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History Dependence in Wages and Cyclical Selection: Evidence from Germany *

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Abstract

Using employer-employee data from Germany, this paper analyzes the relationship between wages and past and contemporaneous labor market conditions. Specifically, we test the implications of implicit contract models (Beaudry and DiNardo, 1991) and an on-the-job search model (Hagedorn and Manovskii, 2013) for the wage formation of different worker types over the business cycle. The results are mixed: On the one hand, the data suggest that wages depend on labor market conditions when a match is formed – as contract theories postulate. On the other hand, past labor market conditions also affect contemporaneous wages through the evolution of match quality over a worker's job history – the main hypothesis of the on-the-job-search model. Using cyclical variation in labor market tightness to control for match quality, as in Hagedorn and Manovskii (2013), we find that previous evidence for the excess wage cyclicality of job changers can be entirely explained by cyclical variation of match quality. Refining the selection model by taking into account occupational mobility within employer-employee matches, we also find no excess wage cyclicality for new hires from unemployment – the key worker type's wage for understanding unemployment fluctuations in matching models.

JEL-Classification: E24, E32, J31, J41
Keywords: Business Cycle, Wage, Wage Rigidity, Implicit Contracts, Match Quality

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1 Introduction

Understanding wage determination and its relationship with the business cycle is key when studying the matching of workers and employers. The standard search and matching model (e.g., Mortensen and Pissarides, 1994) assumes that wages are set through period-by-period Nash bargaining, meaning that workers and firms constantly renegotiate over the match surplus. In this framework, wages follow the up- and downswings of the business cycle, rising and falling reasonably symmetrically. According to the Nash wage equation, the wages of all workers are equally responsive to cyclical conditions. However, these assumptions have been challenged. On the one hand, there is substantial empirical evidence that violates the standard model's spot wage assumption. Beaudry and DiNardo (1991) (henceforth BDN) show that current wages depend on functions of past labor market conditions rather than on contemporaneous conditions – a phenomenon often termed "history dependence in wages". These results are interpreted as wage rigidity induced by long-term implicit contracts that enable risk-sharing among workers and employers. In these models, risk-neutral firms shield risk-averse workers from income loss by absorbing the volatility in productivity as long as it is rational for both to remain matched. Thus, the wage does not constantly respond to current economic conditions but is only revised infrequently. On the other hand, there is also substantial empirical evidence that wages are, at least to some degree, procyclical. Pissarides (2009) surveys several empirical studies on wage cyclicality, especially of new hires and workers in ongoing employment relationships. He concludes that virtually every extant study finds that the wages of new hires are more responsive to the business cycle than those of job stayers. In the baseline search and matching model, this means that the empirical results are problematic for both the model's spot wage assumption and for attempts to improve the model's empirical performance by introducing wage rigidity (Shimer, 2005; Hall, 2005) because, as emphasized by Pissarides (2009), the wages of newly hired workers are what matter for employment dynamics. These conclusions call for modifications to make the baseline model more consistent with empirical evidence.

In a recent contribution, Hagedorn and Manovskii (2013) (henceforth HM) offer a promising theoretical framework that is able to reconcile the empirical findings of history dependence in wages in a matching model with on-the-job-search without abandoning the assumption of spot wages. They show that the conclusions from regressions a la BDN should be taken with a grain of salt and argue that wages are driven by cyclical selection rather than by implicit contracts. In their model, workers may quit their jobs in favor of jobs with higher quality, leading to the selection of more productive matches over time, most predominantly during economic upswings. Historical labor market conditions influence a worker's outside option, leading to wage changes, either directly through renegotiation or indirectly by triggering quits. The authors conclude that the regressions in BDN suffer from omitted variable inconsistency such that variables that reflect past aggregate conditions appear to be important predictors of wages, while these variables actually proxy for unmeasured match productivities. In particular, when the authors include measures of match quality to correct for these confounding variables, past labor market conditions are no longer important determinants of wages. Interestingly, the model has also implications for the predicted wage responsiveness of job switchers vis-a-vis workers in ongoing jobs. HM argue that by introducing their match quality proxies, they can isolate the true cyclical variation in wages, and thus, the wages of job stayers and job switchers are equally cyclical. This finding is consistent with the recent critique that evidence in previous studies of excess wage cyclicality for job switchers is an artifact of composition bias. As emphasized by Gertler et al. (2016), omitting appropriate controls for match quality leads to an overestimation of the wage cyclicality of job changers due to procyclical improvements in match quality. Following this line of literature, this paper recapitulates the potential links between wages and labor market conditions in the German labor market. First, we apply the BDN methodology and test implications from their implicit contract models using administrative data from Germany. Second, we consider the model with on-the-job search proposed by HM to explicitly control for cyclical selection. As in HM, we use proxies for the number of job offers during a worker's history of jobs without intervening unemployment to measure the quality of a match. In addition, we refine these proxies by exploiting our rich data on workers' occupation histories. This refinement allows us to separately identify different types of job switches and estimate the wage sensitivity to changes in aggregate unemployment while controlling for job selection (as in HM) and implicit contracts (as in BDN).

Our results suggest that wages depend on *both* past *and* contemporaneous labor market conditions. We find support for the on-the-job search model. However, we also find evidence for history dependence – in particular, we find a strong relationship between the labor market conditions at the start of a job and contemporaneous wages. In addition, we find that – without match quality proxies – the wages of workers who switch employers appear more procyclical than the average for all workers. When we introduce the match quality controls, we find that wages of job switchers are no longer more cyclical. In line with Gertler and Trigari (2009), we argue that previous studies' evidence for excess wage cyclicality for job changers is driven by composition bias that disappears in the presence of appropriate match quality controls. When we disaggregate the HM model and allow for occupational mobility within employer-employee matches, we find no excess wage cyclicality for new hires from unemployment once we control for match quality at the occupational level. Surprisingly, we find excess wage cyclicality for job switchers that simultaneously change occupation and employer. At least three features of this analysis distinguish it from previous work and help us to overcome some of the main methodological challenges affecting previous literature: First, to the best of our knowledge, this is the first paper that applies the method proposed by HM to control for match quality in administrative data.[1] Our data set is well-suited because it contains a large number of high-frequency employer-employee relationships over a reasonably long sample period, which allows us to address unobserved worker heterogeneity. Moreover, it contains a large set of observable worker information, reliable wage information, a large number of hirings and job-to-job transitions, and a large amount of variation in aggregate business cycle indicators.

Second, we are able to add new insights to the debate on composition effects and the correct measuring of the wage cyclicality for certain worker types. Applying the HM model makes it possible to directly control for procyclical improvements in match quality. Those controls are crucial in our analysis because it has been found that failing to account for cyclical movements in the composition of match quality can lead to the false impression that wages are procyclical when in fact the procyclicality results from job changes (Bils, 1985; Solon et al., 1994; Gertler and Trigari, 2009; Stüber, 2017).

Third, the refinement of the match quality proxies allows us to both identify and control for within employer-employee occupational mobility (job regrading). This refinement is important because job regrading is another source of composition bias for which one has to correct. The argument is that even within employer-employee matches, workers might select into better matches during good times through internal promotions. We argue that internal job regrading contaminates the original model's reference group (job stayers) since such job switches would be misleadingly counted as ongoing jobs. Our occupation-specific match proxies deliver finer control compared

[1] To the best of our knowledge, the only other paper that builds on the idea of identifying match quality proxies through the cyclical variation of the labor market in an on-the-job model is Gottfries and Teulings (2017a). These authors abstract from treating the labor market tightness during an employment cycle to develop match quality proxies. However, they derive the exact relationship between the time elapsed since the start of the current employment cycle until the end of the current job. In contrast to HM and our findings, they report that the starting date of a job does not provide any additional information for contemporaneous wages.

with previous studies since they allow us to distinguish each worker group in greater detail and control for each group's cyclical selection.

The remainder of the paper proceeds as follows: in Section 2, we recapitulate the theoretical framework of implicit contracts and outline HM's selection model. Section 2.3 provides refinements of the original selection model. In Section 3, we describe our empirical methodology and our data. Section 4 provides the empirical results. Section 5 underlines the robustness of our results. The last section summarizes and compares the results to the existing literature.

2 Theoretical framework

In this section, we recapitulate the theoretical models that previous research has derived to explain the relationship between past labor market conditions and contemporaneous wages. Specifically, we review and contrast outcomes of implicit contract models with the cyclical selection model that incorporates on-the-job search developed by HM.

2.1 Implicit contracts

In spot labor markets, the wage rate is affected only by contemporaneous market conditions. This includes any form of bargaining over the match surplus, as long as the bargaining takes place period-by-period – as in the canonical search and matching model, which assumes continuous re-contracting between workers and employers. Real wages follow the up- and downswings of the cycle, rising and falling reasonably symmetrically. In contrast, the theory of implicit contracts focuses on the engagement of workers and firms in long-lasting relationships that enable risk sharing.

BDN present two implicit wage contract models from which they derive implications about the potential link between wages and past labor market conditions. In the first model, risk-neutral employers insure risk-averse workers against income fluctuations over the business cycle. Employers commit to contracts, while workers do not (one-sided commitment). The authors prove that in this environment, and when workers are completely mobile, the wage is only revised infrequently. Whenever the worker's outside option improves above its maximum since the start of the worker's tenure, employers are willing to adjust the wage upward to prevent the worker from accepting a better job offer from another employer as long as it is jointly rational to continue the job. Thus, in this model, a worker's current wage is a function of all historical maxima of the worker's outside option.

The second model is a risk-sharing model with full commitment by both the worker and employer. The optimal contract in this environment implies a constant wage that is equal to the initial wage negotiated when the worker and employer formed their match. BDN test the implications of the two implicit contract models in an augmented Mincer wage regression using U.S. micro-level data. To control for the wage setting mechanism of the one-sided commitment model, they include the minimum unemployment rate since the start of a worker's current job (U^{min}) in the regression. They also include the unemployment rate at the time of hiring (U^{begin}) to account for economic conditions at the start of the employment relationship, representing the full commitment model. They let their measures of past labor market conditions compete against a spot wage model that is represented by the contemporaneous unemployment rate. They estimate the following wage equation:

$$w(i, t+s, t) = \gamma X_{i,t+s,t} + C(t, s) + \alpha_i + \eta_{i,t+s} \tag{1}$$

$$C(t, s) = \begin{cases} U_{t+s} & \text{contemporaneous conditions} \\ U_t^{begin} & \text{contracts with two-sided commitment} \\ U_{t+s,t}^{min} & \text{contracts with one-sided commitment} \end{cases} \tag{2}$$

The wage of worker i in the current period $t+s$ who started a job in period t is regressed on a vector of controls, $X_{i,t+s}$, which includes individual-specific characteristics such as labor market experience, tenure, gender, race, region, and schooling. To control for time-invariant unobserved worker characteristics, BDN include a worker fixed effect, α_i. $\eta_{i,t+s}$ is the usual error term. It is important to note that BDN can uncover the worker fixed effect using panel data. However, they do not control for an unobservable idiosyncratic match component. $C(t, s)$ is a link variable distinguishing between the different model predictions about the relationship of current wages and labor market conditions. U_{t+s} represents the contemporaneous unemployment rate and is treated as an indicator of current labor market conditions. $U_{t+s,t}^{min}$ denotes the minimum unemployment rate since the start of the job, and U_t^{begin} denotes the unemployment rate when the job started.

