The Aggregate Effects of the Hartz Reforms in Germany *

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Abstract

This paper quantifies the impact of the Hartz reforms on matching efficiency, using monthly SOEP gross worker flows (1983-2009). We show that, until the early 2000s, close to 60% of changes in the unemployment rate are due to changes in the inflow rate (job separation). On the contrary, since the implementation of the reforms in the mid-2000s, the importance of the outflow rate (job finding) has been steadily increasing. This indicates that matching efficiency has improved substantially in recent years. Results from an estimated matching function — pointing to efficiency gains of more than 20% — corroborate this finding.

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1 Introduction

Following the financial crisis, unemployment rates across most European countries surged to unprecedented levels — particularly in the southern periphery. In contrast to this dramatic development, the trend of the German unemployment rate started to decline in 2005 and continued to fall even during the Great Recession. The resulting drop in the German unemployment rate is often attributed, at least in part, to the so-called "Hartz reforms", a series of labor market reforms implemented by the German government in the years 2003-2005 (Sala et al. 2012). The Hartz reforms aimed at increasing the efficiency of the matching process by stimulating the search effort of the unemployed (Fahr & Sunde 2009) and by re-organizing the Federal Employment Agency into a customer-orientated service provider (Jacobi & Kluve 2007). Due to the extremely favorable performance of the German labor market in recent years, many European countries are currently planning to undertake similar structural reforms of their national labor markets (Ehlers et al. 2012).

Despite the good reputation of the Hartz reforms among policy advisors, scientific evidence on its macroeconomic effectiveness remains inconclusive and mixed. Using calibrated macro models, Krebs & Scheffel (2010) as well as Krause & Uhlig (2012) find that the Hartz reforms have reduced the equilibrium unemployment rate substantially. Launov & Wälde (2010), by contrast, argue that the effects are rather close to zero. Most empirical policy evaluations (Fertig et al. 2007, Fahr & Sunde 2009, Klinger & Rothe 2012), on the other hand, are based on regional and/or occupational panel data from the Federal Employment Agency. However, due to several methodological breaks, the time series published prior to January 2008 are not fully consistent (Bundesagentur für Arbeit 2009, Section 4.1.2). These limitations make it difficult to obtain reliable estimates on the effect of the Hartz reforms, even though the authors make best efforts to take these issues into account (see Fahr & Sunde 2009, pp. 292–294).

This paper, instead, quantifies the macroeconomic effectiveness of the Hartz reforms using *long* time series on *aggregate* labor market transition rates.[1] In particular, we test the hypothesis of higher matching efficiency in the post-Hartz period on two different grounds.[2] First, we decompose the fluctuations of the German unemployment rate into changes in the two underlying channels — the inflow rate (job separation) and the outflow rate (job finding) — and examine whether the relative contributions are stable over time. We show that, until the early 2000s, close to 60% of changes in the unemployment rate are due to changes in the inflow rate — whereas the reverse situation prevails in the United States.[3] This finding corroborates the conclusion by Jung & Kuhn (2011) that the German labor market suffers from a low degree of matching efficiency. Furthermore, we provide evidence that the dominance of inflows over outflows is a

[1]The only other paper, to our knowledge, that uses aggregate labor market transition rates in a similar context is the one by Klinger & Weber (2012). Based on a correlated unobserved components model, the authors decompose the inward shift of the German Beveridge curve occurring in the mid-2000s.

[2]As is standard in this strand of the literature (Barnichon & Figura 2011), we define matching efficiency as the Solow residual of an aggregate matching function with the observed levels of unemployment and vacancies as explanatory variables. Improvements in the Solow residual may, therefore, reflect a more efficient organization of the Federal Employment Agency as well as increased search effort of the unemployed. The study of questions related to mismatch unemployment (Şahin et al. 2012), however, is beyond the scope of this paper.

[3]Interestingly, in the United Kingdom, the relative contributions show a cyclical pattern. While inflows dominate during recessions, outflows dominate in periods of moderation (Smith 2011).

very robust feature across all demographic subsamples but the young.[4] Since the implementation of the Hartz reforms, however, the importance of the outflow rate has been steadily increasing, indicating a substantial improvement in matching efficiency. Second, we quantify these effects by estimating an empirical matching function (Petrongolo & Pissarides 2001), where we allow for a structural break around the year 2003. Our estimates – which are robust across various specifications — point to efficiency gains of more than 20%.

For this purpose, we use West-German SOEP gross worker flows from 1983-2009. The household survey data are representative for the entire population in Germany and provide detailed information on each individual's labor market status at a monthly frequency. Moreover, SOEP data allow us to study not only transitions between employment and unemployment, but also indirect transitions involving inactivity. This is important, as indirect transitions account for roughly 20% of all transitions between employment and unemployment. Furthermore, we document that the SOEP unemployment rate behaves very similarly to the West-German unemployment rate according to the ILO definition. This facilitates comparisons of the situation in West-Germany with evidence from the CPS for the United States. This is advantageous, as the United States serves as a well-understood benchmark case (Yashiv 2008, Elsby et al. 2009, Fujita & Ramey 2009, Shimer 2012) of a flexible labor market with stable institutions.

In order to decompose the fluctuations in the West-German unemployment rate, we use the non-steady state approach developed by Elsby et al. (2011) and Smith (2011). Compared to the steady state approach pioneered by Fujita & Ramey (2009) and Shimer (2012) — which is nested as a special case — the non-steady state method is able to capture the sluggishness of the West-German labor market more appropriately.[5] In recent years, both methods have been applied to German data. However, the picture remains disturbingly opaque. Jung & Kuhn (2011), based on a steady state decomposition of IAB gross worker flows, find that the inflow rate is more important than the outflow rate; Elsby et al. (2011), based on a non-steady state decomposition of annual OECD unemployment duration data, observe approximately a 50:50 split; and Nordmeier (2012), based on a non-steady state decomposition of IAB gross worker flows, argues that the outflow rate is more important than the inflow rate.

As demonstrated by Jung & Kuhn (2011), the observed dominance of inflows over outflows can consistently be replicated by a job matching model with endogenous separations (den Haan et al. 2000); calibrated with low matching efficiency for West-Germany and high matching efficiency for the United States. The dominance of inflows over outflows is driven by the fact that the relative volatility of the inflow rate in West-Germany is larger by factor four, while the relative volatility of the outflow rate is similar across countries. In addition, we note that labor market transition rates in West-Germany are smaller by an order of magnitude.

By contrast, when the low level of both transition rates is matched by calibrating the West-German model economy with high unemployment benefits and high firing costs, the model of Jung & Kuhn (2011) generates not only the required amplification in the inflow rate, but also a counterfactual amplification in the outflow rate. The key difference between the two channels is

[4] Jung & Kuhn (2011), in contrast, find the described pattern only in the male subsample and in the subsample of medium skilled workers (see Table I in their paper).

[5] Adaptations of the steady state methodology to European economies include Petrongolo & Pissarides (2008) for the UK, France, and Spain; Gomes (2011) for the UK, using a longer sample period; and Şengül (2012) for Turkey. The non-steady state approach has been applied to French data by Hairault et al. (2012).

that low matching efficiency leaves the relative volatility of the match surplus unchanged, while the calibration with high unemployment benefits and high firing costs increases the relative volatility of the match surplus — which causes the counterfactual amplification in the outflow rate (following the argument made by Hagedorn & Manovskii 2008). Moreover, we note that other potential sources, e.g. wage rigidity or union density also fail to replicate the first and second moments of both transition rates (Jung & Kuhn 2011).

The remainder of this paper is organized as follows. Section (2) describes the data construction. Section (3) presents the non-steady state decomposition method. Section (4) studies the "ins and outs" of unemployment in West-Germany. Section (5) examines the impact of the Hartz reforms on matching efficiency. Section (6) concludes.

2 Data

We measure gross worker flows between the labor force states of employment, E, unemployment, U, and inactivity, I, using the German Socio-Economic Panel (SOEP) for West-Germany and the Current Population Survey[6] (CPS) for the United States. Both data sets are representative household surveys, which ensures best possible comparability. The raw data are from the period 1983M1-2009M12. We reconcile the West-German data set using overlapping information. This requires that we drop all observations prior to 1984M1. In the following analysis, both reconciled West-German data and U.S. data are treated equally. In particular, we first take 12-month centered moving averages in order to remove high-frequency movements including seasonal variations. Second, we estimate weights in order to reconcile measured stocks and flows. Third, we correct for time aggregation bias in the data. The resulting final sample covers the period 1984M7-2009M6.

2.1 Direct and Indirect Transition Rates

We consider a three-state model, where individuals are either employed, E, unemployed, U, or inactive, I. In continuous time, these three states evolve according to the following system of equations:

$$\dot{U}_t = \lambda_t^{EU} E_t + \lambda_t^{IU} I_t - \left(\lambda_t^{UE} + \lambda_t^{UI}\right) U_t, \tag{1}$$

$$\dot{E}_t = \lambda_t^{UE} U_t + \lambda_t^{IE} I_t - \left(\lambda_t^{EU} + \lambda_t^{EI}\right) E_t, \tag{2}$$

$$\dot{I}_t = \lambda_t^{UI} U_t + \lambda_t^{EI} E_t - \left(\lambda_t^{IU} + \lambda_t^{IE}\right) I_t, \tag{3}$$

where λ_t^{XY} denotes the instantaneous transition rate from labor force state X to labor force state Y at time t; i.e., $\lambda_t^{XY} = XY_t/X_{t-1}$. In the steady state, when all three labor force states are constant; i.e., $\dot{U}_t = \dot{E}_t = \dot{I}_t = 0$, we can express the *steady state* unemployment rate, u_t^*, as:

$$u_t^* = \frac{s_t}{s_t + f_t} = \frac{\left(\lambda_t^{EU} + \lambda_t^{EI} \frac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}}\right)}{\left(\lambda_t^{EU} + \lambda_t^{EI} \frac{\lambda_t^{IU}}{\lambda_t^{IU} + \lambda_t^{IE}}\right) + \left(\lambda_t^{UE} + \lambda_t^{UI} \frac{\lambda_t^{IE}}{\lambda_t^{IU} + \lambda_t^{IE}}\right)}, \tag{4}$$

[6]The data are available from the following website: `http : //www.nber.org/data/cps_basic.html`.

where the total inflow rate, s_t, is defined as the sum of the direct transition rate from employment to unemployment, λ_t^{EU}, plus the indirect transition rate, λ_t^{EIU}. The latter is given by the product of the transition rate from employment to inactivity, λ_t^{EI}, times the share of inactivity exits to unemployment. The total outflow rate, f_t, is defined accordingly.

2.2 West-German Data

The SOEP is an annual survey of households representative for the entire population in Germany.[7] Launched in 1984, it constitutes the longest-running household survey in Europe spanning more than three complete business cycles (Haile 2009). The West-German sample covers, on average, 10,134 individuals aged 16-65. Individual weights are adjusted to the marginal distributions of age, gender, and nationality. Moreover, the SOEP attempts to relocate all individuals interviewed in the preceding wave. The share of successful follow-ups is remarkable; with more than 25% of first-wave respondents still being interviewed after 27 years in 2010 (ignoring deaths and moves abroad).[8]

At the annual interview, individuals are asked to fill in a detailed questionnaire on their *current* socio-economic situation —– including their current labor force status, C-LFS, the incidence of job change since the last interview, JOBCH, the start date of the current job, SCJ, the end date of the last job, ELJ, and the start date of the last job, SLJ —– and a calendar form that collects the *historical* labor force status, H-LFS, for each month of the preceding year.[9] Individual respondents are only allowed to declare themselves "unemployed" if they are registered accordingly at the Federal Employment Agency. If multiple labor force states are recorded for a single person in a given month, we prioritize employment, E, over unemployment, U, over inactivity, I (see Table 1).[10] The current SOEP (2011) version covers historical calendar data from 1983-2009 (which was collected in the years 1984-2010). The calendar data entries allow us to estimate aggregate labor market transition rates at a monthly frequency.

In addition, in order to facilitate comparison, the left panel of Figure (1) depicts the annual West-German unemployment rate according to the ILO definition (red solid line), the unemployment rate in our SOEP sample (blue dashed line), and the official West-German unemployment rate (black solid line).[11] Compared to the ILO unemployment rate, we note a difference in level, which changes over the business cycle, but does not display a long-term trend. We also

[7]Gross worker flows from the IAB, in contrast, are not representative for the entire population in Germany, as the IAB data set covers only employment subject to social security contributions and officially registered unemployment (Bachmann & Schaffner 2009). For this reason, civil servants, self-employed individuals (who together make up about 15% of the labor force, see Bundesagentur für Arbeit 2012*a*) and inactive individuals are observationally equivalent in this data set.

[8]For more detailed information see the official documentation (Kroh 2011).

[9]Given that JOBCH is available only at an annual frequency, we are unable include job-to-job transitions in this analysis.

[10]Note that giving multiple answers is not necessarily contradictory. For instance, an individual may have changed her labor force state in the middle of the month. Furthermore, being officially registered as unemployed does not rule out a certain form of part-time employment, so-called "mini-jobs". According to the ILO definition, our prioritization procedure ensures that these individuals are considered as employed (see also Table 1).

