-linear ML estimation by using the quasi-Newton algorithm in Matlab. We run this algorithm with analytical forms for the corresponding gradient vector and the approximated Hessian matrix as derived by Amisano and Giannini (1997: Sects. 4.1 and 4.2). The Hessian matrix is approximated by the information matrix.

A.2.2. Inference Procedures

In this subsection, we first discuss our framework for structural impulse response analysis and then describe how we have obtained the historical decompositions.

The responses to the structural shocks could be obtained from (4.4). However, it is very difficult to explicitly determine the coefficient matrices C_j, $j = 0, 1, \dots,$. Therefore, we follow the common and more convenient approach that relies on the MA representation of the corresponding structural VAR. To be precise, we first transform the subset VECM parameters into the corresponding VAR parameters according to $A_1 = \alpha\beta' + I_K + \Gamma_1$, $A_i = \Gamma_i - \Gamma_{i-1}$, $i = 2, \dots, p-1$, and $A_q = -\Gamma_{p-1}$. Then, the structural impulse response coefficient matrix at horizon i is given by $\Theta_i = \Phi_i B$, $i = 0, 1, \dots$, where $\Phi_0 = I_K$ and $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_i$, $i = 1, 2, \dots$, are the reduced form MA parameter matrices, see Lütkepohl (2005: Sect. 2.1). Obviously, we have $\Theta_0 = B$. To sum up, the following structural MA representation is considered

$$y_t = \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i} \tag{A.1}$$

in which we have disregarded deterministic terms as they are not relevant for the impulse response analysis.

In order to estimate the structural impulse responses we simply replace the above VECM parameters with their estimators, taking account of the subset restrictions. Thereby, we obtain the estimators $\hat{\Theta}_i$, $i = 0, 1, 2, \dots$ with $\hat{\Theta}_0 = \hat{B}$.

The confidence intervals for the impulse responses are obtained from a recursive semiparametric bootstrap scheme as outlined in the following. Let us focus on a structural impulse response coefficient of interest and its estimator labeled by θ and $\hat{\theta}$, respectively.

1. Estimate the reduced form VECM (4.2) by reduced rank ML in order to get the estimator $\hat{\beta}^+ = (\hat{\beta}' : \hat{\tau}_1)'$. Conditional on $\hat{\beta}^+$, fit a subset VECM as described in section A.2.1 in order to get the restricted FGLS estimators $\hat{\alpha}$ and $\hat{\Gamma}_i$, $i = 1, \dots, q-1$, the restricted FGLS residual vectors $\hat{u}_2, \dots, \hat{u}_T$, and $\hat{\Sigma}_u = T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$.
2. Compute the estimators $\hat{\Phi}_i$, $i = 1, 2, \dots$, and obtain the nonlinear ML estimator $\hat{B}$ using $\hat{\Sigma}_u$ as described in section A.2.1. Finally, use these estimators to determine the impulse response estimator $\hat{\theta}$ as described above.

3. Construct the bootstrap sample data, $y_t^*, \ t = 1, \dots, T$, recursively from

$$\Delta y_t^* = \hat{\alpha}\hat{\beta}' y_{t-1}^* + \sum_{j=1}^{p-1} \hat{\Gamma}_j \Delta y_{t-j}^* + u_t^*, \tag{A.2}$$

with sampled residuals u_t^* drawn with replacement from the FGLS residuals $\hat{u}_1, \dots, \hat{u}_T$. The starting values of the recursion, $y_{-p+1}^*, \dots, y_0^*$, are set equal to 0.
4. Compute the bootstrap structural impulse response estimator $\hat{\theta}^*$ in the same way as $\hat{\theta}$ using the bootstrap sample $y_t^*, \ t = 1, \dots, T$. This requires to estimate a subset VECM with respect to $y_t^*, \ t = 1, \dots, T$. To this end, we use the subset VECM structure obtained in step 1.
5. Repeat steps 3 and 4 B times in order to get B bootstrap versions of θ^*. Obtain the $\gamma/2$- and $(1-\gamma/2)$-quantiles of $[\hat{\theta}^* - \hat{\theta}]$, $\gamma \in (0,1)$, labeled as $c_{\gamma/2}^*$ and $c_{(1-\gamma/2)}^*$, respectively.
6. Determine Hall's percentile interval by

$$\left[\hat{\theta} - c_{(1-\gamma/2)}^*; \hat{\theta} - c_{\gamma/2}^*\right].$$

Some remarks are in order. First, our bootstrap approach is asymptotically valid under the assumptions spelled out in subsection 4.1, see Kilian and Lütkepohl (2017: Sect. 12.2). In step 3, we have generated the bootstrap data with zero deterministics and zero initial values. Cavaliere et al. (2013) provide evidence that this approach may lead to better finite sample properties compared to a bootstrap scheme that includes the deterministic terms and initial values as $y_t^* = y_t$, $t = -p+1, \dots, 0$. Note, however, that the subset VECM estimated in step 4 contains the same deterministic terms as the one estimated in step 1 in order to ensure asymptotic validity.