Separately estimating this equation for every combination of the unemployment variables using CPS data, they find that the coefficients are negative and significantly different from zero, except when nesting all three variables in one regression. In this case, the minimum unemployment rate variable dominates the two other variables. Specifically, the contemporaneous unemployment rate loses all its predictive power in the nested estimation. BDN conclude that the contract model with one-sided commitment fits the data best while the spot wage model performs the worst. In this context, one interpretation of the results is that wages are history dependent, meaning that they carry information about past aggregate labor market conditions, even long after the match has been formed.

2.2 Cyclical job selection model

HM question the direct influence of historical labor market conditions on contemporaneous wages. The authors propose a matching model with on-the-job search, in which wages are determined by current labor market conditions and current idiosyncratic match quality only. However, the current match quality carries information about the evolution of past match qualities over a worker's employment career. This evolution is influenced by the labor market conditions at that time and thereby affects contemporaneous wages. The main argument is that the link between past conditions and wages is visible in the BDN regression because they do not account for any measures of match quality. The next section outlines HM's selection model and offers implications regarding the relationship to past labor market conditions.

Environment

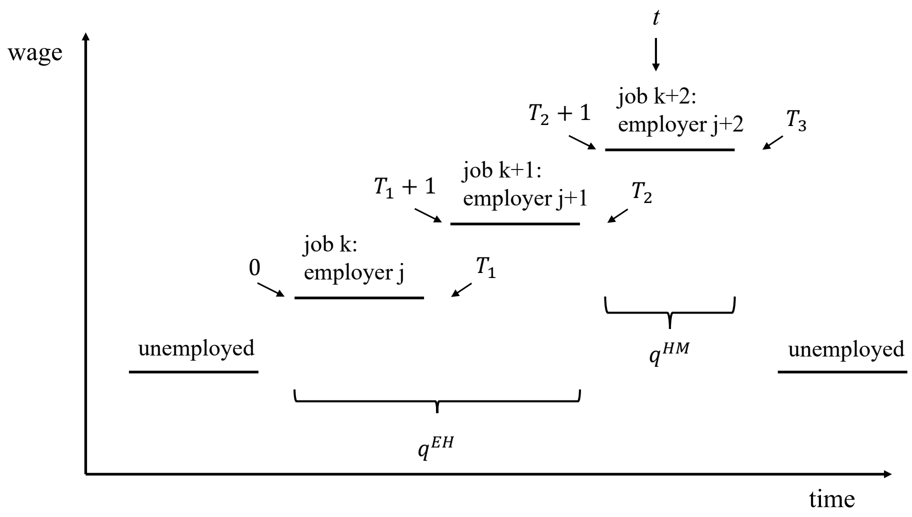
Workers are either employed or unemployed. In every period, unemployed workers receive a job offer with probability λ, which is increasing in the business cycle indicator. Employed workers receive job offers with probability q. Matches dissolve exogenously. In this model, the wage depends solely on contemporaneous conditions. On the one hand, it depends on the business cycle indicator C_t, which is assumed to be an exogenous stochastic process drawn from a stationary distribution and common to all workers. On the other hand, it depends on the match-specific idiosyncratic productivity, m_{ijt}. The wage equation can be written as

$$log\, w_{ijt} = log\, C_t + log\, m_{ijt}. \tag{3}$$

HM define the sequence of jobs between two unemployment spells as an employment cycle. Figure 1 displays this definition using the example of an employment cycle with three jobs at time t for worker i. In this example, the worker switched employers at times $T_1 + 1$ and $T_2 + 1$.

While being employed in the k_{th} job, the worker receives job offers. The worker's decision to switch jobs depends on the worker's current match-specific productivity and the match-specific productivity in the potential new job. The worker quits the current job if and only if a job offer arrives that offers a higher wage. Better job offers must be due to a higher m_{ij}, as this is the only component of the wage that varies across different jobs. On the one hand, if

Figure 1: Definition of an employment cycle with three jobs



an employed worker receives a job offer and accepts it, this means that the match quality must increase when switching. On the other hand, if the worker rejects the offer, the match quality of the offered job must be lower than the current job. Hence, the number of job offers must be positively correlated with the quality of the match because either the match quality has improved or the current match is already of high quality.

HM derive measures that summarize the probabilities of a job offer within each job spell, and this sum corresponds to the total number of job offers. First, they define q^{EH} as the sum of job offer probabilities since the start of the first job until the beginning of the current job within an employment cycle. Second, they sum all job offer probabilities during all periods of the current job and define this sum as q^{HM}. The first is supposed to summarize the employment history and thereby the evolution of match quality. The second summarizes the selection of workers into better matches from the most recent previous job to the current one.[2] HM prove that the expected value of the specific match productivity can be expressed by a linear function of q^{HM} and q^{EH}, which makes it applicable for linear estimation.[3]

[2]HM's identification strategy is to divide the match quality proxies into the two components q^{EH} and q^{HM} calculated from national labor market tightness. Gottfries and Teulings (2017b) show how to use alternative strategies using job finding rates.

[3]They first set up the conditional expected value of m_{ijt} for workers that have not been

However, the number of job offers is usually difficult for the econometrician to observe. Since the probability of receiving a job offer depends positively on labor market tightness, HM use the sum of labor market tightness to define q^{HM} and q^{EH}. The idea is that in tight labor markets, the arrival of job offers is more rapid, and as a consequence, the selection of workers into better matches via the switching of employers proceeds more rapidly. This gives workers greater opportunities to obtain a high-quality match.

Replicating the regressions of BDN, HM find strong support for the predictions of their selection model. In particular, they find that, when including the match quality measures in the typical regression, the past unemployment variables lose both their economic and statistic significance. Their concluding critique is that these regressions fail to include measures of unobserved match quality (m_{ijt}). They argue that the omission of match quality confounds the regressions. This leads to the false impression that wages are history dependent, while in fact, this is only due to the correlation of the past labor market conditions with the number of job offers and hence the quality of a match. Although in their model wages by definition depend only on contemporaneous labor market conditions and contemporaneous idiosyncratic match quality, they are thus consistent with the findings of history-dependent wages. The intuition is that if job offers are procyclical, the selection of better matches applies more stringently to those workers who experienced better economic conditions. This is because workers receive job offers with a probability that increases in the business cycle indicator, which is higher during booms than during recessions. Hence, past unemployment affects current wages, not directly but through the evolution of the match quality distribution.

2.3 Model extension – occupational refinement

One of the contributions of HM is the detailed derivation of a theoretical framework that takes into account the evolution of match quality and its relationship to the business cycle. They show that this evolution can rationalize the empirical support for history dependence in wages despite that the wages in their models are by definition pure spot wages. In the original HM model, a worker switches employers whenever the idiosyncratic match productivity is higher in the new match. However, the literature demonstrates that internal "job" switches are important when studying wage cyclicality. Among others, Devereux and Hart (2006) show that the proportion of internal and external job moves varies over the business cycle and that the wages of internal and

separated exogenously. Given that, they derive the distribution of m_{ijt} using the job switching rule from above. After further derivation, linearization and iteration, the following approximation holds: $\log(m_{ij}) \approx c_0 + c_1 \log(q^{EH}) + c_2 \log(q^{HM})$, where c_i are coefficients. For further details on this proof, see HM, page 779 and Appendix IA, IB.

external movers are considerably more procyclical than those of stayers (see also Hart and Roberts, 2011; Büttner et al., 2010). One reason for this is associated with within-firm job regrading over the cycle. The intuition is that during a cyclical boom, employers react to labor shortages through internal promotions. Existing workers can be trained and upgraded from low- to high-paid jobs. During economic downswings, excess labor supply forces employers to downgrade certain workers within the firm, leading to lower wages. The procyclical up- and downgrading per se generates cyclicality in wages among internal job movers. The original HM model does not take into account these internal job changes. If these job switches are in fact procyclical, this would lead to an overestimation of the cyclicality of job stayers because these internal job switches would be erroneously counted as such. Even their measures for match quality do not capture the effects of internal job switches because they only take into account employer switches.

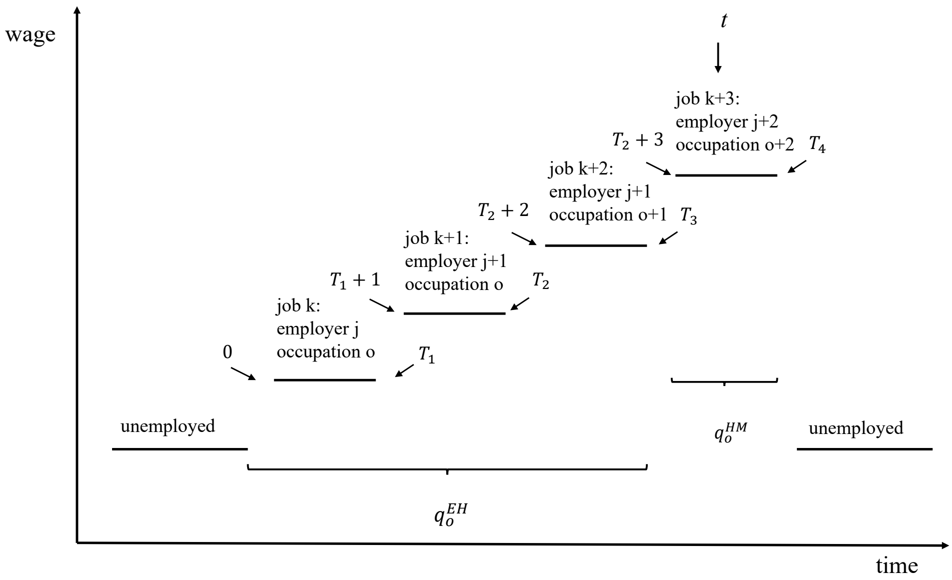
Following this argumentation, the main objective of this section is to develop a framework that accounts for both cyclical up- and downgrading within companies and cyclical selection across employers. By using detailed data on occupational labor market conditions, we are able to control for both types of selection.[4]

We start by relaxing the definition of a "job" and allow for occupational switches at the same employer. Specifically, a worker can also receive job offers from her current employer but for jobs in a different occupation. Given the new definition of a job, switching jobs means either (i) changing the employer but staying in an occupation, (ii) changing occupations but staying with the employer or (iii) simultaneously changing occupations and employers. Figure 2 shows all switching schemes using an illustrative employment cycle with four subsequent jobs between two unemployment spells. The switch from the first job to the second is due to i), while the switch from the second to the third results from ii). The last switch is illustrated in (iii).

The job switching rule is the same as above: The worker will change jobs (i, ii, iii), if and only if she receives a job offer that incorporates a higher match-occupation-specific productivity. For simplicity, we assume that every time one of the three possible switches occurs, that is there is a new combination of worker, employer and occupation, a new value of the idiosyncratic match

[4] Occupational selection is only one aspect of different wage profiles among workers. Wage profiles along the employment cycles of workers in certain occupations could differ due to institutional settings or investment in occupation-specific human capital. Workers could have different wage profiles over time because tenure is remunerated differently. Even the same firm could use different contracts to discriminate between workers in different occupations. Such patterns could be due to history dependence, the coexistence of wage bargaining and wage posting (Gartner and Holzner, 2015), or even complementarities of unobserved firm and worker characteristics (Lochner and Schulz, 2016).