[11]The ILO unemployment rate is taken from microcensus data (Statistisches Bundesamt 2010), missing values prior to 2005 are fitted using other non-IL0 microcensus data (Statistisches Bundesamt 2012, the correlation coefficient between the two series is 0.9995 for the overlapping sample). The official West-German unemployment rate is taken from the Deutsche Bundesbank (2012) Time Series Databases. The gray shaded areas in Figure (1) denote recessions dated by the Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2009, p. 260) and the NBER (2010), respectively.

note that the level of the SOEP unemployment rate is lower than the level of the official rate, given that we consider all individuals as employed who are registered as unemployed at the Federal Employment Agency, but who hold a so-called "mini-job" (see Kluve et al. 2009, and Footnote 10). However, the level difference between these two rates is stable only until the mid-2000s. In January 2005, the Hartz IV reform widened the official definition of unemployment (Hartmann 2005), which explains why the hike in the official rate does not show up either in the ILO unemployment rate or in the SOEP unemployment rate. In the following years, the level difference seems to have diminished over time. This may be due to changes in the social security law criteria that aimed at increasing the incentives for job search (Statistische Ämter des Bundes und der Länder 2012, p. 36). Moreover, in first differences (see the right panel of Figure 1), we note that the SOEP unemployment rate leads the official rate and is more volatile at high frequencies (which is likely due to sampling error). Otherwise, both series behave very similarly.

2.2.1 Reconciling Inconsistent Calendar Data Entries

As pointed out by Wolff (1998) and Jürges (2007), information drawn from retrospective calendar data may be prone to systematic recall error. Even though the recall period in SOEP data is rather short, we address this potential bias by using a reconciliation method based on overlapping information of two consecutive years.[12] Therefore, all calendar data from the year 1983 or the entire first year of appearance of an individual are used for reconciliation purposes only, but ignored in the following analysis. In total, our reconciliation procedure reduces the average number of individuals from 10,134 to 9,044 in a typical month.

We assume that the statement on the current labor force status, C-LFS, is the most reliable source of information, followed up by JOBCH, SCJ, ELJ, and SLJ (where available). Therefore, we first check the consistency of the C-LFS entry of the current year, the C-LFS entry of the previous year, and the JOBCH entry. If there is any contradiction, we delete the individual calendar data between the last and the current interview (including the months of the current and the last interview). If the reported information is consistent, we further check whether the pattern is in line with the reported information on SCJ, ELJ, and SLJ. We also delete the individual calendar data when SCJ or ELJ is 'missing' or when the month of the interview is not known. In the following, we categorize the answers of the individual respondents (see Sub-section A.1 in the Appendix) and manipulate the calendar data accordingly (see Sub-section A.2).

Individuals without a recent employment spell (JOBCH: 'not employed') are not able to answer SCJ appropriately. Hence, the present reconciliation procedure risks being biased toward a certain subsample. Therefore, we extend the reconciliation procedure in order to eliminate potentially spurious transitions between the labor force states unemployment, U, and inactivity, I; e.g., U-I-U or I-U-I. We first check whether the C-LFS entry of both unemployed and inactive individuals *without a recent employment spell* at the time of the interview is identical to the H-LFS entry $i = 5$ months after/prior to the interview.[13] If this is the case, we set all

[12] Our reconciliation method is inspired by the work of Paull (2002) on BHPS data, but differs in several aspects from her approach.

[13] We choose $i_{max} = 5$, since more than 80% of the interviews were conducted before the end of April (Jürges 2007). Thus, for most individuals, we are able to compare the C-LFS entry with the H-LFS entries from the

calendar data entries in between these bounds equal to the C-LFS entry. If this is not the case, we iterate the procedure for $i = 4, 3, 2, 1$ months after/prior to the interview.

2.2.2 Margin Error Correction

As demonstrated by Fujita & Ramey (2009), panel survey data may be subject to margin error. Accordingly, missing observations are systematically related to changes in the labor force status and, consequently, should not be treated as random. For instance, margin error in our data set arises when SOEP fails to follow-up an individual who changes residence after taking a new job – even though SOEP makes best efforts to avoid this. As a result, the stock measure of employment (left-hand side) and the corresponding flow measure (right-hand side) do not exactly coincide:

$$E_{t-1} = EU_t + EI_t + EE_t, \tag{5}$$

$$E_t = UE_t + IE_t + EE_t, \tag{6}$$

where, for example, EU_t measures the gross worker flow from employment, E, to unemployment, U, in period t. The corresponding stock-flow equations for the remaining two labor force states of unemployment, U, and inactivity, I, are defined accordingly.

In order to reconcile stock and flow measures in our data set, we perform the following margin error correction procedure.[14] First, we split the sample into "German" males, "German" females, and "foreigners".[15] Thus, we explicitly control for gender composition effects — the most important source of margin error effects in U.S. data (Bleakley et al. 1999). Second, we smooth the stocks and the flows by taking 12-month centered moving averages. Given that the West-German labor market is characterized by relatively low transition rates, we are able to observe only slightly more than 100 transitions between the three labor force states from one typical month to the next — even though the reconciled SOEP data set covers on average 9,044 individuals. In particular, the average number of transitions between the states unemployment, U, and inactivity, I, is below ten, which inevitably results in large percentage changes from one month to the next. The 12-month centered moving average removes these high-frequency movements including seasonal variations (Fujita et al. 2007). Third, for each of the nine measured gross worker flows — including $EE(t)$, $UU(t)$, and $II(t)$ — we estimate a fixed weight[16] in order to reconcile aggregate stocks and flows. Therefore, we normalize the measured gross worker flows, z_{ij}, as follows:

$$\mu_{ij}(t) = \frac{z_{ij}(t)}{\sum_i \sum_j z_{ij}(t)}, \quad i, j = E, U, I. \tag{7}$$

current and the previous year. This allows us to eliminate spurious transitions at the beginning/end of the calendar year (so-called "seam bias" or "heaping", see Kraus & Steiner 1998, Wolff & Augustin 2003). Thus, in contrast to Biewen & Wilke (2005), we are unable to observe a peak in the UE transition rates at an unemployment duration of about 12 months (see Figure 2).

[14] The current paragraph follows largely the procedure described in Fujita & Ramey (2009). Further technical details can be found in the corresponding working paper version (Fujita & Ramey 2007).

[15] Note that the "foreigner" sample covers households with a household head from one of the five traditional immigrant nationalities in West-Germany (Greek, Italian, Spanish, Turkish, and Former-Yugoslavian). The "German sample" covers all other households.

[16] Due to data limitations, we are unable to estimate time-varying weights as in Fujita & Ramey (2009).

The adjusted measure of gross flows, $\gamma_{ij}(t)$, is defined as:

$$\gamma_{ij}(t) = \frac{\mu_{ij}(t)^{\theta_{ij}}}{\sum_i \sum_j \mu_{ij}(t)^{\theta_{ij}}}, \tag{8}$$

where θ_{ij} is the weight that captures the percentage factor by which the normalized flow, μ_{ij}, must be exponentiated in order to minimize the squared difference between the stocks implied by the fitted flows and the reported stocks. We estimate the weights using the following system of nonlinear equations:

$$x_{i*}(t) = \sum_j \gamma_{ij}(t) + \epsilon_{i*}(t), \quad i = E, U, I, \tag{9}$$

$$x_{*j}(t) = \sum_i \gamma_{ij}(t) + \epsilon_{*j}(t), \quad j = E, U, I, \tag{10}$$

where $x_{i*}(t)$ and $x_{*j}(t)$ indicate the SOEP stocks at the beginning of months $t-1$ and t, respectively. Finally, we merge the weighted three subsamples in order to obtain the full margin error corrected sample for West-Germany.

2.2.3 Time Aggregation

We measure *instantaneous* transition rates between labor force states using survey data which are available at *discrete* points in time only. However, direct measures of gross worker flows may be biased downward — given that workers may experience more than one transition between two observation points (Shimer 2012). Evidence from German IAB data indicates that these "time-aggregation" effects are not only important in the United States — where labor force transition rates are substantially higher — but also in Germany.[17] Therefore, in the following, we estimate instantaneous labor force transition rates using a continuous-time model that encompasses all transitions between two observation points.[18]

2.2.4 Subsamples

We analyze the properties of the full sample for West-Germany, the "Foreigner" sample (see Footnote 15), the "German" sample, and the "German" sample disaggregated by gender, age (young, prime-age, and old), and educational background (low-skilled and high-skilled). We define the set of prime-age individuals using changes in the labor force participation rate (see Figure 3). We observe that the labor force participation rate of the population in West-Germany is extremely stable between the ages 29 and 49; i.e., the change in the labor force participation rate from one cohort to the next is below one percentage point. High-skilled individuals are required to hold a degree qualifying for admission to a university of applied sciences ("Fachhochschulreife") or higher.

[17] In particular, Nordmeier (2012) argues that time-aggregation effects seem to bias not only the level, but also the cyclicality of the estimated labor force transition rates.

[18] See Shimer (2012, pp. 133–134) and the Mathematica code available on the corresponding website: `http://sites.google.com/site/robertshimer/research/flows`.

2.3 United States

Launched in 1948, the CPS is the major source of U.S. labor market statistics, including the official measures of unemployment and labor force participation. The CPS is designed as a rotating panel; i.e., households are surveyed for four consecutive months, rotated out for the next eight months, and then surveyed again for another four consecutive months. In an average month, the CPS covers 67,045 individuals aged 16-65. We match individual records across periods using the code of Shimer (2012). Due to panel rotation, at most 75% of all individuals can be matched from one month to the next. In practice, however, the share of matched records is considerably lower. As no attempt is made to follow-up individuals who change residence (Fujita et al. 2007), we note that panel attrition in the CPS is more severe than in SOEP data.

As mentioned above, both reconciled West-German data and U.S. data are treated equally. In particular, we take 12-month centered moving averages in order to remove high-frequency movements including seasonal variations, we estimate fixed weights in order to reconcile measured stocks and flows (for this purpose, we split the sample into males and females), and we correct for time aggregation bias.

In order to define the sample of prime-age workers (here: all cohorts between 25 and 49 years), we apply the same criterion as for SOEP data; i.e. the change in the labor force participation rate must be below one percentage point from one cohort to the next (see Figure 3). High-skilled individuals are required to have completed at least “some college”.

2.4 Comparative Descriptive Statistics

Figure (4) depicts the unadjusted and adjusted total inflow and total outflow rate, respectively, for both countries.[19] The graphs illustrate that our data treatment procedure affects mainly their level, rather than their cyclical behavior. In particular, we find that the margin error correction reduces the level of both series in both countries, while the time aggregation adjustment has the opposite effect. In West-Germany, the impact of margin error correction seems quantitatively more important. In the United States, on the other hand, the effects of time aggregation adjustment are substantially larger than the effects of the margin error correction.

Tables (2) and (3) summarize the first and second moments, respectively, for West-Germany and the United States. We observe that the average unemployment rate for the period 1984M7-2009M6 is close to 5.5% in both countries. However, compared to the United States, the transition rates in West-Germany are lower by an order of magnitude (see also Schmidt 2000, Gartner et al. 2012). Indirect transitions via inactivity constitute about 18% (females: 22%) of all transitions in West-Germany and even more than 28% (females: 32%) in the United States. Young adult unemployment seems to be a more serious problem in the United States (U=11.6%) than in West-Germany (U=5.0%), while the older unemployed in West-Germany have a very hard time finding a job (F=3.0%). In both countries, the level of education seems to be a very important determinant of the sample-specific unemployment rate. In West-Germany, the unemployment rate in the high-skilled subsample (U = 2.5%) is lower than in the low-skilled subsample (U = 5.9%), since high-skilled individuals find new jobs much faster (F=13.8%)

[19] The total inflow and the total outflow rate are defined in Equation (4).

than their low-skilled counterparts (F=5.2%). In the United States, on the other hand, the unemployment rate in the high-skilled subsample (U = 2.8%) is lower than in the low-skilled subsample (U = 7.1%), since the risk of job loss is substantially higher for low-skilled individuals (S=3.7%) than for high-skilled individuals (S=1.6%).

Figure (5) illustrates the total inflow rate, the total outflow rate, and the sample-specific unemployment rate in both countries. From 1990 to 2005, the West-German unemployment rate displays a protracted rise, which was only shortly interrupted between the years 1997-2000. Since 2005, we note a gradual but steady decline. Importantly, the unemployment rate continued to fall even during the Great Recession.[20] Over the full sample period, the unemployment rate co-moves positively with the total inflow rate and negatively with the total outflow rate, where — at first glance — the cyclical co-movement with the total inflow rate seems stronger. We also note that both transition rates are subject to substantial high-frequency variations.

Quite surprisingly, the observed pattern in the United States is very different. After a long-lasting downward trend, which started in the mid-1980s, the U.S. unemployment rate reached a bottom at the beginning of the new millennium. Between the years 2000 and 2007, the U.S. unemployment rate remained at low level. After the outbreak of the Great Recession, however, we observe a steep increase. In contrast to West-Germany, the cyclical co-movement between the unemployment rate and the total inflow rate seems stronger than the cyclical co-movement with the total outflow rate. We also note that both transition rates exhibit much weaker high-frequency movements than in West-Germany. This observation is very likely due to the fact that the average number of individuals in the CPS is larger by factor eight (see Table 2).