Let us turn to the historical decompositions. For the presentation we intensively rely on Kilian and Lütkepohl (2017: Sect. 4.3) to which we refer for further details. Initially, assume that y_t is integrated of order zero, i.e., stationary, and has mean zero such that no deterministic terms enter the model. Then, the VAR-related structural MA representation in (A.1) holds exactly and can be written as

$$y_t = \sum_{i=0}^{t-1} \Theta_i \epsilon_{t-i} + \sum_{i=t}^{\infty} \Theta_i \epsilon_{t-i}. \tag{A.3}$$

Hence, y_t depends on the structural shocks $\epsilon_1, \dots, \epsilon_t$ that can be estimated and on the structural shocks predating period $t = 1$ that cannot be estimated. Accordingly, the second term in (A.3) has to be disregarded for the decompositions of the K components in y_t which are given by

$$\hat{y}_{kt} = \sum_{j=1}^{K} \hat{y}_{kt}^{(j)} \quad \text{with} \quad \hat{y}_{kt}^{(j)} = \sum_{i=0}^{t-1} \theta_{kj,i} \epsilon_{j,t-i}, \quad k = 1, \dots, K, \tag{A.4}$$

where $\theta_{kj,i}$ denotes the (k,j)-th element of Θ_i that represents the response of the variable k at horizon i to the structural shock $\epsilon_{j,t}$. Thus, $\hat{y}_{kt}^{(j)}$ measures the cumulative contribution of the j-th structural shock on the k-th variable in the VAR model at time t.

Two remarks are in order. First, dropping the second term in (A.3) produces an approximation error. In case of stationarity, this error vanishes, however, for increasing t as $\Theta_i \overset{i\to\infty}{\longrightarrow} 0_{K\times K}$. Second, the historical decompositions do not decompose the effect of deterministic components added to the model. Obviously, they just refer to the variables' development driven by the shocks.

Our case of $I(1)$ variables requires some modifications as the historical decompositions rely on a stationary MA representation of the VAR process. To be precise, we cannot reasonably decompose a variable into the cumulative effects of the shocks due to the stochastic trend underlying the series. However, we can reasonably "quantify the ability of a given shock to explain the cumulative change" in the variables "since a given point in time", Kilian and Lütkepohl (2017: Sect. 4.3). Therefore, we show the decompositions of the actual changes of the variables over certain subperiods of interest in Figures 6 and 7.

To obtain these decompositions, we first compute the estimators $\hat{\Theta}_i$, $i = 0, 1, ...$, as explained above and estimate the structural shocks by $\hat{\epsilon}_t = \hat{B}^{-1}\hat{u}_t$, $t = 1, \dots, T$. Then, we determine the decompositions between two periods t_r and t_1 for $t_r = t_1 + 1, \dots, t_2$, as

$$\Delta\hat{\hat{y}}_{k,t_r-t_1} = \sum_{j=1}^{K} \Delta\hat{\hat{y}}^{(j)}_{k,t_r-t_1} \text{ with } \Delta\hat{\hat{y}}^{(j)}_{k,t_r-t_1} = \sum_{i=0}^{t_1-1} (\hat{\theta}_{kj,t_r-t_1+i} - \hat{\theta}_{kj,i})\hat{\epsilon}_{j,t_1-i} + \sum_{i=t_1}^{t_r-1} \hat{\theta}_{kj,t_r-1-i}\hat{\epsilon}_{j,i+1}, \tag{A.5}$$

$$k = 1, \dots, K.$$

In line with the remark regarding a stationary setting, changes in the variables between periods t_2 and t_1 that are due to deterministic trends remain unexplained by the decompositions.