Figure 2: Definition of an employment cycle with four jobs



productivity is drawn from an exogenous distribution. We define the measures of job quality in the same manner as above, namely as the sum of the job offer probabilities. However, these measures are now occupation specific. Again, we use the definition of employment cycles according to which the current period is stepwise moving over employment cycles and disaggregate the overall measure into a variable that controls for the history of the employment cycle (q_o^{EH}) and one that controls for the selection in the current period (q_o^{HM}). For clarity, in the example at hand, we would define q_o^{EH} and q_o^{EH} in period t as $q_{EH,o,t} = q_{j,o,t-3} + q_{j+1,o,t-2} + q_{j+1,o+1,t-1}$ and $q_{HM,o,t} = q_{j+2,o+2,t}$.

2.4 Wage volatility of job stayers and switchers

Implicit contract models predict that the wages of workers who switched jobs are more cyclical than those of stayers. The logic is simple: In the model with perfect mobility, job stayers hired before an economic downswing are protected against income loss by their contract. Their wage only responds during an upswing. In the two-sided commitment model, there is no wage cyclicality for job stayers because the wage is equal to the initial wage, irrespective of business cycle conditions, as long as the contract is effective. The wages of workers who change jobs, however, react to the economic conditions at the time the contract enters into force. In the selection model, the wage is a function of current business cycle conditions and the current idiosyncratic match quality. The former are the same for all workers, irrespective of whether they change jobs. The latter is assumed to be constant within a job, which implies that business cycle conditions are the only component that changes the wage of job stayers. The difference in wage cyclicality between stayers and switchers thus is related to the idiosyncratic match component in wages. Since it is, by definition, increasing in the number of job offers and thereby also in economic upswings, the wage of job switchers is higher during booms than during recessions. Overall, the selection model predicts that the wages of job switchers are more volatile than those of stayers.

To test these model implications, we show how we identify job stayers and job switchers using the definition of employment cycles. We suppose that each lth employment cycle starts at period t_l^{UE} and ends in period t_l^{EU}. The former is the first period of the first job after leaving unemployment, and the latter is the last period of the last job before being unemployed. The worker starts new jobs in period t_l^{k+s}. The employment cycle can be defined as the vector

$$z_l = (t_l^{UE}, t_l^{k+1}, t_l^{k+2}, ..., t_l^{k+s}, t_l^{EU}) \tag{4}$$

and consolidated in a sequence of employment cycles, defined as

$$z_l = (z_1, z_2, ..., z_L). \tag{5}$$

In the original HM model, there are three types of workers: new hires from unemployment, job stayers, and job (employer) switchers. New hires from unemployment are identified by collecting all t_l^{UE} period(s). We collect each of these periods for every worker. To identify job stayers, we collect any period that is neither a t_l^{UE} nor a t_l^{k+s} period. This gives a sequence of periods in which a worker has stayed at the same job. For job switchers, we collect the sequence of the switching periods $t_l^{k+1}, t_l^{k+2}, ..., t^{k+s}$. Note that the measures of match quality (q^{EH}, q^{HM}) are constant within a job spell and that only employer switchers and job stayers, who have at least two jobs, have a history of labor market tightness within an employment cycle. For new hires from unemployment, q^{EH} is, by definition, zero.

In the occupationally refined model, there are five worker types: new hires from unemployment, job stayers, workers who switch only their occupation, workers who switch only their employer, and those who switch both. The definitions of new hires from unemployment and of job stayers are the same as above. For job switchers, we separately identify the reason for the job switch and separately collect each switching period.

3 Empirical methodology

3.1 Estimation approach

As in HM, we use the BDN methodology for studying the response of individual wages to changes in past and contemporaneous labor market conditions. The following measurement equation is the basis of our analysis:

$$\begin{aligned}\ln w(i, t+s, t) = {} & \beta_0 X_{i,t+s} + \beta_1 U_{i,t+s} + \beta_2 U^{min}_{i,t+s,t} + \beta_3 U^{begin}_{i,t} + \beta_4 q^{EH}_{i,t+s} + \beta_5 q^{HM}_{i,t+s} \\ & + \alpha_i + \eta_{i,t+s}\end{aligned} \tag{6}$$

$\ln w_{i,t+s,t}$ denotes the daily log wage in period $t+s$ for a male full-time worker i, who started a job in period t. The vector of controls, $X_{i,t+s}$, includes dummies for education, experience, tenure, West/East Germany, and a 2^{nd} degree polynomial in time. α_i denotes a worker fixed effect. $U_{i,t+s}$ is the current unemployment rate – our primary indicator of current labor market conditions. $U^{min}_{i,t+s,t} = \min\{U_{t+s-z}\}^{s}_{z=0}$ is the minimum unemployment rate during a worker's tenure and reflects the implicit contract model with mobile workers. $U^{begin}_{i,t}$ denotes the unemployment rate in period t, the start of a job, representing the implicit contract model with full commitment. $q^{EH}_{i,t+s}$ and $q^{HM}_{i,t+s}$ are proxies for unobserved match quality, constructed as explained above. $\eta_{i,t+s}$ is an error term. We follow HM and prefer using a full set of experience and tenure dummies over a more restricted specification because otherwise the true returns to tenure or experience could be masked by other variables, especially the minimum unemployment since the start of a job.[5]

Moulton (1986) identifies a potential problem affecting all regressions fitting micro-level data as functions of some independent variables that have a grouped structure. In short, if any of the unemployment variables varies only at the group level, which in our exercise is the time span of an employment spell, the OLS standard errors can be sharply biased downward. In our analyses, this could be an issue whenever employment spells (observations) start and end in the same month of the same year. This is specifically true for all ongoing jobs for which we have only one observation per year (e.g., the annual report). To address this concern, we cluster standard errors at the employment spell level and correct for potential within (time span) correlation.

We separately estimate equation 6 for each of the unemployment variables and then add the proxies for cyclical job selection. The typical result in the literature is that the coefficients of both the past and current unemployment are negative, but the latter loses predictive power (Grant, 2003; Devereux

[5] Our results are not altered when we instead use a specification with 2^{nd} degree polynomial in tenure and experience.

and Hart, 2007) or even becomes insignificant (BDN) in a nested regression. The results in HM show that, when adding the proxies for cyclical selection, the coefficients of the past unemployment variables lose their economic and statistical significance.

When analyzing the volatility of wages for job stayers and switchers, we follow the methodology in Gertler et al. (2016) and Carneiro et al. (2012) to estimate the following regression considering the original HM model:

$$\begin{aligned}\ln w_{i,t+s,t} &= \beta_0 X_{i,t+s} + \beta_1 U_{i,t+s} + \beta_2 U^{min}_{i,t+s,t} + \beta_3 U^{begin}_{i,t} + \beta_4 q^{EH}_{i,t+s} + \beta_5 q^{HM}_{i,t+s} \\ &+ \beta_{NH} I^{NH}_{i,t+s} + \beta_{NHU} I^{NH}_{i,t+s} U_{i,t+s} + \beta_{SW} I^{SW}_{i,t+s} + \beta_{SWU} I^{SW}_{i,t+s} U_{t+s} \\ &+ \alpha_i + \eta_{i,t+s}\end{aligned} \tag{7}$$

I^{NH} (I^{SW}) equals unity for new hires from unemployment (employer switchers) and zero otherwise. Workers who stay with the same employer are the reference category. HM find that once they add the match quality controls, the formerly negative incremental effects for job switchers and new hires from unemployment decrease and the wages of all worker types are equally cyclical.

We estimate the following equation to test the implications of the refined model with the occupational dimension.

$$\begin{aligned}\ln w_{i,t+s,t} &= \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_2 U^{min}_{i,t+s,t} + \beta_3 U^{begin}_{i,t} + \beta_4 q^{EH}_{i,t+s} + \beta_5 q^{HM}_{i,t+s} \\ &+ \beta_{NH} I^{NH}_{i,t+s} + \beta_{NHU} I^{NH}_{i,t+s} U_{t+s} + \beta_{OSW} I^{OSW}_{i,t+s} + \beta_{OSWU} I^{OSW}_{i,t+s} U_{t+s} \\ &+ \beta_{ESW} I^{ESW}_{i,t+s} + \beta_{ESWU} I^{ESW}_{i,t+s} U_{t+s} + \beta_{OESW} I^{OESW}_{i,t+s} \\ &+ \beta_{OESWU} I^{OESW}_{i,t+s} U_{t+s} + \alpha_i + \eta_{i,t+s}\end{aligned} \tag{8}$$

I^{NH} is a zero/one indicator for new hires, I^{OSW} for occupational switchers but employer stayers, I^{ESW} for employer switchers but occupation stayers, and I^{OESW} for workers who switch both employers and occupations. As in equation 7, all estimates must be interpreted in comparison to the reference group of job stayers. The coefficient in front of each interaction term measures the incremental effect of a job switcher in the wage responsiveness to changes in the unemployment rate.

3.2 Data

The analyses are conducted using a 2 percent sample of German register data provided by the Institute for Employment Research (IAB), the so-called Sample of Integrated Labor Market Biographies (SIAB). The SIAB covers approximately 80 percent of the German workforce and provides information with daily precision on employment subject to social security, job search and receipt of unemployment compensation. Not included are civil servants, self-employed workers and students. The SIAB data are ideal for our purposes, as they provide complete work and unemployment histories for each worker and a large number of individual- and match-specific characteristics (e.g., age, gender, education, occupation, wage). Most important, these earnings data have a high degree of reliability as a result of the plausibility checks performed by the social security institutions and the existence of legal sanctions for misreporting. Measurement errors due to misreporting should thus be much lower than in household surveys. We restrict our sample to male full-time workers between 20 and 65 years of age. We exclude workers in part-time jobs, marginal jobs and apprenticeships to obtain a homogenous sample with respect to working hours. Workers are considered unemployed if they are registered as unemployed at the Federal Employment Agency. The SIAB data deliver information on average daily wages for each employment spell. We deflate wages using the CPI. One limitation of the wage data is that the German social security system tracks earnings only up to a certain threshold, the contribution assessment ceiling ("Beitragsbemessungsgrenze"). We apply consistent topcoding and use only non-censored wages in our analyses. This approach has the advantage that the same part of the wage distribution is considered throughout the sample period.[6] We exclude all observations with wages under the time-varying marginal employment threshold ("Geringfügigkeitsgrenze"). Every wage observation corresponds to one employment spell, which can last from one day up to one year due to the reporting rules of the German social security system. According to the reporting rules, employers are required to file a report whenever an employee joins or leaves the establishment or, in the event of no change in an ongoing employment relationship, on December 31 of each year (annual report). As in HM, we structure all jobs into employment cycles. Any employment cycle starts with the first job after a period of unemployment. It lasts as long as the worker is employed – including job switches. The unit of our analysis is driven by the structure of the SIAB data, specifically by the fact that for existing jobs, we observe wage information at least once a year (annual report). Hence, a new observation starts either on January 1 or whenever a worker starts a new job in the course of the year (daily accuracy). It ends either when the worker enters unemployment or at the end of the calendar year, whichever happens first. Note that the data structure is comparable to the "job-interview-intersection" logic in HM (see Section IV.A). Using this procedure has the advantage of allowing us to observe wage changes within the same job, which is crucial for the purpose of

[6] We apply separate topcoding for West Germany and East Germany. We first identify the fraction of censored wages in each year and then drop the highest fraction in every sample year. For further details, see (Feng et al., 2006)

our analysis, especially for comparing the cyclicality of different worker types. After the initial data preparation, we merge official statistics of the Federal Employment Agency on monthly nationwide unemployment (level and rate) and vacancies to our data. We calculate the average monthly unemployment rate over an observation (denoted by U) and interpret it as an indicator of the contemporaneous business cycle. We calculate the lowest unemployment rate (denoted by U^{min}) since the start of a job as the average of minimum unemployment across all months corresponding to a job. The unemployment rate at the start of a job (denoted by U^{begin}) is the unemployment rate in the month a job starts and hence is constant across a job but might vary across employment cycles.