3 Dynamic Decomposition Model

The following section presents a method to decompose changes in the unemployment rate into changes in the total inflow rate and changes in the total outflow rate — both directly and indirectly via inactivity. We quantify the relative importance of these channels using the non-steady state decomposition method developed by Smith (2011).

3.1 Steady State Decomposition

3.1.1 Formal Derivation

As demonstrated by Shimer (2012), Equation (4) can be used to decompose changes in the steady state unemployment rate, $\Delta u_t^*/u_{t-1}^*$, into changes in the total inflow rate, s_t, and changes in the total outflow rate, f_t. Therefore, we take first differences and re-arrange terms in order to obtain:[21]

$$\frac{\Delta u_t^*}{u_{t-1}^*} = \underbrace{(1-u_t^*)\left(\frac{\Delta s_t}{s_{t-1}}\right)}_{\bar{C}_t^S} \underbrace{-\left(u_t^*/u_{t-1}^*\right)\left(1-u_{t-1}^*\right)\left(\frac{\Delta f_t}{f_{t-1}}\right)}_{\bar{C}_t^F}, \tag{11}$$

[20] As documented by Burda & Hunt (2011), Germany experienced an even sharper decline in GDP than the United States.

[21] Equation (11) is not identical to Equation (8) in Smith (2011) as we do not approximate u_t^* by u_{t-1}^*.

where $\bar{C}_t^S$ and $\bar{C}_t^F$ represent the contributions of percentage changes in the total inflow rate and the total outflow rate, respectively, to percentage changes in the steady state unemployment rate. Furthermore, we are able to decompose $\bar{C}_t^S$ and $\bar{C}_t^F$ into changes in the direct and the indirect components (which are defined accordingly):

$$\begin{aligned}\frac{\Delta u_t^*}{u_{t-1}^*} = & \overbrace{\frac{(1-u_t^*)}{s_{t-1}}\Delta\lambda_t^{EU}}^{\bar{C}_t^{EU}} + \overbrace{\frac{(1-u_t^*)}{s_{t-1}}\Delta\left[\frac{\lambda_t^{EI}\lambda_t^{IU}}{\lambda_t^{IU}+\lambda_t^{IE}}\right]}^{\bar{C}_t^{EIU}} \\ & \underbrace{-\frac{u_t^*}{u_{t-1}^*}\frac{(1-u_{t-1}^*)}{f_{t-1}}\Delta\lambda_t^{UE}}_{\bar{C}_t^{UE}} \underbrace{-\frac{u_t^*}{u_{t-1}^*}\frac{(1-u_{t-1}^*)}{f_{t-1}}\Delta\left[\frac{\lambda_t^{UI}\lambda_t^{IE}}{\lambda_t^{IU}+\lambda_t^{IE}}\right]}_{\bar{C}_t^{UIE}}\end{aligned} \tag{12}$$

Following Fujita & Ramey (2009), the relative contribution of margin X to the variability in the steady state unemployment rate in a given sample period can be quantified as:

$$\beta^{*,X} = \frac{\operatorname{Cov}\left(\Delta u_t^*/u_{t-1}^*, \bar{C}_t^X\right)}{\operatorname{Var}\left(\Delta u_t^*/u_{t-1}^*\right)} \tag{13}$$

3.1.2 Applicability in Practice

In recent years, the steady state decomposition method has attracted a great deal of attention, with a particular focus on the United States (Yashiv 2008, Elsby et al. 2009, Fujita & Ramey 2009, Shimer 2012). Adaptations of this methodology to European economies include Petrongolo & Pissarides (2008) for the UK, France, and Spain; Gomes (2011) for the UK, using a longer sample period; Şengül (2012) for Turkey; and Jung & Kuhn (2011), using German IAB data (see also Footnote 7).

The steady state decomposition method accurately determines the "ins and outs" of unemployment if changes in the *actual* unemployment rate, u_t, are sufficiently well approximated by changes in the *steady state* unemployment rate, u_t^*. The right panel of Figure (6) illustrates that, in the United States, both time series behave remarkably similar at business cycle frequencies as well as in first differences. We only note that the volatility of the differenced steady state unemployment rate is slightly higher. Thus, it is a straightforward exercise to decompose changes in the unemployment rate into changes in the underlying transition rates.

Unfortunately, however, the United States is a major exception. In West-Germany, as in most other developed economies, the steady state unemployment rate does not serve as a good approximation, but only as a noisy indicator which leads the actual unemployment rate by almost one year. Even more importantly, in first differences, the volatility of the steady state unemployment rate is greater by several orders of magnitude (see the left panel of Figure 6). The reason why the steady state unemployment rate constitutes a very good approximation of the actual unemployment rate in the United States — but not in West-Germany — is the level of the underlying transition rates. In the United States, both the total inflow rate, s_t, and the total outflow rate, f_t, are on average greater by an order of magnitude (see Table 2). This is important, as the sum of the two transition rates determines the rate of convergence of the actual unemployment rate to its flow steady state value. As documented by Elsby et al. (2009), the U.S. unemployment rate converges very fast — the half-life of a deviation from the flow steady state value is only about one month. In West-Germany, by contrast, our estimates imply that the half-life of a deviation is more than nine months.

Due to the sluggish behavior of the West-German labor market, large percentage changes in the underlying transition rates (represented by large percentage changes in the *steady state* unemployment rate) have only a partial contemporaneous effect on the current *actual* unemployment rate (Elsby et al. 2011, Footnote 26). This explains the large discrepancy between these two time series in first differences. However, as further argued by these authors, the decomposition exercise based on Equation (13) erroneously attributes the full effect contemporaneously. Therefore, we observe that changes in the transition rates "explain" more than 164% of the movements in the actual West-German unemployment rate. Obviously, this method is unable to provide reasonable estimates for the driving forces of unemployment variation in countries with low labor market transition rates.

3.2 Non-Steady State Decomposition

In order to account for the sluggish labor market adjustments in West-Germany, we decompose the ins and outs of unemployment using the dynamic factor approach developed by Elsby et al. (2011) and Smith (2011). The starting point of this decomposition method is the law of motion of the actual unemployment rate, u_t:

$$\dot{u}_t = (1 - u_t)s_t - f_t u_t \tag{14}$$

$$u_t = \underbrace{\frac{s_t}{s_t + f_t}}_{u_t^*} - \frac{\dot{u}_t}{s_t + f_t} \tag{15}$$

where implicitly zero labor force growth, $\dot{I} = 0$, is assumed; i.e., workers may flow between all three labor force states, but the change in the number of unemployed workers, $\dot{U}_t$, is assumed to equal the negative of the change in the number of employed workers, $-\dot{E}_t$, at all times.[22].Next, we differentiate Equation (15) with respect to time t, discretize, and rearrange terms. This yields the following recursive structure:

$$\Delta u_t = \frac{\Delta u_t^*}{u_{t-1}^*} \underbrace{\frac{s_{t-1}(s_t + f_t)}{(s_t + f_t)^2 + (s_{t-1} + f_{t-1})}}_{F_t} + \Delta u_{t-1} \underbrace{\frac{(s_t + f_t)}{(s_t + f_t)^2 + (s_{t-1} + f_{t-1})}}_{G_t} + \epsilon_t \tag{16}$$

where the residual, ϵ_t, captures violations of maintained assumptions; i.e., zero labor force growth, constant transition rates within months, or linearity (Smith 2011). According to Equation (16), the change in the actual unemployment rate, Δu_t, is a function of the percentage change in the steady state unemployment rate, $\Delta u_t^*/u_{t-1}^*$, and the lagged change in the actual unemployment rate, Δu_{t-1}; with time-varying coefficients, F_t and G_t, respectively. The mean value of F_t/u_{t-1}^* can be interpreted as the average monthly rate of convergence, the mean value

[22]In our sample period, labor force growth averages around 0.0005 on a monthly basis (Statistisches Bundesamt 2012), while the sum of the two transition rates, $f_t + s_t = 0.063$, is greater by more than two orders of magnitude (see Table 2). Thus, allowing for labor force growth seems quantitatively not important (Elsby et al. 2011)

of G_t is the corresponding autoregressive coefficient which represents the impact of *past* changes in the underlying transition rates on the *current* unemployment rate. In West-Germany, we observe that the average monthly rate of convergence is only 6%, compared to 37% in the United States. This result illustrates formally that the (change in the) steady state unemployment rate approximates the (change in the) actual unemployment rate reasonably well if — and only if — the underlying labor market transition rates are sufficiently large.

The top left panel of Figure (7) displays the time path of the actual West-German unemployment rate, u_t, represented by the blue dashed line, and the time path of the unemployment rate generated by the right-hand side of Equation (16), Δu_t^{RHS}, represented by the red solid line. We observe that the generated unemployment rate is about one percentage point lower (due to the initial deviation from steady state), but the cyclical properties are extremely similar. In addition, the bottom left panel of Figure (7) shows that the theoretical relationship holds remarkably well also in first differences (note the striking difference compared to Figure 6). Moreover, in the United States, the two time series are virtually identical — both in levels and in first differences.

The advantage of the representation in Equation (16) is that the percentage change in the steady state unemployment rate, $\Delta u_t^*/u_{t-1}^*$, can be decomposed into the steady state contributions of total inflows and total outflows (see Equation 11). We then iterate the resulting expression ad infinitum. Consequently, the *dynamic* contributions of total inflows and total outflows, respectively, are given as (see Appendix C):

$$C_t^S = F_t\bar{C}_t^S + G_t C_{t-1}^S \tag{17}$$

$$C_t^F = -F_t\bar{C}_t^F - G_t C_{t-1}^F \tag{18}$$

where $C_0^S = C_0^F = 0$. Figure (8) depicts the time paths of the dynamic contributions (red solid line) and the first difference of the actual unemployment rate (blue dashed line) for both countries. The graphs confirm the impression drawn from Figure (5). In West-Germany, the co-movement between Δu_t and C_t^S seems closer than with C_t^F, whereas in the United States the reverse situation prevails. In addition, analogously to Equation (12), we are able to decompose both C_t^S and C_t^F into changes in the direct and the indirect components (not shown here).

Finally, we quantify the relative contribution of margin X to the variability in the *actual* unemployment rate in two stages. First, we compute the β-values between the change in the actual unemployment rate, u_t, on the one hand, and the change in the unemployment rate generated by the right-hand side of Equation (16), Δu_t^{RHS}, and the residual, ϵ_t, on the other hand:[23]

$$\beta^U = \frac{\text{Cov}\left(\Delta u_t, \Delta u_t^{RHS}\right)}{\text{Var}\left(\Delta u_t\right)}, \quad \beta^\epsilon = \frac{\text{Cov}\left(\Delta u_t, \epsilon_t\right)}{\text{Var}\left(\Delta u_t\right)} \tag{19}$$

[23] The advantage of our two-stage procedure is that, by construction, the relative contributions of the total inflow rate and the total outflow rate add up to one.

Second, we compute the average contribution of margin X to changes in Δu_t^{RHS}:

$$\beta^X = \frac{\text{Cov}\left(\Delta u_t^{RHS}, C_t^X\right)}{\text{Var}\left(\Delta u_t^{RHS}\right)} \tag{20}$$

where, in order to capture deviations from the steady state in the initial period, the first 18 data points are discarded.[24] Consequently, the relative contributions are estimated based on the period 1986M1-2009M6.

4 The Ins and Outs of Unemployment in West-Germany

We now study the "ins and outs" of unemployment in West-Germany. First, we present descriptive statistics of the data described in Section (2). Second, we analyze the relative contributions of changes in the total inflow and the total outflow rate to the variability in the actual unemployment rate; i.e., the "difference specification". Third, we examine the corresponding estimates at medium and low frequencies; i.e, the "bandpass filter specification". This allows us to analyze whether the relative importance of inflows and outflows differs along the frequency domain.

4.1 Difference Specification

In the United States, there seems to be consensus that movements in the total outflow rate are the principal driving force of fluctuations in the U.S. unemployment rate.[25] In Germany, on the other hand, the picture remains disturbingly opaque. Jung & Kuhn (2011), based on a steady state decomposition of IAB gross worker flows, find that the inflow rate is more important than the ouflow rate; Elsby et al. (2011), based on a non-steady state decomposition of annual OECD unemployment duration data,[26] observe approximately a 50:50 split; and Nordmeier (2012), based on a non-steady state decomposition of IAB gross worker flows, argues that the outflow rate is more important than the inflow rate. To our knowledge, the latter work is the only study that has attempted to conduct a non-steady state decomposition using German gross worker flows so far. In contrast to our paper, however, Nordmeier considers only two labor force states (employment and unemployment) and defines unemployment more broadly than we do.

Overall Model Fit Table (4) shows the decomposition results for West-Germany and the United States. The estimate in the first row, β^U, measures the overall model fit (see Equation 19). In the full sample representative for the entire population in West-Germany, the dynamic decomposition accounts for 83% of all changes in the actual unemployment rate, Δu_t. Put differently, 17% of all changes in the actual unemployment rate remain unexplained. The

[24] The lower left panel of Figure (7) shows that the impact of deviations from the steady state in the initial period vanishes after about 18 months.

[25] The estimates range from close to 50% (Fujita & Ramey 2009) to 75% (Shimer 2012).