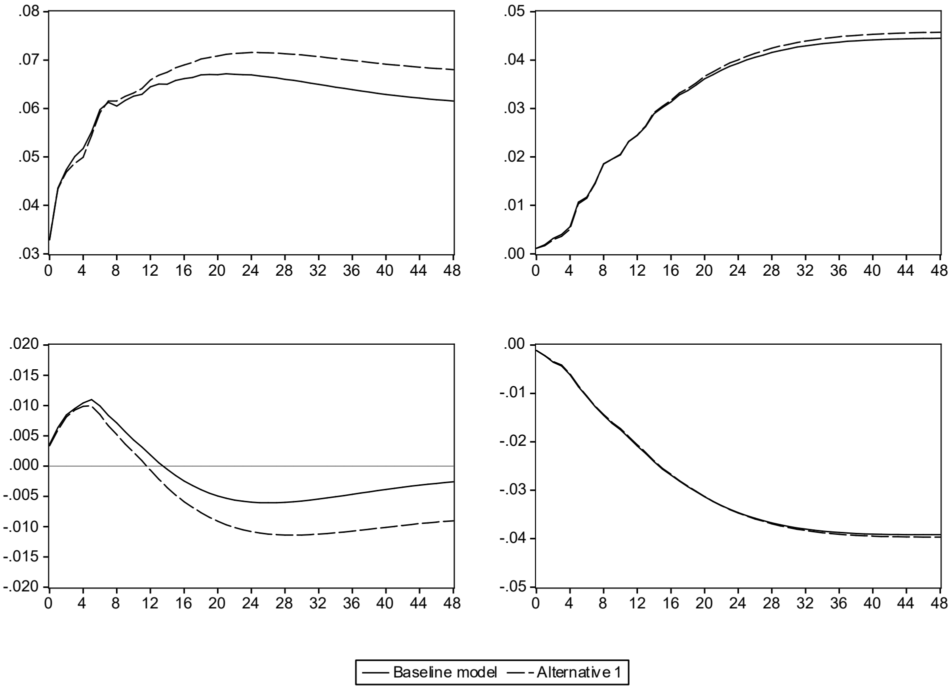
A.3. Robustness checks

As noted in the main body, we pursue the following robustness checks:

- Alternative 1: We follow Gali (1999) without exception, i.e., the additional long run restriction $\xi_{P,lf} = 0$ is set.
- Alternative 2: We abstain from an exception concerning the contemporaneous reaction of working time and set $\theta_{H,tech} = 0$.
- Alternative 3: In the last step of the Hartz reforms, former welfare recipients were registered as unemployed. This shift in the pool of official unemployment might have affected the job finding rate that draws on administrative data. Therefore, as e.g. Klinger and Weber (2016), we include three impulse dummies (2005m1 to 2005m3) in the F-equation of our VECM.

With respect to alternative 1, Figure 10 shows that the reactions of employment and unemployment to technology shocks remain basically unchanged. Hence, the results of our baseline model

Figure 10.: Robustness of impulse responses: Setting $\xi_{P,lf} = 0$



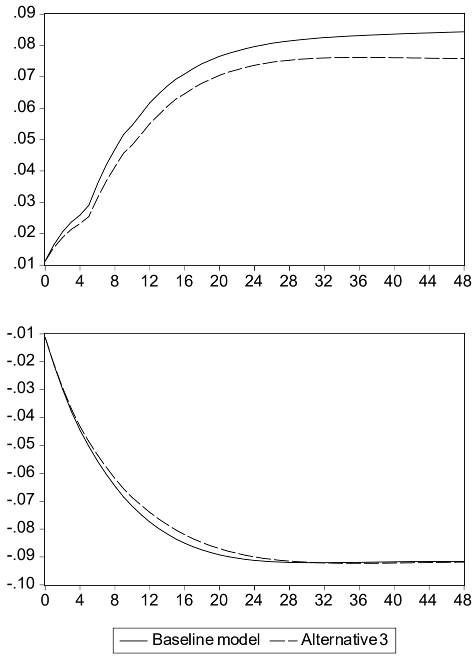
Notes: The figure shows the responses of employment (upper panels) and unemployment (lower panels) to 1 unit shocks of technology (right panels) and labour force (left panels). Unit: 1 million. Source: Own calculations.

do not hinge on restricting or not restricting the long run productivity reaction to labour force shocks. The reactions to labour force shocks are also rather stable, albeit with slightly stronger employment increases and unemployment decreases the latter of which are still insignificant in the long run. Since the likelihood reduction is quite substantial for the over-identified model, the data prefer $\xi_{P,lf}$ to remain unconstrained.

The second alternative identification scheme (adding $\theta_{H,tech} = 0$) has almost no effects compared to the baseline model, neither on the impulse responses of employment nor of unemployment. The likelihood reduction is marginal, which emphasizes that the data estimate $\theta_{H,tech}$ to be close to zero anyway.

The additional impulse dummies potentially have an impact on the matching efficiency shock since, in case impulse dummies are included, the decrease of F during that time is not attributable to shocks any more. However, Figure 11 shows that the impulse responses are rather stable.

Figure 11.: Robustness of impulse responses: Control for statistical effects in F



Notes: The figure shows the responses of employment (upper panel) and unemployment (lower panel) to 1 unit efficiency shocks. Unit: 1 million. Source: Own calculations.

Imprint

IAB-Discussion Paper 20|2019EN

Publication Date

27 September 2019

Publisher

Institute for Employment Research
of the Federal Employment Agency
Regensburger Straße 104
90478 Nürnberg
Germany

Download

http://doku.iab.de/discussionpapers/2019/dp2019.pdf

All publications in the series "IAB-Discusssion Paper" can be downloaded from

https://www.iab.de/en/publikationen/discussionpaper.aspx

Website

www.iab.de/en

Corresponding author

Christian Hutter
Telefon 0911 179-3057
E-Mail christian.hutter@iab.de