To construct the original HM measures of match quality, we calculate the nationwide labor market tightness (vacancy-unemployment ratio) in every month of an observation and sum it over the employment cycle. q^{EH} is a cumulative sum over labor market tightness before the last job, and q^{HM} summarizes the labor market tightness of the last job in the employment cycle.[7]

For our exercises at the occupational level, we rely on the 2-digit occupational classification of the German Classification of Occupations (KldB88), which comprises 33 different occupation sections. Since occupation-specific unemployment rates are not available in the official statistics of the Federal Employment Agency, we extract this information from the data set by taking stocks of employed and unemployed workers at our evaluation date and approximate the unemployment rate as $U_{o,t}/(U_{o,t} + E_{o,t})$. To count the stock of unemployed workers in occupation o at time t, we assume that the unemployed workers proceed to search for a job in the occupation they worked in last.[8] We merge occupation-specific vacancy data from the Federal Employment Agency with the data, which allows us to compute an occupation-specific labor market tightness and, given that, q_o^{HM} and q_o^{EH}. To fully exploit all the advantages of the disaggregation, we need to modify the definition of a job within an employment cycle. Thus, in this exercise, we assume that each job either starts when switching employers but keeping the same occupation, taking-up a new occupation with a new employer, or switching occupations but keeping the same employer. After our data preparation and keeping only complete employment cycles, we are left with 174,219 workers and 1,700,843 observations in the main sample that we use to analyze the "original" HM model. Our data on the occupational level, which we call the "refined" model, contain 130,860

[7] Note that q^{EH} and q^{HM} are constant across jobs, but q^{EH} is increasing in the employment cycle.

[8] Assuming instead that workers search in the occupation they take up after unemployment does not substantively alter the results of our analyses.

individuals and 1,152,698 observations because for some occupations, we cannot observe vacancy data. Our sample period is restricted to the years 2000 to 2014 since vacancy data on the occupational level are not available for the preceding years.[9]

4 Results

4.1 Implicit contracts and cyclical selection

Table 1: Estimation results of original model - comparable to HM

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.92***	-0.43**	-0.55**	-0.36*	-0.70***	-0.31*
	(0.21)	(0.17)	(0.23)	(0.21)	(0.20)	(0.18)
$ln(q^{EH})$		3.64***		3.62***		3.57***
		(0.07)		(0.07)		(0.07)
$ln(q^{HM})$		3.95***		3.92***		3.93***
		(0.07)		(0.08)		(0.07)
U^{min}			-0.96***	-0.19		
			(0.11)	(0.13)		
U_{begin}					-0.74***	-0.42***
					(0.06)	(0.06)
Adj. R^2	0.8254	0.8315	0.8256	0.8315	0.8256	0.8315

Notes: number of obs. is 1,700,843; dependent variable is $ln(w_{it})$; and controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); the estimation period is 2000-2014; q^{EH} and q^{HM} are calculated using the national labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 1 shows the results for the estimation of Equation (6). Note that the tables contain only the estimated coefficients on the main variables of interest. However, all the regressions contain the full list of variables described in the caption of each table. Column 1 of Table 1 shows the relationship between contemporaneous unemployment and wages. We find that wages are procyclical: A one-percentage-point decrease in the unemployment rate is associated with a 0.92 percent increase in wages.[10] HM claim that without appropriate controls for match quality, the regression from column 1 suffers from omitted variable bias. Hence, in column 2, we add q^{HM} and q^{EH} to the regression, thereby controlling for match quality as proposed by HM. If

[9] Appendix A provides descriptive statistics for our samples.

[10] To interpret the coefficients of the unemployment variables as semi-elasticities, we multiplied the coefficients and standard errors in all tables by 100.

the regression from column 1 suffers from omitted variable inconsistency and if the match quality proxies are negatively correlated with the business cycle indicator U and positively correlated with wages, then U should be biased downward.

In line with HM's theory, the coefficients for q^{HM} and q^{EH} are both positive and statistically significant, indicating that the expected wage depends positively on the number of offers received before the current job started and during the current job. In column 2, we indeed find that the coefficient on the contemporaneous unemployment rate falls by more than half after we include the match quality proxies; however, it is still negative.[11]

Columns 3 and 5 replicate the BDN methodology, regressing functions of past labor market conditions on contemporaneous wages. We find the usual BDN results, which were interpreted as history dependence. The coefficients of U^{begin} and U^{min} are both negative and significantly different from zero, thus indicating a strong relationship between past labor market conditions and contemporaneous wages.

In columns 4 and 6, we include the match quality measures in the regressions that also contain the indicators for past unemployment. If these indicators remain significant, they contain independent information on contemporaneous wages that might indicate support for history dependence in wages. We observe that the coefficients on q^{HM} and q^{EH} are relatively similar compared to the regressions without past unemployment variables. Again, the coefficient of the contemporaneous unemployment rate declines in magnitude.

On the one hand, we can replicate and confirm HM's findings with respect to the lowest unemployment rate over a worker's tenure. After including q^{HM} and q^{EH}, the coefficient on U^{min} decreases by more than 80 percent and becomes insignificant. We conclude that U^{min} has no independent predictive power for contemporaneous wages after including the match quality proxies – a result that is robust in each of our regressions.

On the other hand, we cannot replicate their results with respect to U^{begin}. Although the coefficient of U^{begin} decreases by approximately 40 percent, it still is negative and significant. Even after controlling for match quality, we find independent predictive power of U^{begin}. We take this as evidence that the predictions of the implicit contract models are not ruled out entirely by the on-the-job search model. U^{begin} is correlated with the match quality proxies; however, our results show that U^{begin} carries independent information about contemporaneous wages. We will see throughout this paper that this result, which we interpret as history dependence, is robust in all of our regressions.

[11] This result is also visible in HM. See Table 1 in HM for a detailed comparison of their results to ours.

Table 2: Estimation results of refined model

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.14***	-0.81***	-0.82***	-0.75***	-0.92***	-0.68***
	(0.14)	(0.13)	(0.2)	(0.19)	(0.16)	(0.15)
$ln(q_o^{EH})$		3.16***		3.15***		3.07***
		(0.07)		(0.07)		(0.07)
$ln(q_o^{HM})$		2.69***		2.68***		2.70***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.64***	-0.12		
			(0.14)	(0.15)		
U^{begin}					-0.58***	-0.32***
					(0.07)	(0.08)
Adj. R^2	0.8084	0.8130	0.8084	0.8130	0.8085	0.8131

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Because, thus far, we have not distinguished between worker types and thus all worker types are pooled in one coefficient, it is unclear which of these types is affected most by the inclusion of the match quality proxies. We will see later in this paper that most of the decrease in the coefficient of U is due to the procyclical improvement in the match quality of job switchers.

4.2 Refined model

Table 2 displays the results from estimating the refined model. Please recall that in this model, the match quality measures are occupation specific, as explained above. Overall, we find that our conclusions drawn from the original model are also valid in the refined model. We find procyclical wages in all our regressions. After including the match quality proxies at the occupational level, we again find no support for implicit contract models with one-sided commitment (insignificant and small coefficient on U^{min}). However, we once again find support for history dependence in the regression with U^{begin} even after controlling for match quality.[12]

[12]The coefficient of q^{HM} decreases in magnitude after we refine the definition of a job, taking into account the occupational variation in job offers. This might be due to the finer fragmentation of jobs leading to an increase in the overall number of jobs and a decrease in the average duration of a job. This is smoothed out in the duration over which we calculate q^{HM}. For q^{EH}, this is not necessarily the case, as it is calculated by summing the

In addition, we find some important differences between the two exercises. First, the magnitudes of the coefficients on the current unemployment rate are higher in the refined model than in the baseline model. This is due to how the original model aggregates over all jobs and neglects occupational job switches. In the original model, the responsiveness of all workers' wages to the aggregate unemployment rate is pooled in the coefficient in column (1). Since the refined model takes into account occupational selection within employer-employee matches, we identify more switches than the original model does.[13] If these switches are procyclical or if the share of workers improving their match quality is procyclical, then this increases the aggregate cyclicality in wages measured by the coefficient on the contemporaneous unemployment rate. When one does not account for these selection processes across employers and occupations, the interpretation of the pooled coefficient can be misleading since it is sensitive to the wage cyclicality of certain worker types' shares in the sample. We will see in the next sections that the wages of employer switchers respond very differently to the business cycle from those of workers who also change their occupations. Applying the refined model allows us to separately uncover these job switches and take the incorporated cyclicality into account. Furthermore, in Section 6, we explore the drivers of the differences between the original model and the refined model in greater detail and show that the results are due to occupational selection and are not different by construction.

4.3 Job stayers and switchers

In Table 3, we compare the estimates of the wage cyclicality for new hires from unemployment, job stayers and job switchers using the original model without the occupational dimension.[14] The first important insight is that we can replicate the results in HM with respect to the cyclicality of job switchers: Without match quality proxies (column 1), the wages of employer switchers appear to be more cyclical than those of employer stayers. However, in column 2, when we add the match quality proxies, the incremental effect for job switchers decreases by over 80 percent and becomes insignificant. We consider this evidence of composition bias in the regressions without match quality proxies. Again the argument goes along with the omitted variable inconsistency: If workers switch jobs and select into better matches during upswings when the unemployment rate is low, omitting match quality controls leads

labor market tightness over all durations of all jobs before the current job. We will show in our robustness exercises that the duration component in these variables is an important determinant of wages in our data

[13] Appendix A reports details on the number of job stayers and switchers

[14] Note that for the sake of readability, we provide only the coefficients of the interaction terms. The pure dummy coefficients can be found in Appendix B.