[26] We prefer to use gross worker flows, as duration dependence in the total outflow rate may bias the conclusions drawn from unemployment duration data. Elsby et al. (2011) are unable to reject the null hypothesis of no duration dependence at the 99% significance level, but they reject the null hypothesis at the 95% significance level. Figure (2) illustrates that, in our sample, the UE transition rate exhibits substantial duration dependence. Similar evidence for the United States is provided by Shimer (2008, Figure 1).

discrepancy is very likely due to sampling error. Note, therefore, that the fit of the "full sample" (9,044 observation on average) is superior to the fit of the "German sample" (81%, with 7,577 observations on average), even though the fit of the "foreigner sample" (61%, with 1467 observations on average) is clearly worse. In the United States, on the other hand, where the average number of observations is larger by factor eight, we observe that the model fit is much better (98% for the full sample). Moreover, consistent with the sampling error hypothesis, we also note that the model fit of small U.S. subsamples (e.g., the young or the old) is somewhat lower (about 89%). The sampling error hypothesis is also confirmed by the near-unity (0.93) correlation coefficient between the log number of observations and the estimated model fit across all subsamples.

West-Germany Table (4a) displays the decomposition results for all West-German subsamples. We observe that, in the full sample, changes in the total inflow rate account for 59% of all changes in u_t^{RHS} (see Equation 19), only 40% are due to changes in the total outflow rate. Most of the variability, about 80%, is due to direct transitions between employment and unemployment, while 20% of the variablility is due indirect transitions through inactivity. Moreover, we find that the dominance of inflows over outflows is very robust across all demographic subsamples but the young. Transitions involving inactivity are particularly important for "foreigners" and females. By comparsion, Jung & Kuhn (2011), based on a steady state decomposition, also find that inflows dominate over outflows in the German labor market. However, their results indicate that this pattern is mainly driven by males and medium skilled workers (see Table I in their paper).

United States Table (4b) illustrates the decomposition results for all U.S. subsamples. In stark contrast to West-Germany, only 20% of all changes in u_t^{RHS} (see Equation 19) are due to changes in the total inflow rate, while 80% are due to changes in the total outflow rate. The relative importance of direct (82%) and indirect (18%) transitions, on the other hand, is very similar to the West-German sample. The dominance of outflows over inflows is robust across all subsamples, while the importance of inflows seems to increase during the working life. Also, in the male subsample, outflows seem somewhat more important than in the female subsample. Transitions involving inactivity are particularly important for females and the old.

Discussion The decomposition exercise has shown that, in West-Germany, changes in the total inflow rate are the most important driving force of changes in the actual unemployment rate — whereas the reverse situation prevails in the United States.[27] This result is driven by the fact that the relative volatility of the total inflow rate in West-Germany is larger by factor four, while the relative volatility of the total outflow rate is similar across countries (see Table 3). In addition, we note that labor market transition rates in West-Germany are smaller by an order of magnitude (see Table 2). Based on the theoretical work by Jung & Kuhn (2011), the following section provides an intuition whether the observed pattern can consistently be replicated by a matching model with endogenous job separations (den Haan et al. 2000).

[27] In both countries, the relative contributions seems to be stable over the business cycle. In the United Kingdom, by contrast, inflows dominate during recessions, while outflows dominate in periods of moderation (Smith 2011).

First, we consider the case when the model is calibrated with low matching efficiency for West-Germany and high matching efficiency for the United States. Low matching efficiency — caused e.g. by low occupational and/or regional mobility among the labor force — reduces the total outflow rate and, thus, the worker's outside option. This implies that the match surplus in West-Germany is much larger. Importantly, the *relative* volatility of the match surplus remains unchanged, since both the surplus size and its *absolute* volatility increase by the same proportion. Given that the relative volatility of the total outflow rate is determined by the *relative* volatility of the match surplus to productivity shocks (Hagedorn & Manovskii 2008), the model predicts, consistently with the data, that the relative volatility of the total outflow rate is similar across countries. On the other hand, the rise in the surplus size reduces the incentives to separate after a negative technology shock. As a result, the total inflow rate falls. Furthermore, the relative volatility of the total inflow rate increases as it depends on the *absolute* volatility of the match surplus to productivity shocks. Therefore, we note that the calibrated model qualitatively replicates the pattern observed in the data.

In addition, we study cross-country differences in the worker's bargaining power, representing e.g. higher union density in West-Germany. We find that this channel has similar implications as low matching efficiency, but its amplification mechanism is much smaller. Intuitively, the potential of this mechanism depends on the difference between the worker's bargaining power and the matching elasticity of the unemployment rate; i.e., the deviation from the Hosios (1990) condition.[28] Thus, this channel is only able to match the relative volatility of the total inflow rate if the worker's bargaining power is close to unity — which in turn implies that the unemployment rate mounts up to more than 20%.

Alternatively, the low level of mean transition rates can also be replicated by calibrating the West-German model economy with high unemployment benefits and high firing costs.[29] The generosity of unemployment benefits dampens the total outflow rate and increases the total inflow rate, whereas the impact of high firing costs on both transition rates is negative. As a result, for reasonable parameter values, the level of both transition rates falls. The key difference to the model with low matching efficiency is that an increase in unemployment benefits increases both the *absolute* and the *relative* volatility of the match surplus; i.e, the size of the match surplus does not increase by the same proportion. More precisely, we note that the effect on the match surplus is ambiguous — as the higher flow income during unemployment increases the worker's outside option, but the lower probability of finding a job has the opposite effect. Thus, by the same reasoning as under low matching efficiency, the rise in the *absolute* volatility of the match surplus amplifies the relative volatility of the total inflow rate. On the other hand, the rise in the *relative* volatility of the match surplus generates a counterfactual amplification in the relative volatility of the total outflow rate (again, following the argument by Hagedorn & Manovskii 2008). For this reason, a job matching model calibrated with high unemployment benefits and high firing costs is unable to qualitatively match the data.

[28] In addition, note that our estimates for the matching elasticity of the unemployment rate using West-German data (see Section 5.2) are even higher than the corresponding values for the United States (Brügemann 2008).

[29] Evidence on the generosity of unemployment benefits and the extent of firing restrictions across countries is provided e.g. Nickell et al. (2005) or Faccini & Rosazza Bondibene (2012).

Furthermore, we learn that the introduction of wage rigidity leaves the mean transition rates unchanged, but amplifies both the total inflow and the total outflow rate (see also Bertola & Rogerson 1997). For this reason, the role of this factor seems unlikely to be important in this context. Hence, in summary, the evidence presented in this section corroborates the conclusion by Jung & Kuhn (2011) that low matching efficiency in the West-German labor market constitutes a very important determinant in explaining the observed cross-country differences.

4.2 Bandpass Filter Specification

In the previous section, we have analyzed the determinants of changes in the actual unemployment rate. However, at least in the United States, there seems to be consensus that the increase in the unemployment rate at the start of a recession is driven by a sharp spike in the inflow rate. During the subsequent recovery, the unemployment rate remains at a high level as the outflow rate falls persistently below the long-term average (Fujita & Ramey 2009, Rogerson & Shimer 2011). In other words, movements in the inflow rate are reported to occur at high frequencies, while movements in the outflow rate seem more important at lower frequencies.[30] For this reason, we examine the corresponding estimates also at medium and low frequencies. Therefore, we remove the high frequencies below eight years from all series using the bandpass filter of Christiano & Fitzgerald (2003) prior to estimation of the relative contributions.

Table (5) and Figures (9)-(10) summarize the results for West-Germany and the United States. All major conclusions are robust to this specification. Put differently, the importance of the total inflow rate in West-Germany prevails not only at high, but also at medium and low frequencies. Furthermore, we observe that the model fit of all West-German subsamples improves considerably. This indicates that a great deal of unexplained variation in the difference specification can indeed be explained by high-frequency noise due to sampling error.

5 Before and After the Hartz Reforms

The main aim of the Hartz reforms was to improve the efficiency of the matching process by stimulating the search effort of the unemployed (Fahr & Sunde 2009) and by re-organizing the Federal Employment Agency into a customer-orientated service center (Jacobi & Kluve 2007). In the following, we test the macroeconomic effectiveness of this policy change on two different grounds. First, we examine whether the relative contributions of the total inflow rate (job separation) and the total outflow rate (job finding) to unemployment variability have changed after the mid-2000s. Following the results discussed in Section (4.1), we expect than an improvement in matching efficiency manifests itself as a rise in the relative contribution of the total outflow rate. Second, we estimate an empirical matching function (Petrongolo & Pissarides 2001) where we allow for a structural break around the year 2003. As is standard in this strand of the literature (Barnichon & Figura 2011), we define matching efficiency as the Solow residual of an aggregate matching function with the observed levels of unemployment and vacancies as explanatory variables.

[30]Note that part of the high-frequency movements in our data set has been already removed by the 12-month centered moving average filter. As argued by Elsby et al. (2011, Footnote 12), it is mainly the inflow rate that exhibits such high-frequency variations.

5.1 Evidence from the Ins and Outs

The West-German labor market underwent a series of institutional changes in our sample period (see Ebbinghaus & Eichhorst 2006, Table 1). For instance, in 1996, the first so-called "Sparpaket" (austerity plan) liberalized the use of temporary employment contracts. As a result, the OECD overall index "strictness of employment protection" dropped from 3.09 in 1996 to 2.34 in 1997 (see Figure 11). Moreover, in the years 2003-2005, the German government implemented a series of reforms, the so-called Hartz reforms, that introduced a large number of new measures with emphasis on activation policies (e.g. stricter mobility requirements, shorter duration of unemployment insurance benefits for older workers, replacement of earnings-related with means-tested unemployment benefits). In addition, the Hartz reforms also involved the reorganization of the Federal Employment Agency. In the following, we examine whether these policy changes are associated with changes in the estimated relative contributions.

Figure (12) displays the centered 95% confidence bands of the point estimates when we estimate the relative contributions of total inflows and total outflows using an eight-year rolling window (such that the estimates capture one full business cycle). We observe that, until the early 2000s, the relative contributions are stable and very close to their long-term average. Since then, however, the relative importance of the total outflow rate (red solid line) has been steadily increasing. The last data point, estimating the average relative contributions for the subsample 2001M7-2009M6, implies that both total inflows (blue dashed line) and total outflows contribute about 50% to the changes in the unemployment rate. Furthermore, we observe that the vanishing dominance of the total inflow rate over the last decade goes along with a drop in the cyclical volatility of the total inflow rate (see the right panel of Figure 13).

The rising importance of the total outflow rate, in conjunction with the falling cyclical volatility of the total inflow rate, is consistent with the predictions of the model by Jung & Kuhn (2011). Prior to the early 2000s, low matching efficiency used to be the main friction in the labor market. For this reason, the 1996 Sparpaket did not change the pattern significantly. The Hartz reforms, instead, focused on improving matching efficiency. Our results indicate that this policy change has in fact improved the efficiency of the matching process, which manifests itself as a rise in the contribution of total outflows to unemployment variability.

5.2 Evidence from a Matching Function

In addition to this, we test the hypothesis of higher matching efficiency since the mid-2000s using a standard matching function (Petrongolo & Pissarides 2001). The matching function postulates that the current matching rate, m_t, is a function of the vacancy rate, v_t, and the unemployment rate, u_t:

$$m_t = \chi v_t^{\alpha} u_t^{1-\alpha} \Rightarrow \tag{21}$$

$$f(\theta_t) = m_t/u_t = \chi\theta^{\alpha}, \quad \text{where} \quad \theta = v_t/u_t \tag{22}$$

Owing to constant returns to scale, the job finding rate, $f(\theta_t)$, is a function of labor market tightness, θ_t, only. Matching efficiency is governed by the parameter χ. For this reason, if the Hartz reforms have increased matching efficiency significantly, we expect to observe a structural break around the year 2003 when we regress the log job finding rate (here: total outflow rate), $f(\theta_t)$, on log labor market tightness, θ_t. The only missing variable in order to estimate Equation (22) is the vacancy rate, v_t. Therefore, we divide the 12-month centered moving average of the West-German job vacancy series (Bundesagentur für Arbeit 2012*b*) by the corresponding labor force (Statistisches Bundesamt 2012).[31]

The top left panel of Figure (14) depicts the evolution of the log total outflow rate (blue dashed line) and log labor market tightness (red solid line). Both time series show a pro-cyclical pattern, particularly labor market tightness. From peak to trough, the v/u ratio falls by about one log point in a typical recession, while the cyclical volatility of the total outflow rate is somewhat weaker. We also note that the log total outflow rate exhibits more high-frequency variation than log labor market tightness. At low frequencies, both series display long cycles. In particular, the downward trend in the (total) outflow rate after 1990 has been extensively documented in the literature (Schmidt 2000, Bachmann 2007, Jung & Kuhn 2011, Nordmeier 2012). This pattern, suggesting a deterioration in matching efficiency, may actually be caused by changes in the composition of the labor force (Barnichon & Figura 2011). Indeed, Figure (14) shows that, from 1984 to 2009, the share of young labor force members — characterized by a relatively high total outflow rate $f(\bar{\theta}) = 10.2\%$ — has decreased from 27% to 18%, while the share of old labor force members — characerized by a relatively low total outflow rate $f(\bar{\theta}) = 3.0\%$ — has increased from 21% to 28% (see also Table 2). Thus, it seems very plausible that the ageing of the labor force has contributed to the decline in the total outflow rate. In addition, at the same time, the share of female labor force members has increased from 40% to 49%. However, the average of the total outflow rate of females, $f(\bar{\theta}) = 6.6\%$, is only slightly below the male average, $f(\bar{\theta}) = 7.4\%$. For this reason, it seems unlikely that the rising trend in female labor force participation is a major driving force of the downward trend in the total outflow rate. Moreover, due to rising educational attaintment, the share of high-skilled labor force members has increased from 26% to 39% in our sample period. Yet, as the average total outflow rate of high-skilled invidiuals, $f(\bar{\theta}) = 13.8\%$, is more than twice as large than the average total outflow rate of low-skilled individuals, $f(\bar{\theta}) = 5.2\%$, rising educational attaintment clearly did not cause, but rather dampened the downward trend in the total outflow rate.