Table 3: Estimation results of original model – new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.87***	-0.42**	-0.53**	-0.32	-0.71***	-0.32*
	(0.22)	(0.18)	(0.24)	(0.22)	(0.21)	(0.19)
$I^{NH}U$	0.16**	0.29***	0.49***	0.39***	0.42***	0.46***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
$I^{SW}U$	-0.59***	-0.10	-0.25**	0.00	-0.31***	0.07
	(0.11)	(0.10)	(0.12)	(0.10)	(0.11)	(0.10)
$ln(q^{EH})$		3.47***		3.45***		3.40***
		(0.07)		(0.07)		(0.07)
$ln(q^{HM})$		3.87***		3.83***		3.85***
		(0.07)		(0.07)		(0.07)
U^{min}			-1.03***	-0.32**		
			(0.12)	(0.14)		
U^{begin}					-0.75***	-0.48***
					(0.07)	(0.06)
Adj. R^2	0.8263	0.8320	0.8266	0.8320	0.8266	0.8321

Notes: number of obs. is 1,700,843; dependent variable is $ln(w_{it})$; and controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); estimation period is 2000-2014; q^{EH} and q^{HM} are calculated using the national labor market tightness; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

to procyclical bias. By adding controls for match quality, we can distinguish which worker type is affected most by this downward bias.

In the pure implicit contract models (columns 3 and 5) we observe the same results: First, without controlling for match quality, we find a significant incremental effect for job switchers. However, when we include the match quality proxies and estimate nested models (columns 4 and 6), we observe that the incremental effects decrease and the wages of job stayers and job switchers are equally responsive to the unemployment rate.

Turning to new hires from unemployment, we find that their wages are less cyclical than those of any other worker type in each of our regressions. In column 1, we estimate a positive incremental effect, indicating that the wages of new hires are 0.16 percent less responsive to the unemployment rate than the wages of job stayers. After adding the match quality controls (column 2), the incremental effect increases to 0.29. In the implicit contract models (columns 3 and 5) and the nested models (columns 4 and 6), we observe the same picture: positive incremental effects for new hires.

On the one hand, we can confirm the conclusion in HM that controlling for match quality equalizes the wage cyclicality of job switchers and stayers. On the other hand, we find a moderate degree of wage rigidity for new hires from unemployment. Unfortunately, HM do not report estimates for the wage cyclicality of new hires from unemployment. From a theoretical perspective, there is no clear-cut prediction on how match quality is related to the cyclicality of the wages of new hires. In on-the-job models, the usual assumption for new hires is that they accept any job offer that includes a wage at least as high as their reservation wage. While these results are consistent with theoretical bargaining mechanisms, such as in Gertler and Trigari (2009), they are in stark contrast to recent empirical evidence, such as in Haefke et al. (2013), of excess wage cyclicality for new hires from unemployment.[15] We believe that part of the differences can be explained if one takes into account within employer-employee match job mobility as we do in the next exercise. The reason is simple: If job mobility is only counted when workers switch employers, the reference group in the regressions is contaminated by job mobility across occupations. Without having a clean reference group, the true incremental effects could be masked by this contamination.

Table 4 shows the results of the estimation of Equation (7) in the occupationally refined version. The results shown in column 1 are qualitatively similar to those in the original model. The wages of job (employer or/ and occupation) switchers respond more strongly to changes in the contemporaneous unemployment rate than those of job stayers. Again, we can observe a positive incremental effects for new hires from unemployment. This result changes, however, when our augmented controls for match quality are added. Both the incremental effect for new hires from unemployment and for job switchers decrease in magnitude and become insignificant. We consider this evidence that cyclical selection also has some impact on the cyclicality of the wages of new hires from unemployment.

In the implicit contract models without the match quality proxies (columns 3 and 5), we find a negative and significant incremental effect for job switchers and a positive and significant incremental effect for new hires from unemployment.

When we add $ln(q_o^{HM})$ and $ln(q_o^{EH})$ (columns 4 and 6), the incremental effect for new hires from unemployment remains positive and significant while the incremental effect for job switchers becomes small and insignificant. It appears that the match quality proxies attenuate the incremental effects for job switchers and new hires while the implicit contract proxies increase the incremental effect for new hires from unemployment.

[15] Haefke et al. (2013) use labor productivity as the main business cycle indicator and find excess wage cyclicality for new hires from unemployment, although this is often imprecisely estimated.

Table 4: Estimation results of refined model – new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.13***	-0.82***	-0.84***	-0.76***	-0.98***	-0.73***
	(0.16)	(0.14)	(0.22)	(0.20)	(0.17)	(0.16)
$I^{NH}U$	0.21***	0.10	0.37***	0.14**	0.36***	0.20***
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
$I^{SW}U$	-0.49***	0.02	-0.34**	0.05	-0.32**	0.10
	(0.13)	(0.15)	(0.13)	(0.14)	(0.13)	(0.14)
$ln(q_o^{EH})$		2.96***		2.94***		2.88***
		(0.07)		(0.07)		(0.07)
$ln(q_o^{HM})$		2.61***		2.61***		2.63***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.65***	-0.14		
			(0.16)	(0.16)		
U^{begin}					-0.52***	-0.31***
					(0.07)	(0.07)
Adj. R^2	0.8094	0.8135	0.8094	0.8135	0.8094	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

To obtain deeper insights into which worker types are affected and how from controlling for match quality, we now distinguish the source of job switching in greater detail. This differentiation allows us to analyze in greater detail the wage cyclicality of different job switches. In particular, we identify workers who only switch employers but stay in their occupation, those who switch only occupations but stay at their employer, and those who switch both occupations and employers at the same time.

Table 5 presents the results of distinguishing the source of every job switch. Column 1 shows the results without controlling for match quality or implicit contracts. We find that the wages of new hires from unemployment respond less than those of job stayers, while the wages of each of the "job" switchers respond more strongly to changes in the contemporaneous unemployment rate. Adding the match quality proxies (column 2) attenuates the incremental effect for workers who only switch their occupation or only switch their employer and for new hires from unemployment. Surprisingly, we estimate a negative and significant incremental effect for workers who simultaneously switch their occupation and employer.

In columns 3 and 5, reporting the results of regressions without proxies for match quality but with proxies for implicit contracts, we find qualitative similar results to those in column 1. If we control for both match quality and implicit contracts (columns 4 and 6), we find a negative and significant incremental effect of those workers who simultaneously switch their occupation and employer and a positive incremental effect for new hires from unemployment. All other incremental effects are small and insignificant.

Table 5: Estimation results of refined model – new hires, stayers, different switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.12***	-0.81***	-0.84***	-0.76***	-0.96***	-0.71***
	(0.16)	(0.14)	(0.21)	(0.20)	(0.17)	(0.16)
$I^{NH}U$	0.20***	0.09	0.36***	0.12*	0.36***	0.19***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
$I^{ESW}U$	-0.38***	0.00	-0.23*	0.02	-0.22*	0.08
	(0.12)	(0.10)	(0.12)	(0.09)	(0.12)	(0.09)
$I^{OSW}U$	-0.79***	-0.01	-0.64***	0.02	-0.60***	0.09
	(0.12)	(0.17)	(0.12)	(0.16)	(0.12)	(0.16)
$I^{OESW}U$	-0.87***	-0.39***	-0.73***	-0.36***	-0.73***	-0.31**
	(0.15)	(0.13)	(0.16)	(0.13)	(0.15)	(0.13)
$ln(q_o^{EH})$		3.02***		3.01***		2.94***
		(0.05)		(0.05)		(0.05)
$ln(q_o^{HM})$		2.61***		2.61***		2.63***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.63***	-0.11		
			(0.16)	(0.16)		
U^{begin}					-0.53***	-0.33***
					(0.07)	(0.07)
Adj. R^2	0.8094	0.8136	0.8094	0.8136	0.8095	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

5 Robustness Analyses

In this section, we demonstrate that none of our substantive results is sensitive to the following robustness checks:

- using detrended unemployment variables and
- changing the definition of a "job".

5.1 Using detrended unemployment variables

A valid concern is that our results are driven by a trend in the unemployment rate. It is thus straightforward to repeat our analyses after detrending the national monthly unemployment rate. Thus, we first regress the monthly national unemployment rate on a linear time trend and retain the residuals. Then, we take these residuals to construct U, U^{min} and U^{begin} and run the regressions from above again using the detrended unemployment variables. Recall that in addition to the detrending the unemployment measures we cope with time trends in the wage variable by controlling for a polynomial in time. The tables in Appendix C report the results and demonstrate that our results qualitatively hold in each of the estimations.

5.2 Changing the definition of a "job"

In the next exercise, we explore whether the differences between the baseline model and the refined model are due to the change in the definition of a job switch or to the usage of occupational labor market tightness vs. aggregate tightness. Recall that in the original model, a job switch within an employment cycle is defined as a change of employer. In the refined model, a job switch is a change of employer, a change of occupation, or both. While we use aggregate labor market tightness to construct the match quality measures in the original, we use occupational labor market tightness to construct these measures in the refined model. To determine the extent to which the differences are due to these two effects, we rerun the regressions after constructing a counterfactual model in the following way:

We construct employment cycles and the job switches therein according to employer switches. Based on this definition of a job switch, we compute the match quality measures using occupational labor market tightness. A comparison of the original model (Table 1) and this counterfactual model (Table 6) shows the differences between using aggregate vs. occupational labor market tightness. A comparison between the counterfactual (Table 6) and refined models (Table 2) illustrates the effect that arises by changing the

Table 6: Estimation results of counterfactual model

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.14***	-0.74***	-0.82***	-0.66***	-0.93***	-0.58***
	(0.14)	(0.13)	(0.20)	(0.18)	(0.16)	(0.14)
$ln(q^{EH})$		3.58***		3.57***		3.50***
		(0.06)		(0.07)		(0.07)
$ln(q^{HM})$		2.84***		2.84***		2.86***
		(0.09)		(0.08)		(0.09)
U^{min}			-0.65***	-0.15		
			(0.13)	(0.14)		
U^{begin}					-0.56***	-0.40***
					(0.06)	(0.06)
Adjusted R^2	0.8084	0.8135	0.8084	0.8135	0.8085	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q^{EH} and q^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

definition of a job switch to be either an employer or occupation change (or both).

The results suggest overall wage cyclicality is higher in the counterfactual model than in the original model, but it is lower in the counterfactual than in the refined model. The same is true for the implicit contract proxies. Our match quality measures are also in between the original model and the refined model. This might be because, on the one hand, changing the definition of a job switch to be either an employer or occupation switch (or both) allows us to identify more switches, which are procyclical. On the other hand, different occupations are differently affected by the business cycle, which is accounted for by using occupational labor market tightness. This second effect is quantitatively more important.

6 Summary and discussion

Our main task in this paper is to empirically study the linkage between real wages and past and contemporaneous labor market conditions. In this context, we directly test whether our administrative data are more consistent with existing evidence for history dependence (BDN) in wages or an on-the-job search model with spot wages (HM). Our results are, at least, fivefold:

First, we replicate the BDN methodology, an approach lacking controls for match quality. BDN use U.S. data and find that once they control for functions of past unemployment, the contemporaneous unemployment rate loses its predictive power for contemporaneous wages. In our German data, we, by contrast, find that indicators of both past unemployment and contemporaneous unemployment are important predictors of the contemporaneous wage. This result is also found in different labor markets, e.g., by Grant (2003) using U.S. survey data and by Devereux and Hart (2007) using British survey data.