Therefore, when estimating Equation (22), we control for all the demographic factors mentioned above.[32] The covariance matrix of the coefficients is determined using the Newey & West (1987) estimator.[33] Thus, we allow for autocorrelation in the error term. Table (6) shows that the baseline model fits the data reasonably well.[34] As expected, we estimate a significantly positive coefficient for the share of young labor force members, a significantly negative coefficient for the share of old labor force members, and a significantly positive coefficient for the share of

[31] Note that the vacancy series "gemeldete Stellen" comprises both subsidized and unsubsidized vacancies. The vacancy series "gemeldete Arbeitsstellen", covering unsubsidized vacancies only, is not available before January 2000. The annual West-German labor force including West-Berlin is only available until 2004. We extend the time series using the growth rate of the German labor force for 2005 and the growth rate of the West-German labor force excluding West-Berlin thereafter. Finally, we interpolate the resulting series to a monthly frequency.

[32] To be precise, we include the log trend component of the four demographic factors, after having filtered out all frequencies below eight years using the default Christiano & Fitzgerald (2003) bandpass filter (see Figure 14).

[33] Both the NW bandwidth = 14 and the NW lag length = 5 are determined automatically.

[34] Furthermore, it would be interesting to adopt the decomposition method suggested by Barnichon & Figura (2012). However, due to the small sample size of the SOEP compared to the CPS, we are unable to split the sample in more than three demographic subsamples at the same time.

high-skilled labor force members (see column 1). Only the sign of the coefficient for the share of female labor force members seems counterintuitive, but its magnitude is relatively low and the level of significance is not very high. The coefficient of log labor market tightness is equal to 0.20 and statistically significant at the 99% level.

Next, in order to test the hypothesis of higher matching efficiency, we include a level dummy in 2003M9 (see clolumn 2, "benchmark specification").[35] We observe that the level dummy is highly significant and that its inclusion improves the goodness of fit as well as the Durbin-Watson test statistics. The estimated coefficient of the level dummy is equal to 0.23, implying that matching efficiency has increased by 23% in late 2003 (see also the top right panel of Figure 14). Moreover, the sign and the magnitude of all demographic controls is intuitive and the coefficients are statistically significant — except for the share of females in the labor force, which seems insignificant across most specifications. The estimated coefficient of log labor market tightness, corresponding to the parameter α in equation (22), is equal to 0.32. This value is almost identical to the estimate by Burda & Wyplosz (1994) for the pre-unification era.

Further robustness checks reveal that the 66% confidence bands of the coefficient of the vacancy rate (0.23) and the negative coefficient of the unemployment rate (-0.45) are overlapping when the two variables enter the estimation equation separately (column 3). This indicates that the imposed specification with constant returns to scale approximates the matching process in West-Germany sufficiently well. In addition, we obtain virtually identical results as in column 2 when we use the lagged value of log labor market tightness as an instrumental variable (not shown here). In order to control for cyclical movements in the quality of the unemployment pool,[36] we additionally control for GDP growth (column 4). We find that the sign of the coefficient is negative, but statistically insignificant. All other results remain virtually unchanged. The results are also similar, but the goodness of fit is slightly worse, when we use the UE_t transition rate (as in Barnichon & Figura 2012), instead of the total outflow rate, f_t, as the endogenous variable in the estimation equation (column 5). In column 6, we additionally include the lagged value of log market tightness as an independent variable. Thus, in the absence of more detailed data for the whole sample period, we control not only for the current level of market tightness, but also for the change between the current and the past period; i.e., the "stock" and the "flow" (Coles & Smith 1998). We find that the sum of the coefficients of the current and lagged value of log labor market tightness matches the value in column 2 closely. Moreover, the estimated coefficent of the Hartz dummy is somewhat lower (10%), but remains statistically significant at the 95% level. The specification in column 7 controls for autocorrelation in the error term by including the lagged total outflow rate as an exogenous variable. The estimated coefficient of the lagged total outflow rate implies that the long-run impact of the dummy variable is equal to $0.04/(1-0.89) = 0.39$. Column 8 reports the results for the post 2000M7 subsample. As demographic developments are less important within a single decade, we do not include the set of control variables for this exercise. We find that the coefficient of log labor market tightness is virtually identical, but the coefficient of the level dummy is somewhat lower. Interestingly, as

[35] We infer the exact dating of the breakpoint; i.e., after the introduction of Hartz I&II, but before the implementation of Hartz III (Ebbinghaus & Eichhorst 2006, Table 1), from the Quandt-Andrews test statistics.

[36] On the one hand, Pries (2008) surveys evidence that recessions are associated with disproportionate increases in unemployment among low-skilled workers. On the other hand, Barnichon & Figura (2011) argue that the fraction of long-term unemployed and the fraction of permanent job losers lags the business cycle.

can be seen in column 9, our results are also very similar when we estimate the post 2000M7 subsample using the new vacancy series “gemeldete Arbeitsstellen” instead of the old series “gemeldete Stellen” (see Footnote 31).

In summary, our results imply that matching efficiency has increased substantially in the mid-2000s. In our benchmark specification, the level dummy indicates an increase in matching efficiency by 23%.[37] Moreover, the secular decline in the total outflow rate after 1990 seems to be due to demographic factors and not to a deterioration in the matching process. This finding is consistent with the results of our analysis in Section (5.1).

6 Conclusion

This paper evaluates the macroeconomic effectiveness of the Hartz reforms on matching efficiency in the West-German labor market. For this purpose, we use monthly SOEP gross worker flows from 1983-2009, which are representative for the entire population. We quantify the impact of the reforms on two different grounds. First, following Smith (2011), we examine whether the relative contributions of the inflow rate (job separation) and the outflow rate (job finding) to unemployment variability have changed after the mid-2000s. Second, we test for a structural break in matching efficiency around the year 2003 using a standard matching function (Petrongolo & Pissarides 2001).

We show that, until the early 2000s, close to 60% of changes in the actual unemployment rate are due to changes in the inflow rate. On the other hand, since the implementation of the Hartz reforms in the mid-2000s, the importance of the outflow rate has been steadily increasing. The rising importance of the outflow rate, in conjunction with the falling cyclical volatility of the inflow rate, indicates a substantial increase in matching efficiency (Jung & Kuhn 2011). Results from an estimated matching function — pointing to efficiency gains of more than 20% — corroborate this finding.

As soon as more recent data are available, it would be interesting to evaluate the behavior of the German labor market during the Great Recession. Its extremely favorable performance — sometimes referred to as the German labor market “miracle” (Möller 2010) — has attracted a great deal of attention in the literature (Sala et al. 2012). Following Şahin et al. (2012), panel data could be used in order to measure the magnitude of the sectoral and/or geographical mismatch in the German labor market. The study of such questions, however, is beyond the scope of this paper.

[37] This value implies a reduction in the steady state unemployment rate by about 20%. This estimate is in the same range as the ones by Krebs & Scheffel (2010) or Krause & Uhlig (2012).

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A Reconciliation Procedure

A.1 Setting Flags (pseudocode of 02_rec_all_flags.do)

Case 1: Move into Employment

- C-LFS current year: 'employed'
- C-LFS previous year: 'unemployed' or 'inactivity'

Step 1: Check Consistency of C-LFS with JOBCH

- JOBCH: 'employed, no info if change', 'employment with change' or 'first time employed' [consistent]
- JOBCH: 'not employed', 'employed no change' [inconsistent]

Step 2: Check Consistency of C-LFS with SCJ/ELJ/SLJ

- SCJ after last interview; ELJ before last interview or 'no last job' [consistent, flag 21]
- both SCJ and SLJ after last interview [consistent, flag 22 and 22.5][38]
- SCJ after last interview; SLJ before last interview; ELJ after last interview [inconsistent, flag 8]
- SCJ before last interview [inconsistent, flag 9]
- SCJ 'not applicable' [inconsistent, flag 10][39]

Case 2: Remaining Employed

- C-LFS current year: 'employed'
- C-LFS previous year: 'employed'

Step 1: Check Consistency of C-LFS with JOBCH

- JOBCH: 'employed no change', 'employed, no info if change', 'employment, with change' or 'first time employed' [consistent]
- JOBCH: 'not employed' [inconsistent]

Step 2: Check Consistency of C-LFS with SCJ/ELJ/SLJ

- SCJ/ELJ/SLJ: no job change since last interview [consistent, flag 20]
- SCJ before last interview [consistent, flag 23]
- SCJ at last interview [consistent, flag 24]
- SCJ after last interview; ELJ after last interview [consistent, flags 25 and 26]
- SCJ before last interview; ELJ after last interview [consistent, flag 27]

[38] Following our assumption that JOBCH is more reliable than SCJ/SLJ, we regard the pattern as 'consistent', even if JOBCH is equal to 'first time employed'.

[39] The label 'not applicable' is not equivalent to 'missing'. Thus, 'not applicable' is not consistent with the C-LFS entry. Note, however, that we do not apply this rule prior to 1990 since we have very little information on SCJ for the years 1986 through 1989.

- SCJ after last interview; ELJ does not exist or ELJ before last interview [inconsistent, flag 11]
- SCJ before last interview; ELJ before last interview; JOBCH 'employment, with change' [inconsistent, flag 12]
- SCJ 'not applicable' [inconsistent, flag 13][40]

Step 3: Check Consistency of JOBCH 'first time employed'

- JOBCH 'first time employed'; C-LFS previous year 'employed' [inconsistent, flag 14][41]
- JOBCH 'first time employed' C-LFS previous year 'employed'; SCJ up to two months before last interview and there was no last job [consistent, overwrite flag 14 with flag 28][42]

Case 3: Currently not Employed

- C-LFS current year: 'unemployed' or 'inactivity'
- C-LFS previous year: 'employed' or 'unemployed' or 'inactivity'

Step 1: Check Consistency of C-LFS with JOBCH

- JOBCH: 'not employed' [consistent]
- JOBCH: 'employed no change', 'employed, no info if change', 'employed, with change' and 'first time employed' [inconsistent]

Step 2: Check Consistency of C-LFS with SCJ/ELJ/SLJ

- SLJ after last interview; ELJ after last interview [consistent, flag 30]
- C-LFS previous year 'employed'; SLJ before last interview; ELJ after last interview [consistent, flag 31]
- ELJ before last interview or there was no last job [consistent, flag 32]
- SLJ 'missing', ELJ exists [consistent, flag 33]
- ELJ 'missing' [inconsistent, flag 15]
- SCJ exists [inconsistent, flag 16]
- SLJ before last interview, ELJ after last interview; C-LFS of the previous year is 'unemployed' or 'inactivity' [inconsistent, flag 17]
- ELJ before last interview or there was no last job; C-LFS of the previous year is 'employed' [inconsistent, flag 18]

[40] See Footnote (39).

[41] JOBCH 'first time employed' refers to the first employment spell of an individual that started between the last and the current interview. Thus, by definition, an individual cannot be employed at the time of the last interview.

[42] The pattern is inconsistent, but tolerated as the current job is indeed the first employment spell of the individual that started at most two month before the last interview.

A.2 Treatment of Calendar Data (pseudocode of 03_reconciliation.do)

- Delete all observations in 1983 (we do not have any C-LFS entries for 1983 and, thus, can not perform the reconciliation procedure).
- Keep observations with at least two consecutive interviews only.
- Flags 2-4, 8, 9, 16, 17, 18: Change all entries in the calendar file to 'missing' between the previous and the current interview including the month of the current interview.
- Flags 5-7, 10-15: Leave everything unchanged.
- Flags 20, 23, 24, 25, 27 and 28: Set the entries in the calendar file — between the previous and the current interview including the month of the current interview — to 'employed' if we can observe at least 6 months of consecutive employment in the calendar data, H-LFS.
- All other flags: We first check whether SCJ and/or ELJ (or any other information available) corresponds to the pattern in the calendar data, H-LFS. We allow for deviations in H-LFS by plus/minus two months. If there is no corresponding pattern, we delete all observations from the last interview to the current interview. If there is a corresponding pattern, we proceed as follows: If, for example, SCJ corresponds to the start of an employment spell in the calendar data, H-LFS, we assign the value 'employment' from the starting point of the employment spell in H-LFS until the month of the interview.

B Coding Rules

SOEP label for spell type in the “artkalen” file	re-coded
Full-Time Employment	Employment (E)
Short Work Hours	Employment (E)
Part-Time Employment	Employment (E)
Vocational Training	Employment (E)
Unemployment	Unemployment (U)
Retired	Inactivity (I)
Maternity Leave	Inactivity (I)
School, College	Inactivity (I)
Military, Community Service	Inactivity (I)
Housewife, Husband	Inactivity (I)
Second Job	Employment (E)
Other	Inactivity (I)
First Job Training, Apprenticeship	Employment (E)
Continuing Education, Retraining	Inactivity (I)
Mini-Job (up to 400 Euro/month)	Employment (E)
Gap	Gap

Table 1: Re-coding of SOEP spell types

C Mathematical Details

$$
\begin{aligned}
\Delta u_t =& \Delta \bar{u}_t \frac{(s_{t-1}+f_{t-1})(s_t+f_t)}{(s_t+f_t)^2+(s_{t-1}+f_{t-1})} + \Delta u_{t-1}\frac{(s_t+f_t)}{(s_t+f_t)^2+(s_{t-1}+f_{t-1})} \\
\Delta u_t =& \frac{\Delta \bar{u}_t}{\bar{u}_{t-1}} \underbrace{\frac{s_{t-1}(s_t+f_t)}{(s_t+f_t)^2+(s_{t-1}+f_{t-1})}}_{F_t} + \Delta u_{t-1}\underbrace{\frac{(s_t+f_t)}{(s_t+f_t)^2+(s_{t-1}+f_{t-1})}}_{G_t} \\
\Delta u_t =& \frac{\Delta \bar{u}_t}{\bar{u}_{t-1}} F_t + \Delta u_{t-1} G_t \\
\frac{\Delta \bar{u}_t}{\bar{u}_{t-1}} =& \bar{C}_t^S - \bar{C}_t^F \\
\Delta u_t =& \left(\bar{C}_t^S - \bar{C}_t^F\right) F_t + \Delta u_{t-1} G_t \\
\Delta u_t =& \left(\bar{C}_t^S - \bar{C}_t^F\right) F_t + \left[F_{t-1}\left(\bar{C}_{t-1}^S - \bar{C}_{t-1}^F\right) + G_{t-1}\Delta u_{t-2}\right] G_t \\
\Delta u_t =& \underbrace{F_t \bar{C}_t^S + \sum_{i=1}^{\infty} F_{t-i}\bar{C}_{t-i}^S \left(\prod_{k=0}^{i-1} G_{t-k}\right)}_{C_t^S} \underbrace{- F_t \bar{C}_t^F - \sum_{i=1}^{\infty} F_{t-i}\bar{C}_{t-i}^F \left(\prod_{k=0}^{i-1} G_{t-k}\right)}_{C_t^F} \\
C_t^S =& F_t \bar{C}_t^S + G_t C_{t-1}^S \\
C_t^F =& -F_t \bar{C}_t^F - G_t C_{t-1}^F \\
\Delta u_t =& C_t^S + C_t^F
\end{aligned}
$$

D Results — Tables

D.1 Descriptive Statistics — First Moments

	Full Sample	German Sample	Foreigners	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
N	9,044	7,577	1,467	3,720	3,857	1,599	3,808	2,169	4,816	2,756
U	5.3%	4.6%	12.1%	4.1%	5.4%	5.0%	3.4%	7.0%	5.9%	2.5%
S	0.3%	0.3%	0.4%	0.3%	0.3%	0.5%	0.3%	0.3%	0.3%	0.3%
F	6.2%	7.1%	2.7%	7.4%	6.6%	10.2%	8.5%	3.0%	5.2%	13.8%
EU	0.3%	0.3%	0.3%	0.3%	0.2%	0.4%	0.2%	0.2%	0.3%	0.3%
EIU	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
UE	5.1%	5.9%	1.8%	6.7%	5.2%	8.6%	7.8%	2.7%	4.0%	11.1%
UIE	1.1%	1.1%	0.9%	0.7%	1.4%	1.6%	0.8%	0.3%	1.2%	2.8%

(a) West-Germany

	Full Sample	*** ***	***	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
N	67,045	***	***	32,286	34,759	12,669	37,598	16,045	46,582	20,429
U	5.6%			5.7%	5.5%	11.6%	4.7%	3.6%	7.1%	2.8%
S	3.0%			3.1%	2.9%	7.6%	2.3%	1.8%	3.7%	1.6%
F	60.5%			60.5%	57.8%	66.2%	54.6%	57.3%	56.1%	66.6%
EU	2.0%			2.3%	1.7%	4.2%	1.7%	1.2%	2.6%	1.2%
EIU	0.9%			0.8%	1.1%	3.4%	0.6%	0.6%	1.1%	0.3%
UE	43.2%			47.2%	39.4%	49.8%	39.6%	37.1%	41.1%	59.7%
UIE	17.3%			13.4%	18.5%	16.4%	14.9%	20.2%	15.0%	6.9%

(b) United States

Table 2: The table shows the means of the unemployment rate and the corresponding transition rates for West-Germany and the United States, respectively.

D.2 Descriptive Statistics — Second Moments

	Full Sample	German Sample	Foreigners	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
$\sigma(U)$	8.6%	9.1%	8.6%	9.1%	11.0%	11.0%	11.6%	8.8%	9.1%	14.0%
$\sigma(S)$	11.8%	12.3%	20.1%	11.4%	17.5%	11.7%	13.6%	20.9%	14.1%	16.1%
$\sigma(F)$	8.3%	8.3%	20.9%	11.4%	10.5%	12.5%	12.3%	20.4%	10.9%	12.4%
$\sigma(EU)$	11.3%	11.3%	22.3%	11.4%	17.8%	12.2%	13.5%	20.2%	13.5%	17.1%
$\sigma(EIU)$	21.2%	24.5%	58.0%	26.1%	25.9%	37.7%	31.9%	78.2%	32.3%	30.7%
$\sigma(UE)$	9.6%	9.6%	23.0%	13.0%	12.7%	13.7%	14.6%	22.6%	12.7%	13.1%
$\sigma(UIE)$	17.2%	17.4%	43.3%	27.3%	25.5%	33.7%	28.6%	28.3%	19.9%	34.3%

(a) West-Germany

	Full Sample	*** ***	***	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
$\sigma(U)$	9.9%			11.3%	8.3%	7.2%	11.3%	12.1%	9.3%	12.3%
$\sigma(S)$	2.8%			4.1%	2.4%	2.3%	3.9%	4.8%	2.6%	4.5%
$\sigma(F)$	10.2%			10.8%	9.7%	8.9%	10.6%	12.1%	10.0%	12.3%
$\sigma(EU)$	3.5%			4.9%	3.0%	3.0%	4.6%	5.5%	3.6%	4.8%
$\sigma(EIU)$	2.3%			3.1%	2.8%	3.8%	2.6%	5.2%	2.4%	5.4%
$\sigma(UE)$	10.7%			11.0%	10.5%	9.8%	10.6%	12.7%	10.3%	12.6%
$\sigma(UIE)$	9.3%			10.6%	8.6%	7.8%	11.1%	11.6%	9.8%	11.3%

(b) United States

Table 3: The table shows the standard deviations of the unemployment rate and the corresponding transition rates for West-Germany and the United States, respectively. In order to facilitate comparison with the literature, all time series are time-aggregated to a quarterly frequency and de-trended using the Hodrick & Prescott (1997) filter with $\lambda = 1600$.

D.3 Dynamic Decomposition — Difference Specification

	Full Sample	German Sample	Foreigners	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
β^{U}	0.83 (0.03)	0.81 (0.03)	0.61 (0.03)	0.72 (0.03)	0.78 (0.03)	0.77 (0.02)	0.70 (0.03)	0.68 (0.05)	0.69 (0.03)	0.74 (0.03)
β^{S}	0.59 (0.02)	0.60 (0.02)	0.57 (0.03)	0.58 (0.02)	0.62 (0.03)	0.45 (0.03)	0.57 (0.02)	0.60 (0.03)	0.55 (0.02)	0.56 (0.03)
β^{F}	0.40 (0.02)	0.38 (0.02)	0.38 (0.03)	0.40 (0.02)	0.38 (0.03)	0.53 (0.03)	0.42 (0.02)	0.33 (0.03)	0.42 (0.02)	0.44 (0.03)
β^{EU}	0.47 (0.02)	0.46 (0.02)	0.52 (0.03)	0.55 (0.02)	0.46 (0.02)	0.37 (0.03)	0.47 (0.02)	0.51 (0.03)	0.46 (0.02)	0.51 (0.03)
β^{EIU}	0.12 (0.01)	0.15 (0.01)	0.05 (0.01)	0.03 (0.01)	0.16 (0.02)	0.08 (0.02)	0.10 (0.01)	0.10 (0.01)	0.09 (0.01)	0.05 (0.01)
β^{UE}	0.31 (0.01)	0.32 (0.02)	0.13 (0.03)	0.34 (0.02)	0.28 (0.02)	0.42 (0.03)	0.41 (0.02)	0.36 (0.03)	0.31 (0.02)	0.34 (0.03)
β^{UIE}	0.09 (0.02)	0.06 (0.02)	0.24 (0.03)	0.07 (0.02)	0.10 (0.02)	0.11 (0.03)	0.01 (0.02)	-0.02 (0.03)	0.11 (0.02)	0.10 (0.03)

(a) West-Germany

	Full Sample	*** ***	***	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
β^{U}	0.98 (0.01)			1.00 (0.01)	0.89 (0.01)	0.89 (0.03)	0.98 (0.01)	0.89 (0.02)	0.98 (0.01)	0.93 (0.01)
β^{S}	0.20 (0.01)			0.27 (0.01)	0.10 (0.02)	0.13 (0.03)	0.26 (0.01)	0.28 (0.02)	0.19 (0.01)	0.26 (0.02)
β^{F}	0.80 (0.01)			0.73 (0.01)	0.90 (0.02)	0.87 (0.03)	0.74 (0.01)	0.72 (0.02)	0.81 (0.01)	0.74 (0.02)
β^{EU}	0.19 (0.01)			0.23 (0.01)	0.10 (0.02)	0.07 (0.02)	0.22 (0.01)	0.22 (0.02)	0.18 (0.01)	0.23 (0.02)
β^{EIU}	0.02 (0.01)			0.04 (0.01)	0.00 (0.01)	0.06 (0.02)	0.04 (0.00)	0.06 (0.01)	0.00 (0.01)	0.03 (0.01)
β^{UE}	0.63 (0.01)			0.56 (0.01)	0.62 (0.02)	0.67 (0.02)	0.53 (0.01)	0.48 (0.02)	0.59 (0.01)	0.66 (0.02)
β^{UIE}	0.16 (0.01)			0.17 (0.01)	0.27 (0.02)	0.19 (0.02)	0.21 (0.01)	0.24 (0.02)	0.22 (0.01)	0.08 (0.02)

(b) United States

Table 4: The table summarizes the dynamic contributions of changes in the total inflow rate and the total outflow rate to the variability in the actual unemployment rate. The β^X value is equivalent to the coefficient of an univariate regression of X_t on U_t, which we use to compute the standard errors.

D.3.1 Dynamic Decomposition — Bandpass Filter Specification

	Full Sample	German Sample	Foreigners	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
β^U	0.94 (0.01)	0.95 (0.01)	0.73 (0.02)	0.92 (0.01)	0.96 (0.01)	0.77 (0.01)	0.90 (0.01)	1.23 (0.03)	0.97 (0.01)	0.89 (0.01)
β^S	0.62 (0.01)	0.64 (0.01)	0.53 (0.02)	0.64 (0.02)	0.60 (0.01)	0.55 (0.02)	0.67 (0.01)	0.59 (0.02)	0.60 (0.01)	0.62 (0.01)
β^F	0.38 (0.01)	0.36 (0.01)	0.47 (0.02)	0.36 (0.02)	0.40 (0.01)	0.45 (0.02)	0.33 (0.01)	0.42 (0.02)	0.40 (0.01)	0.38 (0.01)
β^{EU}	0.54 (0.01)	0.54 (0.01)	0.53 (0.02)	0.62 (0.02)	0.46 (0.01)	0.43 (0.02)	0.62 (0.01)	0.56 (0.02)	0.54 (0.01)	0.60 (0.01)
β^{EIU}	0.08 (0.00)	0.10 (0.00)	0.00 (0.00)	0.01 (0.00)	0.14 (0.01)	0.12 (0.01)	0.05 (0.00)	0.03 (0.00)	0.06 (0.00)	0.01 (0.00)
β^{UE}	0.25 (0.01)	0.23 (0.01)	0.25 (0.02)	0.27 (0.02)	0.24 (0.01)	0.39 (0.02)	0.25 (0.01)	0.40 (0.02)	0.22 (0.01)	0.24 (0.01)
β^{UIE}	0.14 (0.01)	0.13 (0.01)	0.22 (0.02)	0.10 (0.02)	0.16 (0.01)	0.06 (0.02)	0.07 (0.01)	0.02 (0.02)	0.18 (0.01)	0.14 (0.01)

(a) West-Germany

	Full Sample	*** ***	***	Males	Females	Young	Prime-Age	Old	Low Skilled	High Skilled
β^U	0.96 (0.00)			1.01 (0.00)	1.00 (0.00)	1.03 (0.00)	1.00 (0.00)	0.99 (0.00)	1.03 (0.00)	0.97 (0.00)
β^S	0.19 (0.01)			0.27 (0.01)	0.07 (0.01)	0.07 (0.01)	0.25 (0.01)	0.27 (0.01)	0.19 (0.01)	0.22 (0.01)
β^F	0.81 (0.01)			0.73 (0.01)	0.93 (0.01)	0.93 (0.01)	0.75 (0.01)	0.73 (0.01)	0.81 (0.01)	0.78 (0.01)
β^{EU}	0.16 (0.01)			0.23 (0.01)	0.05 (0.01)	0.08 (0.00)	0.21 (0.01)	0.18 (0.00)	0.17 (0.01)	0.19 (0.01)
β^{EIU}	0.04 (0.00)			0.04 (0.00)	0.03 (0.00)	-0.01 (0.00)	0.04 (0.00)	0.09 (0.00)	0.02 (0.00)	0.03 (0.00)
β^{UE}	0.59 (0.01)			0.56 (0.01)	0.66 (0.01)	0.73 (0.00)	0.53 (0.01)	0.47 (0.00)	0.59 (0.01)	0.70 (0.01)
β^{UIE}	0.22 (0.01)			0.17 (0.01)	0.26 (0.01)	0.20 (0.00)	0.22 (0.01)	0.26 (0.00)	0.22 (0.01)	0.08 (0.01)

(b) United States

Table 5: The table summarizes the dynamic contributions of changes in the total inflow rate and the total outflow rate to the variability in the actual unemployment rate (*note that all frequencies higher than eight years were filtered out prior to estimation*). The β^X value is equivalent to the coefficient of an univariate regression of X_t on U_t, which we use to compute the standard errors.