Second, we test the implications of HM's on-the-job search model. The key feature of the HM method is that it allows the researcher to identify the quality of job matches in the data. In their model, the expected job match quality is approximated by the expected number of job offers, which is measured by the sum of market tightness. We find that HM's match quality measures are indeed important predictors of contemporaneous wages. We can confirm that after controlling for the match quality proxies, the on-the-job model with spot wages outperforms the implicit contract model with one-sided commitment. However, we find independent predictive power of the initial unemployment rate for contemporaneous wages. Overall, we do not conclude that one model supersedes the other. Both models independently help us understand the movement of wages over the business cycle.

Third, we investigate whether wage cyclicality differs across employer stayers, employer switchers and new hires from unemployment. As Gertler et al. (2016), we argue that if workers select into better matches by switching employers during upswings, then there is composition bias in the absence of appropriate controls for match quality. We find that – without match quality controls – the wages of employer switchers appear to be more volatile than those of stayers. However, this result changes after adding HM's controls for match quality: We find no excess cyclicality for job switchers.

Fourth, in the original HM setup, we find that the wages of new hires from unemployment are less cyclical than those of any other group. These results contrast with the conclusion of HM, who find that, after controlling for selection, the wages of stayers and switchers are equally cyclical.[16]

Fifth, we augment the original HM model by taking occupational mobility into account. In this setup, we construct match quality that is occupational and employer specific. We show that it is important to identify employees' within-employer job mobility because, otherwise, these job switches contaminate the reference group and are another source of cyclical selection. Estimating the refined model, we find that the wages of new hires from unemployment are approximately as cyclical than those of job stayers. The only worker group

[16]HM do not explicitly report estimation results for new hires from unemployment. They state that their wage cyclicality is similar to that of employer switchers.

for which we find excess wage cyclicality is that of workers who simultaneously change employers and occupations.

We interpret our results as confirmation of the results in Gertler et al. (2016), who study U.S. data and find no excess wage cyclicality for new hires from unemployment. In addition, our results are consistent with those of Stüber (2017) using data from Germany. He finds that wages from newly hired workers (from non-employment and employer switchers) are not significantly more cyclical than those of other workers when controlling simultaneously for worker and firm-occupation fixed effects. Our results, however, contrast with the results in Haefke et al. (2013), who find excess wage cyclicality for new hires from unemployment in U.S. data. Our results are also contrast with those of studies using data from other European countries. Using Portuguese data, Carneiro et al. (2012) show that the wages of newly hired workers – those from non-employment and between-firm movers – respond more strongly to changes in the unemployment rate than those of employer stayers, even after controlling for firm, worker and job heterogeneity. In addition, Martins et al. (2012) find higher wage cyclicality for job movers, also using data from Portugal.

Throughout the paper, we strictly interpret our results in light of both the BDN implicit contract model and the HM on-the-job search model. We show that controlling for cyclical selection is crucial for the responsiveness of wages to the business cycle. We believe that HM's match quality is an appropriate tool for capturing composition effects. While we believe that the process of selection into better matches over the course of an employment cycle is most apparent for job changers, our results also show that cyclical selection (in aggregate or at the occupational level) affects the wages of new hires from unemployment. However, the on-the-job model lacks a clear theoretical strategy for explaining this empirical result. Thus, we believe that there is considerable scope for further research to explore the specific mechanisms at work.

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A Descriptives statistics

A.1 Original model

Table 7: Main variables - original model

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
$ln(wage)$	4.12	0.45	2.20	6.89
U	9.83	1.81	7	14.1
U^{begin}	10.37	1.78	3.3	14.1
U^{min}	9.58	1.58	3.3	14.1
θ (tightness)	0.10	0.04	0.04	0.19
$ln(q^{EH})$	0.24	0.85	-3.61	3.77
$ln(q^{HM})$	1.37	1.41	-3.15	3.86
# employm. cycles	2.56	2.53	1	51
# jobs in cycle	1.48	0.88	1	23

Notes: Original model sample: descriptive statistics on main variables, sample years 2000-2014. source: SIAB-7514-V1

Table 8: Shares of switches, stayings and new hirings - original model

Variable	**Share**
Switches/New Hirings	36 %
Switches/Stayings	8 %

Notes: Original model sample: descriptive statistics on number of job switches, stayings and new hirings, sample years 2000-2014. source: SIAB-7514-V1

A.2 Refined model

Table 9: Main variables - refined model

Variable	Mean	Std. Dev.	Min.	Max.
$ln(wage)$	4.07	0.45	2.20	6.47
U	9.70	1.80	7.2	14.1
U^{begin}	10.23	1.76	7.2	14.1
U^{min}	9.61	1.61	7.2	14.1
$ln(q^{EH})$	0.21	0.82	-4.16	4.66
$ln(q^{HM})$	1.23	1.49	-4.30	4.72
# employm. cycles	1.94	1.62	1	33
# jobs in cycle	1.48	0.74	1	11

Notes: Refined model sample: descriptive statistics on main variables, sample years 2000-2014. source: SIAB-7514-V1

Table 10: Shares of switches, stayings and new hirings - refined model

Variable	Share
Switches/ New Hirings	35 %
Switches/ Stayings	12 %

Notes: Refined model sample: descriptive statistics on number of job switches, stayings and new hirings, sample years 2000-2014. source: SIAB-7514-V1

Table 11: Number of switches - refined model

Variable	Total number of switches	% of total switches
All Switches	96,238	100
Occup. Switcher/Empl. Stayer	17,162	18
Occup. Stayer/ Empl. Switcher	47,749	50
Occup. Switcher/Empl .Switcher	31,327	33

Notes: Refined model sample: descriptive statistics on number of job switches, sample years 2000-2014. source: SIAB-7514-V1

B Detailed tables from the text

Table 12: Estimation results of original model - new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.87***	-0.42**	-0.53**	-0.32	-0.71***	-0.32*
	(0.22)	(0.18)	(0.24)	(0.22)	(0.21)	(0.19)
I^{NH}	-2.96***	-3.21***	-5.95***	-4.14***	-5.54***	-4.87***
	(0.83)	(0.72)	(0.70)	(0.68)	(0.74)	(0.70)
$I^{NH}U$	0.16**	0.29***	0.49***	0.39***	0.42***	0.46***
	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
I^{SW}	10.5***	5.00***	7.32***	4.06***	7.63***	3.31***
	(1.13)	(1.00)	(1.14)	(0.97)	(1.09)	(0.93)
$I^{SW}U$	-0.59***	-0.10	-0.25**	0.00	-0.31***	0.07
	(0.11)	(0.10)	(0.12)	(0.10)	(0.11)	(0.10)
$ln(q^{EH})$		3.47***		3.45***		3.40***
		(0.07)		(0.07)		(0.07)
$ln(q^{HM})$		3.87***		3.83***		3.85***
		(0.07)		(0.07)		(0.07)
U^{min}			-1.03***	-0.32**		
			(0.12)	(0.14)		
U^{begin}					-0.75***	-0.48***
					(0.07)	(0.06)
Adj. R^2	0.8263	0.8320	0.8266	0.8320	0.8266	0.8321

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 13: Estimation results of refined model - new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.13***	-0.82***	-0.84***	-0.76***	-0.98***	-0.73***
	(0.16)	(0.14)	(0.22)	(0.20)	(0.17)	(0.16)
I^{NH}	-3.58***	-2.07***	-4.98***	-2.38***	-5.07***	-3.00***
	(0.75)	(0.71)	(0.73)	(0.65)	(0.73)	(0.65)
$I^{NH}U$	0.21***	0.10	0.37***	0.14**	0.36***	0.20***
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)
I^{SW}	8.43***	2.78*	7.15***	2.54	6.81***	2.01
	(1.42)	(1.66)	(1.42)	(1.58)	(1.46)	(1.55)
$I^{SW}U$	-0.49***	0.02	-0.34**	0.05	-0.32**	0.10
	(0.13)	(0.15)	(0.13)	(0.14)	(0.13)	(0.14)
$ln(q_o^{EH})$		2.96***		2.94***		2.88***
		(0.07)		(0.07)		(0.07)
$ln(q_o^{HM})$		2.61***		2.61***		2.63***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.65***	-0.14		
			(0.16)	(0.16)		
U^{begin}					-0.52***	-0.31***
					(0.07)	(0.07)
Adj. R^2	0.8094	0.8135	0.8094	0.8135	0.8094	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 14: Estimation results of refined model - new hires, stayers, different switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.12***	-0.81***	-0.84***	-0.76***	-0.96***	-0.71***
	(0.16)	(0.14)	(0.21)	(0.20)	(0.17)	(0.16)
I^{NH}	-3.48***	-1.89***	-4.85***	-2.13***	-5.02***	-2.87***
	(0.74)	(0.68)	(0.71)	(0.62)	(0.72)	(0.64)
$I^{NH}U$	0.20***	0.09	0.36***	0.12*	0.36***	0.19***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
I^{ESW}	7.72***	3.36***	6.44***	3.17***	6.17***	2.60***
	(1.21)	(1.01)	(1.21)	(0.92)	(1.20)	(0.91)
$I^{ESW}U$	-0.38***	0.00	-0.23*	0.02	-0.22*	0.08
	(0.12)	(0.10)	(0.12)	(0.09)	(0.12)	(0.09)
I^{OSW}	8.90***	-0.11	7.62***	-0.29	6.94***	-1.07
	(1.17)	(1.74)	(1.20)	(1.67)	(1.23)	(1.68)
$I^{OSW}U$	-0.79***	-0.01	-0.64***	0.02	-0.60***	0.09
	(0.12)	(0.17)	(0.12)	(0.16)	(0.12)	(0.16)
I^{OESW}	12.4***	7.25***	11.1***	7.07***	10.9***	6.52***
	(1.46)	(1.23)	(1.50)	(1.20)	(1.48)	(1.19)
$I^{OESW}U$	-0.87***	-0.39***	-0.73***	-0.36***	-0.73***	-0.31**
	(0.15)	(0.13)	(0.16)	(0.13)	(0.15)	(0.13)
$ln(q_o^{EH})$		3.02***		3.01***		2.94***
		(0.05)		(0.05)		(0.05)
$ln(q_o^{HM})$		2.61***		2.61***		2.63***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.63***	-0.11		
			(0.16)	(0.16)		
U^{begin}					-0.53***	-0.33***
					(0.07)	(0.07)
Adj. R^2	0.8094	0.8136	0.8094	0.8136	0.8095	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

C Tables from robustness check

C.1 Original model - detrended unemployment rate

Table 15: Estimation results of original model

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.93***	-0.43**	-0.57**	-0.38*	-0.73***	-0.32*
	(0.21)	(0.17)	(0.23)	(0.21)	(0.20)	(0.18)
$ln(q^{EH})$		3.64***		3.62***		3.57***
		(0.07)		(0.07)		(0.07)
$ln(q^{HM})$		3.95***		3.93***		3.93***
		(0.07)		(0.08)		(0.07)
U^{min}			-0.91***	-0.14		
			(0.11)	(0.14)		
U^{begin}					-0.69***	-0.38***
					(0.06)	(0.06)
Adjusted R^2	0.8254	0.8315	0.8256	0.8315	0.8256	0.8315