D.4 Matching Function Estimation

Variable	No Dummy	Benchmark Specification	Vacancies & U'ment	ΔGDP	UE-Rate	lagged Tightness	lagged Outflows	2000 old data	2000-09 new data
Tightness	0.20***	0.32***		0.35***	0.30***	1.85***	0.03**	0.28***	0.28***
Tightness(-1)						−1.58***			
Vacancies			0.23***						
Unemployment			−0.45***						
Outflows(-1)							0.89***		
Young	3.19***	2.51***	2.70***	2.48***	2.68***	2.05***	0.29**		
Old	−2.82***	−3.45***	−3.60***	−3.61***	−3.72***	−2.45***	−0.47***		
Women	0.82**	−0.66	−0.71	−0.83	−0.76	−0.20	−0.19*		
Education	4.19***	3.48***	4.15***	3.47***	3.73***	2.54***	0.46**		
Δ GDP				−5.83					
Dummy		0.23***	0.26***	0.26***	0.31***	0.12**	0.04***	0.12***	0.19***
R^2	0.86	0.89	0.89	0.89	0.84	0.90	0.97	0.62	0.67
DWS	0.20	0.28	0.30	0.30	0.26	0.25	1.86	0.27	0.35

Table 6: The table displays the coefficients of the estimated matching function. Stars ($*$,$**$,$***$) indicate significance at the 90%, 95%, and 99% level, respectively.

D.5 Results — Figures

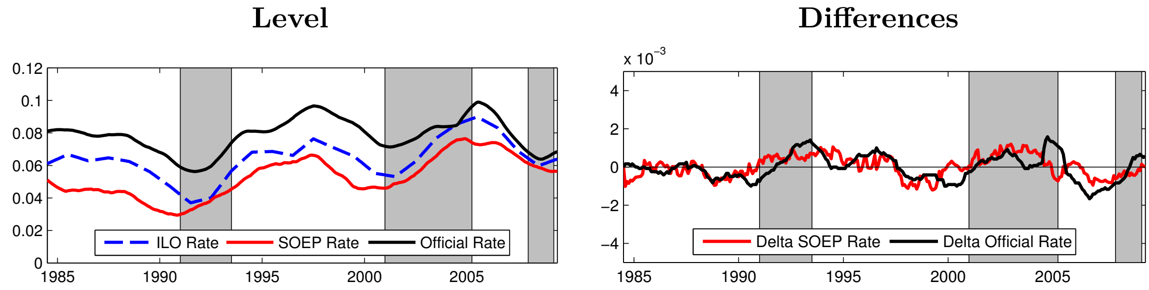

Figure 1: The figure compares the annual West-German unemployment rate according to the ILO definition (blue dashed line), the unemployment rate in our SOEP sample (red solid line), and the official West-German unemployment rate (black solid line). See Footnote (11) for the source of the recession dates and more details on the series.

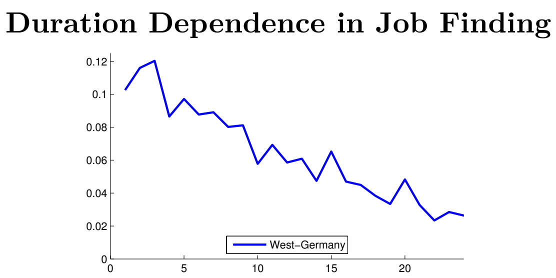

Figure 2: Monthly transition rate from unemployment to employment, depending on unemployment duration in months. Evidence for the United States is provided by Shimer (2008, Figure 1).

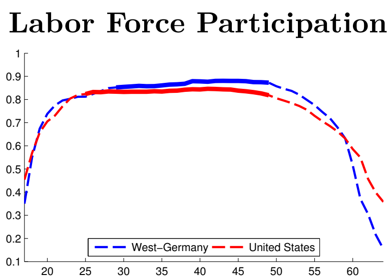

Figure 3: Labor force participation rates in West-Germany (blue) and the United States (red) over the life-cycle. The bold section denotes the country-specific *prime-age* cohorts. The dashed sections denote the young and the old cohorts, respectively.

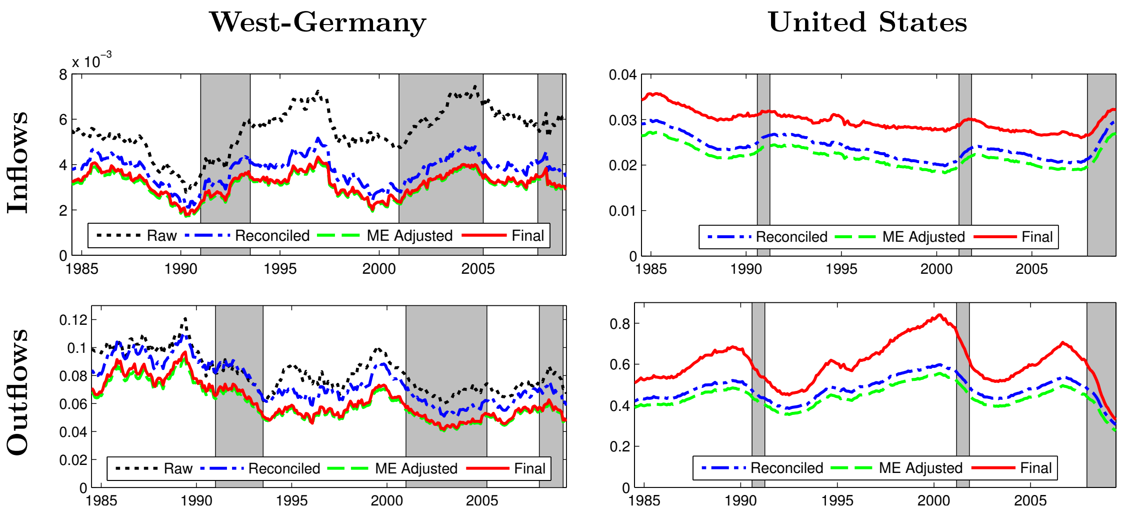

Figure 4: The graph illustrates the raw transition rates (black dotted line, West-Germany only), the reconciled rates (blue dashed-dotted line), the margin error adjustment rates (green dashed line), and the final transition rates (red solid line), for West-Germany (left panel) and the United States (right panel), respectively. See Footnote (11) for the source of the recession dates.

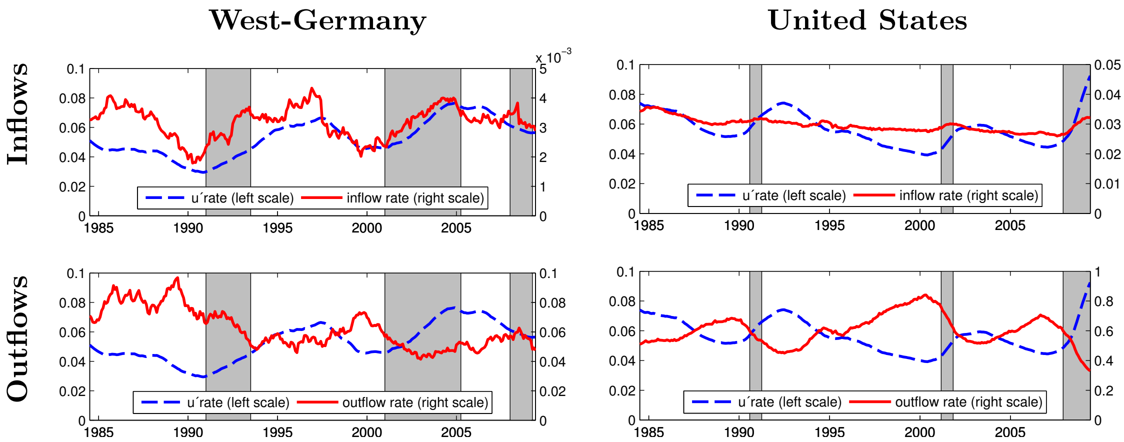

Figure 5: The graph contrasts the unemployment rate (blue dashed line) with the total inflow rate (red solid line, top panel) and the total outflow rate (red solid line, bottom panel), respectively. See Footnote (11) for the source of the recession dates.

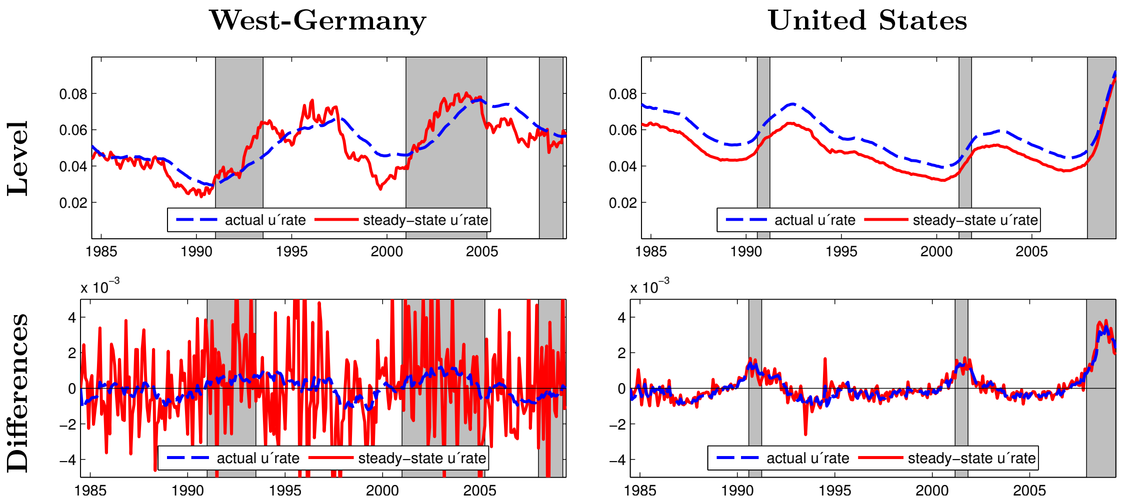

Figure 6: The graph illustrates the actual (blue dashed line) and the *steady state* (red solid line) unemployment rate in levels (top panel) and in first differences (bottom panel), for West-Germany (left panel) and the United States (right panel), respectively. See Footnote (11) for the source of the recession dates.

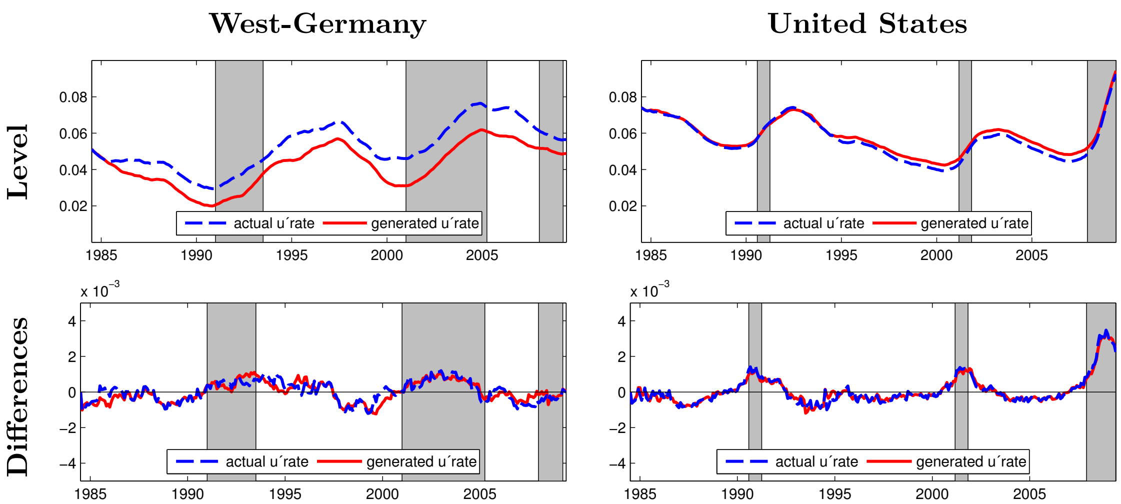

Figure 7: The graph illustrates the actual (blue dashed line) and the *model generated* (red solid line) unemployment rate in levels (top panel) and in first differences (bottom panel), for West-Germany (left panel) and the United States (right panel), respectively. See Footnote (11) for the source of the recession dates.

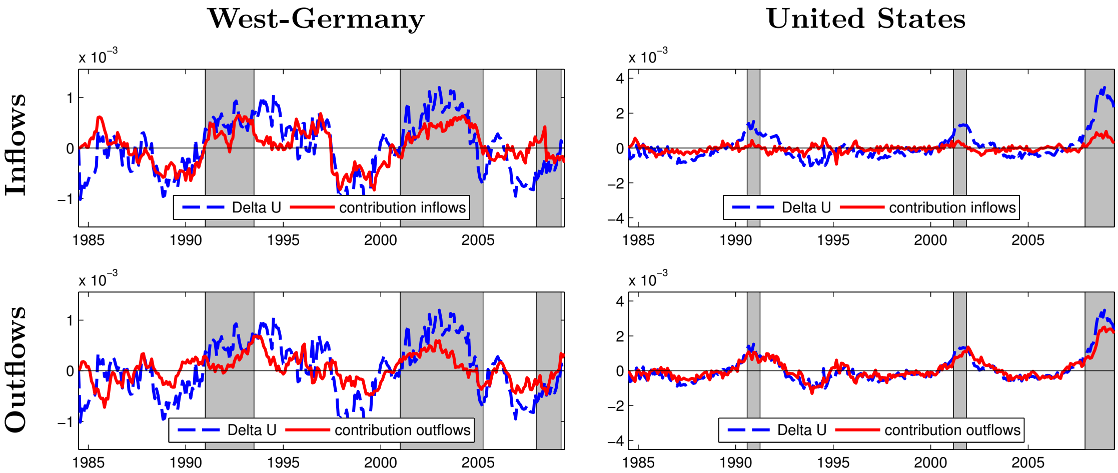

Figure 8: The graph illustrates the contributions of the total inflow rate (red solid line, top panel) and the total outflow rate (red solid line, bottom panel) to changes in the model generated unemployment rate (blue dashed line), for West-Germany (left panel) and the United States (right panel), respectively. See Footnote (11) for the source of the recession dates.

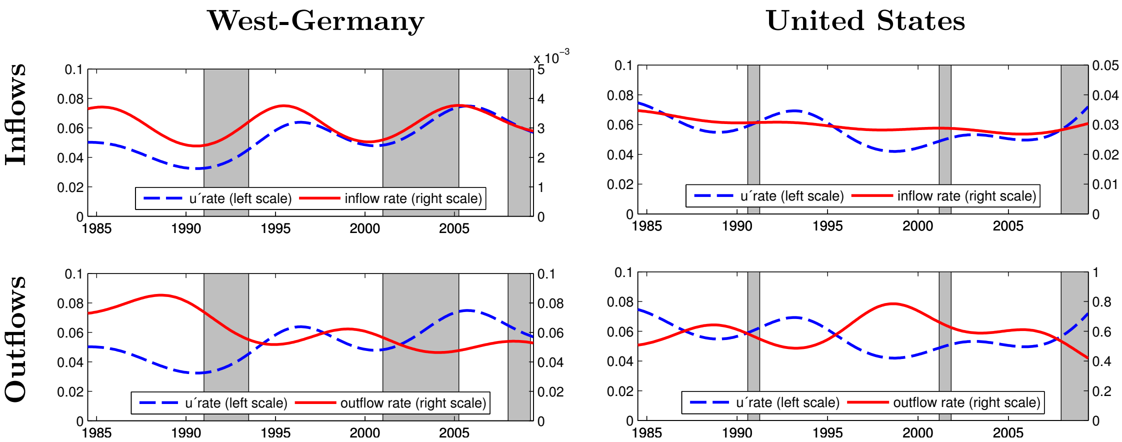

Figure 9: The top panel contrasts the unemployment rate (blue dashed line) with the total inflow rate (red solid line, top panel) and the total outflow rate (red solid line, bottom panel), respectively, for West-Germany (left panel) and the United States (right panel). *Note that all frequencies higher than eight years were filtered out.* See Footnote (11) for the source of the recession dates.

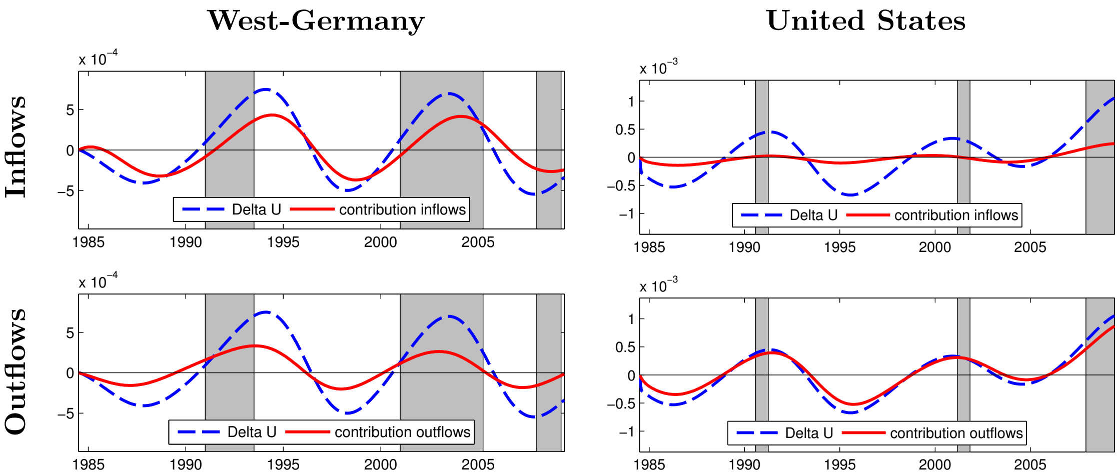

Figure 10: The graph illustrates the contributions of the total inflow rate (red solid line, top panel) and the total outflow rate (red solid line, bottom panel) to changes in the model generated unemployment rate (blue dashed line), for West-Germany (left panel) and the United States (right panel), respectively. *Note that all frequencies higher than eight years were filtered out prior to estimation.* See Footnote (11) for the source of the recession dates.

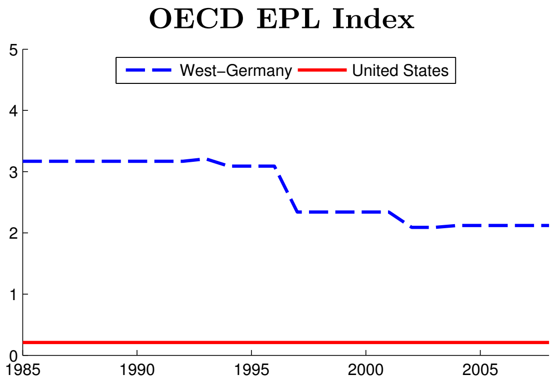

Figure 11: The graph illustrates the OECD overall index "strictness of employment protection for West-Germany (blue dashed line) and the United States (red line).

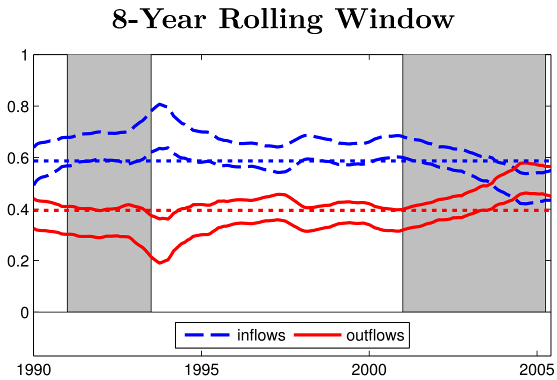

Figure 12: The graph illustrates the 95% confidence bands of the relative contributions of inflows (blue dashed line) and outflows (red solid line) using an eight-year rolling window and the point estimates over the whole sample period (dotted lines).

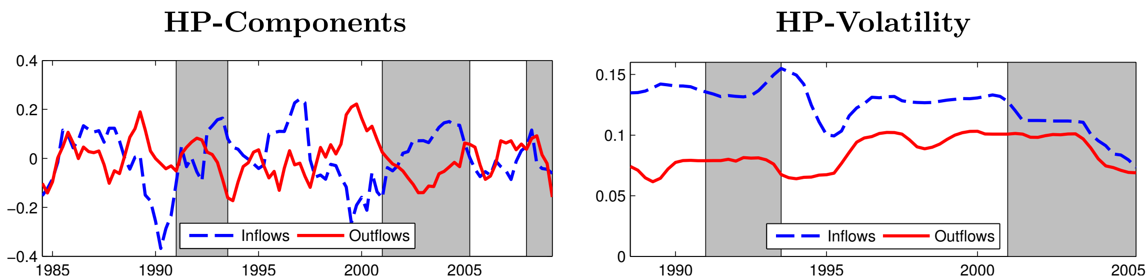

Figure 13: The left panel displays the Hodrick & Prescott (1997) cyclical components of the total inflow rate (blue dashed line) and the total outflow rate (red solid line), respectively. The right panel displays the time-varying standard deviation of these two series, which is estimated using an eight-year rolling window.

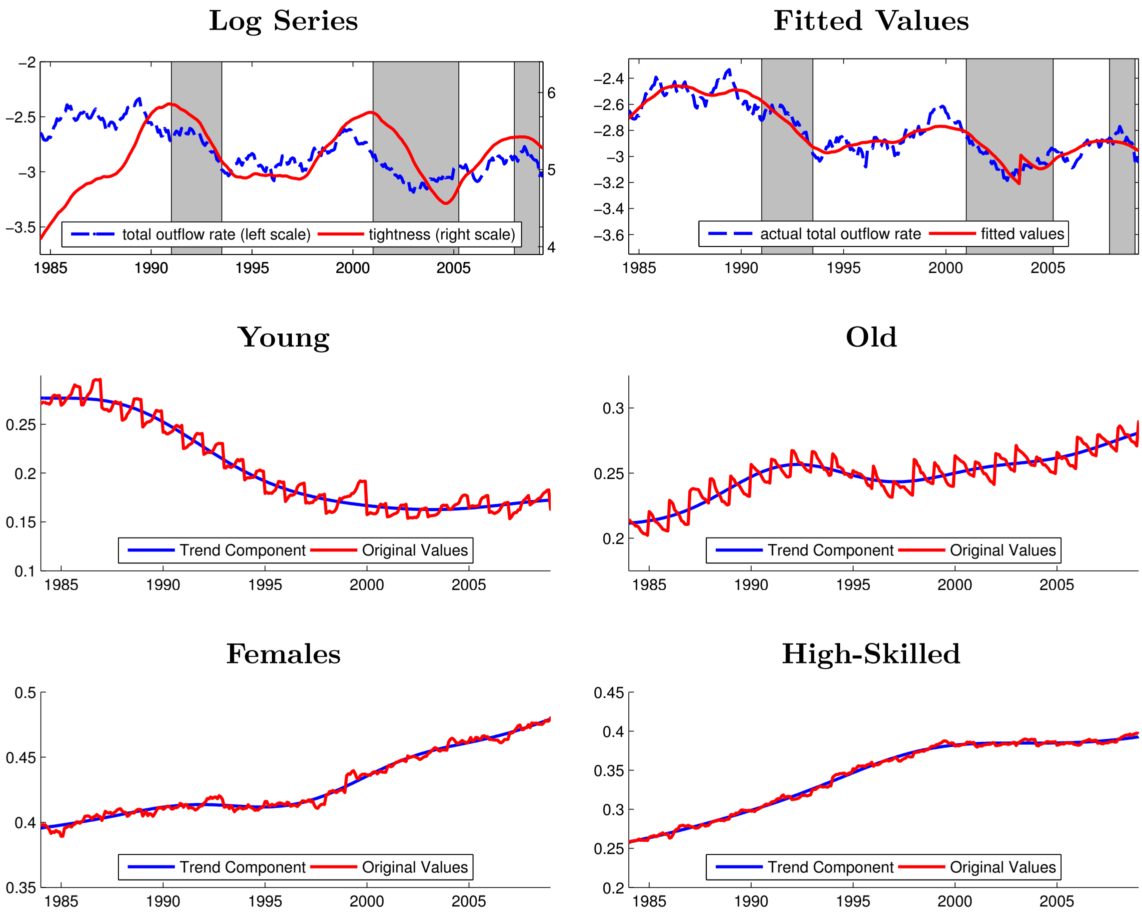

Figure 14: The top right panel illustrates the log total outflow rate (blue dashed line) and log labor market tightness (red solid line). The top level panel contrasts the log total outflow rate (blue dashed line) and the fitted values (red solid line) corresponding to column 2 in Table (6). The remaining panels show the evolution of the fraction of young/old/female/high-skilled labor force members and the corresponding bandpass trend (all frequencies below eight years are removed). Given that the SOEP adjusts the individual weights to the marginal distributions of age, gender, and nationality, but not to the skill level, the share of high-skilled individuals exhibits implausible jumps when new innovation/refreshment samples are added. We smooth out these jumps prior to applying the default Christiano & Fitzgerald (2003) bandpass filter.