Notes: number of obs. is 1,700,843; dependent variable is $ln(w_{it})$; and controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); the estimation period is 2000-2014; q^{EH} and q^{HM} are calculated using the national labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 16: Estimation results of original model - new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.89***	-0.43**	-0.55**	-0.34	-0.73***	-0.33*
	(0.21)	(0.18)	(0.24)	(0.22)	(0.21)	(0.19)
I^{NH}	-1.39***	-0.34**	-1.18***	-0.29*	-1.45***	-0.38**
	(0.14)	(0.16)	(0.16)	(0.17)	(0.14)	(0.16)
$I^{NH}U$	0.19***	0.30***	0.45***	0.37***	0.39***	0.43***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
I^{SW}	4.61***	3.99***	4.82***	4.05***	4.57***	3.97***
	(0.21)	(0.18)	(0.22)	(0.20)	(0.20)	(0.18)
$I^{SW}U$	-0.53***	-0.10	-0.26**	-0.03	-0.30***	0.03
	(0.10)	(0.09)	(0.11)	(0.09)	(0.10)	(0.09)
$ln(q^{EH})$		3.46***		3.44***		3.39***
		(0.07)		(0.07)		(0.07)
$ln(q^{HM})$		3.87***		3.84***		3.86***
		(0.07)		(0.07)		(0.07)
U^{min}			-0.96***	-0.26*		
			(0.13)	(0.15)		
U^{begin}					-0.69***	-0.44***
					(0.07)	(0.06)
Adjusted R^2	0.8264	0.8320	0.8266	0.8320	0.8266	0.8321

Notes: number of obs. is 1,700,843; dependent variable is $ln(w_{it})$; and controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); the estimation period is 2000-2014; q^{EH} and q^{HM} are calculated using the national labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

C.2 Refined model - detrended unemployment rate

Table 17: Estimation results of refined model

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.15***	-0.81***	-0.83***	-0.78***	-0.93***	-0.70***
	(0.14)	(0.13)	(0.2)	(0.19)	(0.16)	(0.15)
$ln(q_o^{EH})$		3.16***		3.15***		3.07***
		(0.07)		(0.07)		(0.07)
$ln(q_o^{HM})$		2.68***		2.68***		2.70***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.63***	-0.06		
			(0.14)	(0.16)		
U^{begin}					-0.56***	-0.27***
					(0.06)	(0.08)
Adjusted R^2	0.8084	0.8130	0.8084	0.8130	0.8085	0.8131

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 18: Estimation results of refined model - new hires, stayers, switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.14***	-0.82***	-0.85***	-0.80***	-0.98***	-0.74***
	(0.16)	(0.14)	(0.22)	(0.20)	(0.17)	(0.16)
I^{NH}	-1.54***	-1.06***	-1.39***	-1.05***	-1.58***	-1.07***
	(0.13)	(0.13)	(0.15)	(0.14)	(0.13)	(0.13)
$I^{NH}U$	0.19***	0.09	0.33***	0.10*	0.32***	0.16***
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
I^{SW}	3.64***	2.96***	3.80***	2.97***	3.58***	2.95***
	(0.29)	(0.32)	(0.29)	(0.34)	(0.29)	(0.32)
$I^{SW}U$	-0.44***	0.02	-0.31**	0.02	-0.30**	0.07
	(0.12)	(0.13)	(0.12)	(0.13)	(0.12)	(0.12)
$ln(q_o^{EH})$		2.96***		2.95***		2.88***
		(0.07)		(0.07)		(0.06)
$ln(q_o^{HM})$		2.61***		2.61***		2.62***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.62***	-0.05		
			(0.16)	(0.16)		
U^{begin}					-0.49***	-0.25***
					(0.07)	(0.07)
Adjusted R^2	0.8094	0.8135	0.8094	0.8135	0.8095	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

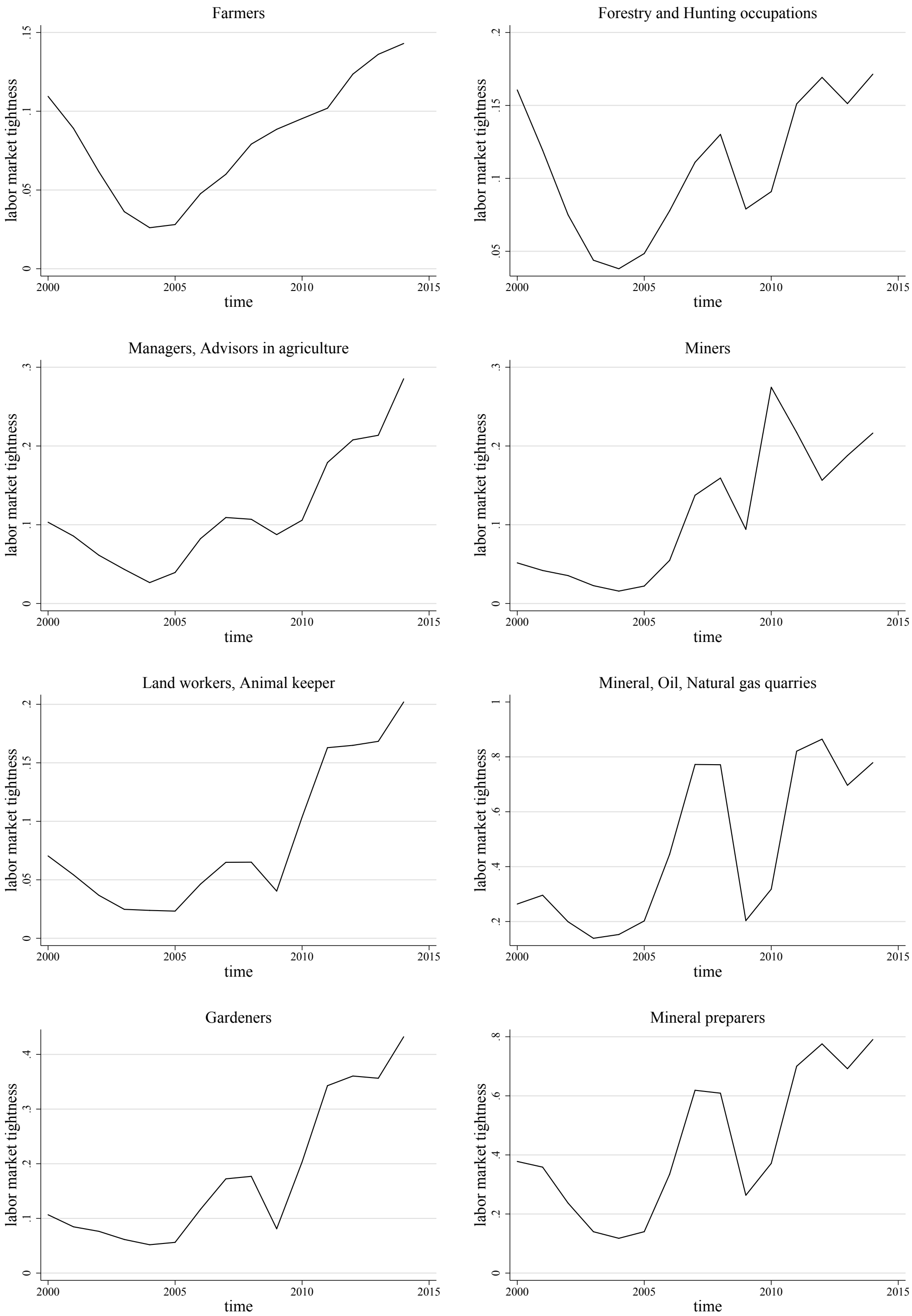
Table 19: Estimation results of refined model - new hires, stayers, different switchers

	(1)	(2)	(3)	(4)	(5)	(6)
U	-1.13***	-0.81***	-0.85***	-0.80***	-0.97***	-0.72***
	(0.15)	(0.14)	(0.21)	(0.20)	(0.17)	(0.16)
I^{NH}	-1.50***	-0.98***	-1.35***	-0.97***	-1.53***	-0.99***
	(0.13)	(0.13)	(0.15)	(0.14)	(0.13)	(0.13)
$I^{NH}U$	0.19***	0.08	0.32***	0.08	0.32***	0.15***
	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
I^{ESW}	4.00***	3.36***	4.15***	3.37***	3.98***	3.37***
	(0.20)	(0.19)	(0.22)	(0.21)	(0.20)	(0.19)
$I^{ESW}U$	-0.34***	-0.00	-0.22**	0.00	-0.21*	0.06
	(0.11)	(0.09)	(0.11)	(0.09)	(0.11)	(0.08)
I^{OSW}	1.02***	-0.22	1.22***	-0.21	0.87***	-0.26
	(0.31)	(0.35)	(0.32)	(0.37)	(0.31)	(0.35)
$I^{OSW}U$	-0.74***	-0.03	-0.60***	-0.03	-0.57***	0.04
	(0.11)	(0.15)	(0.11)	(0.15)	(0.11)	(0.15)
I^{OESW}	3.76***	3.45***	3.89***	3.45***	3.72***	3.43***
	(0.31)	(0.25)	(0.31)	(0.27)	(0.30)	(0.25)
$I^{OESW}U$	-0.80***	-0.36***	-0.68***	-0.35***	-0.67***	-0.30***
	(0.13)	(0.12)	(0.14)	(0.12)	(0.14)	(0.11)
$ln(q_o^{EH})$		3.02***		3.02***		2.94***
		(0.05)		(0.05)		(0.05)
$ln(q_o^{HM})$		2.61***		2.61***		2.63***
		(0.09)		(0.09)		(0.09)
U^{min}			-0.61***	-0.03		
			(0.15)	(0.16)		
U^{begin}					-0.51***	-0.28***
					(0.07)	(0.07)
Adjusted R^2	0.8094	0.8136	0.8094	0.8136	0.8095	0.8136

Notes: number of obs. is 1,152,698; the dependent variable is $ln(w_{it})$; and the controls are west, dummies for education and schooling, dummies for tenure and experience, 2^{nd} degree polynomial in time, and dummy for the period after 2003. Estimation details are as follows: fixed-effects regression for males with clustered standard errors (by beginning and end dates of observation); and the estimation period is 2000-2014; q_o^{EH} and q_o^{HM} are calculated using the occupational labor market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

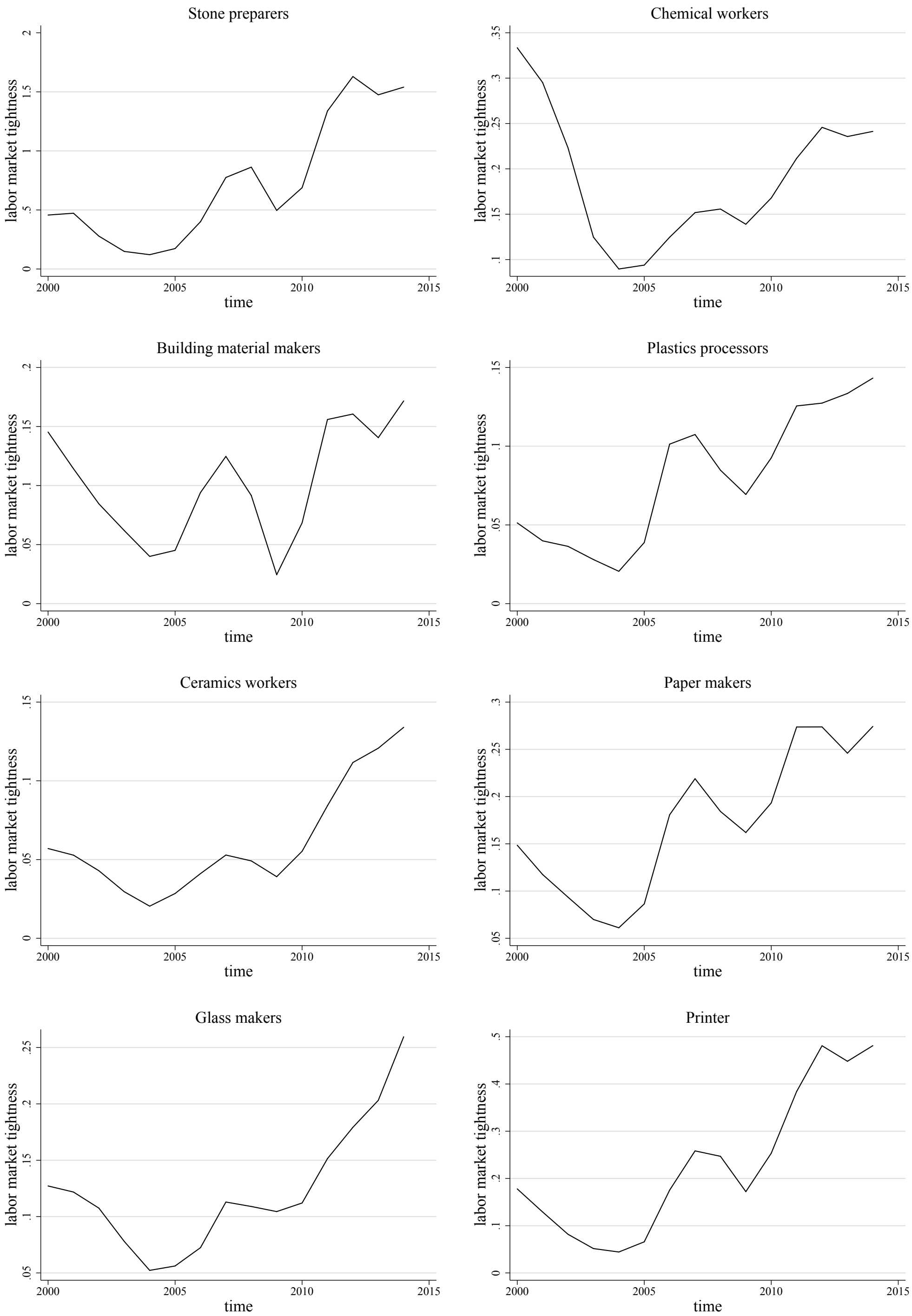
D Occupational labor market tightness

Figure 3: Occupational labor market tightness – 2000-2014



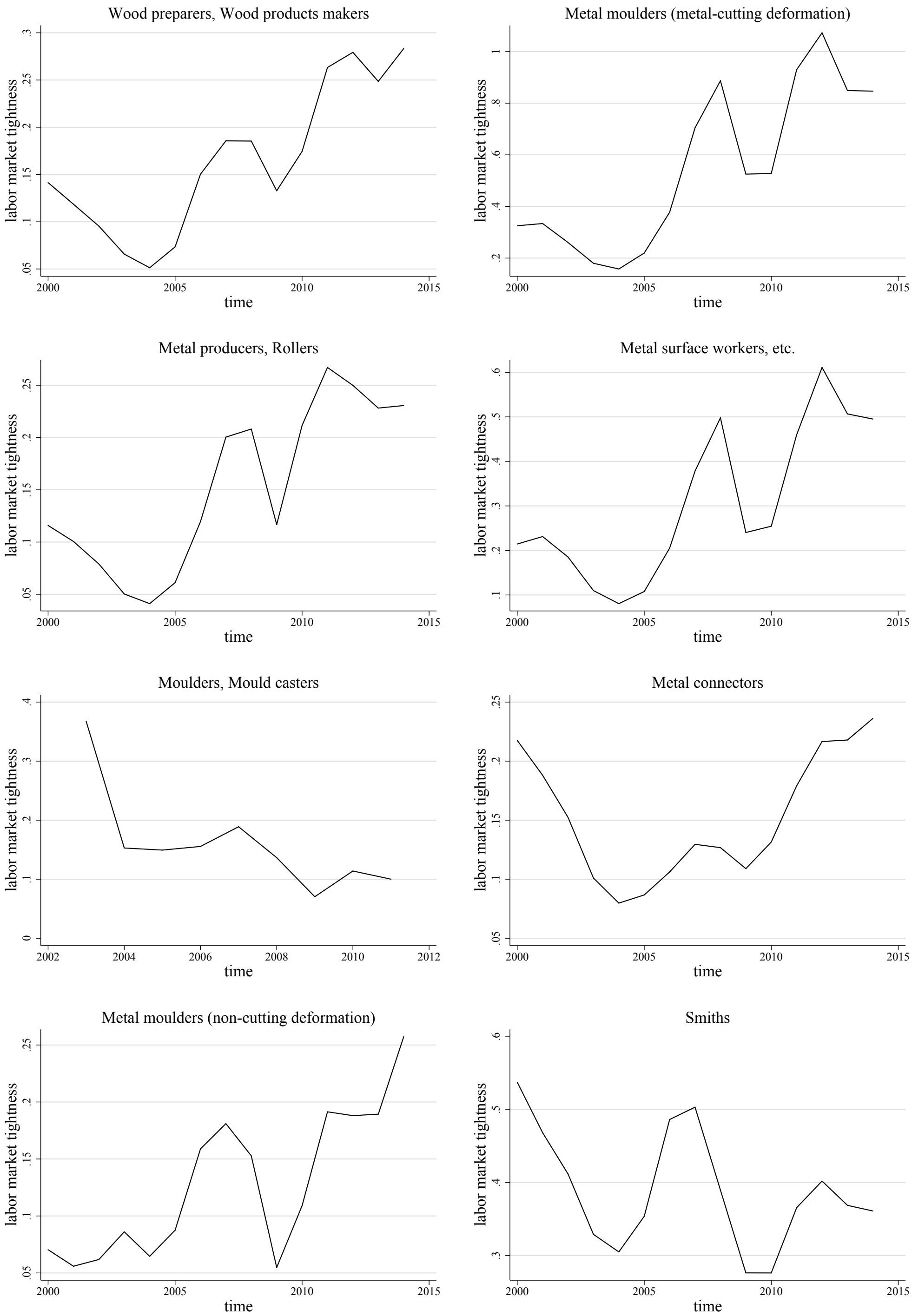
Note: Yearly average of the occupational labor market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)

Occupational labor Market tightness – 2000-2014



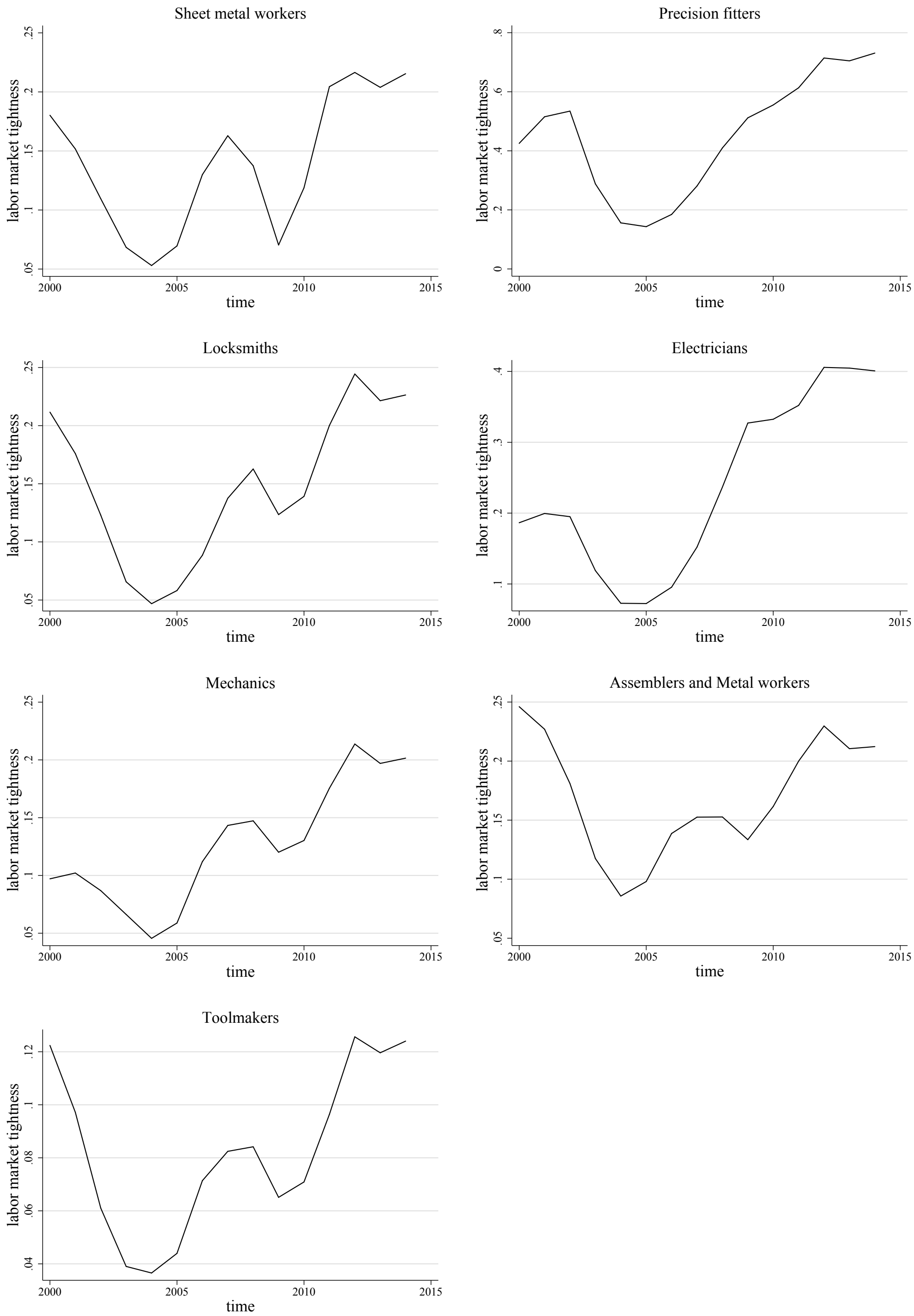
Note: Yearly average of the occupational labor market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)

Occupational labor market tightness – 2000-2014



Note: Yearly average of the occupational labor market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)

Occupational labor market tightness – 2000-2014



Note: Yearly average of the occupational labor market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)