Discussion Papers in Economics

No. 05/2019

History Dependence in Wages and Cyclical Selection:

Evidence from Germany

Anja Bauer
Institute for Employment Research

Benjamin Lochner
FAU Erlangen-Nürnberg

ISSN 1867-6707

Friedrich-Alexander-Universität Erlangen-Nürnberg
Institute for Economics
https://www.iwf.rw.fau.de/discussion-papers/

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

Anja Bauer[†]

Institute for Employment Research

Benjamin Lochner[‡]

University of Erlangen-Nuremberg
Institute for Employment Research

July 2019

Abstract

Using administrative employer-employee data from Germany, we investigate the relationship between wages and past and present labor market conditions. Furthermore, we revisit recent findings of greater wage cyclicality of new hires. Overall, we find strong evidence for history dependent wages, manifested in both hiring and retention premiums – which is consistent with a variety of contract models. Taking into account composition effects as well as cyclical variation in unobserved match quality, we find that wages of new hires from unemployment are no more cyclical, but those of job changers are more cyclical than those of existing workers. We argue that much of the excess wage cyclicality of new hires discussed by the literature can be explained by cyclical job ladder movements in match quality of new hires from employment. In a novel empirical approach, where we further take into account occupational selection, we show that if job ladder movements accompany a simultaneous change of employers and occupations, the resulting wages are particularly cyclical sensitive.

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

---

*First draft: October 2016. We thank Daniel Bias, Mike Elsby, Axel Gottfries, Johannes Ludsteck, Christian Merkl, Jean-Marc Robin, Bastian Schulz, Heiko Stüber, Coen Teulings, Antonella Trigari, and two anonymous referees for their comments and suggestions. Feedback from seminar and conference participants at the Universities of Cambridge, Erlangen-Nuremberg, the Institute for Employment Research (IAB), Conference on Markets with Search Frictions 2016 (Sonderborg), SaM 2017 (Barcelona), and EALE 2017 (St. Gallen) has greatly improved the paper. All remaining errors are our own. A very preliminary version of this article was published in Lochner's doctoral thesis (Lochner, 2016).

[†]Contact: Institute for Employment Research, Regensburger Str. 104, 90478 Nuremberg, Germany, Anja.Bauer@iab.de, +49 911 179 3366.

[‡]Contact: Institute for Employment Research, Regensburger Str. 104, 90478 Nuremberg, Germany, Benjamin.Lochner@fau.de, +49 911 5302 319.

1 Introduction

How flexible, or rigid, are real wages over the business cycle? This is an old question in macroeconomics, for both theorists and policymakers, and one with yet no conclusive answer. On the one hand, there is substantial empirical evidence for wage rigidity induced by long-term (implicit) contracts that enable risk-sharing among workers and employers. Beaudry and DiNardo (1991) (henceforth BDN) were among the first to show that current wages depend on (functions of) past labour market conditions rather than on contemporaneous conditions – a phenomenon often termed "history dependence in wages". Due to some degree of commitment by workers and firms the wage in ongoing jobs does not instantaneously respond to current economic conditions and is only revised infrequently. On the other hand, there is substantial micro-level evidence that wages are considerably 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.

While the empirical observation of history dependence in wages for ongoing jobs is hard to square with the period-by-period Nash bargaining assumption of the canonical search and matching model, it is more consistent with a variety of search models which incorporate on-the-job-search (OJS). OJS-models in the spirit of Burdett and Mortensen (1998) often rely on a wage posting assumption that states that the wage rate is set at the time of hiring, and firms and workers commit to this wage in the future. Other search models (e.g. Postel-Vinay and Robin, 2002; Cahuc et al., 2006) assume that firms can counter the offers received by their employees from competing firms. Hence, wages might increase in ongoing jobs due to incoming outside offers. Both wage setting theories are consistent with the evidence by BDN and with the general idea that labor market conditions asymmetrically affect wages.

However recently, many authors question the empirical evidence on both history dependence in wages and excess wage cyclicality of new hires. These authors argue that the empirical models lack proper correction for the quality of a worker-employer match (see among others Solon et al., 1994; Hagedorn and Manovskii, 2013; Stüber, 2017; Gertler et al., 2016). Their argument is that if match quality is correlated with aggregate labor market conditions, any model that does not incorporate match quality suffer from misspecification error. Hence, past aggregate conditions appear to be important predictors of wages, while these variables actually proxy for unmeasured match quality.

Against this background, in this paper we recapitulate the potential links between wages and labour market conditions in the German labour market. Our goal is to use our administrative individual data to deliver fresh estimates that help us to better understand how flexible wages in the German labor market are and which models describes the wage setting process best.

To this end, we proceed in three main steps: First, we offer a walk through the empirical literature on the cyclicality of wages, testing different wage-setting models. Second, we confront these estimates with a correction for the selection of better matches following the method proposed by Hagedorn and Manovskii (2013) (henceforth HM). Third, we provide a refined approach to measure match qualities that takes into account the cyclical re-assignments of workers within the same firm. This refinement allows us to uncover the relative importance of composition bias among different worker groups in previous results.

In the first part of the paper, we apply the standard BDN methodology and nest three wage-setting models into one regression equation, that is, we use the unemployment rate at the start of a job, the lowest unemployment rate during a worker's tenure, and the current unemployment rate to test how contemporaneous and past labor market conditions are related to current wages. In all our analyses, we find a robust and significant procyclical relationship between past labor market indicators and contemporaneous wages, but, unlike BDN, none of these indicators outperform contemporaneous conditions. These results are consistent with models that incorporate credible counter offers such as Cahuc et al. (2006), indicating wages to increase when labor market conditions improve over the course of workers' tenure. Furthermore, our results point to hiring premiums as workers who started their job during periods of higher unemployment seem to experience lower wages – a result that is coherent with OJS-models with wage posting. However, since we observe coefficients of about the same magnitude for all three wage-setting models, we conclude that contract models do not supersede the pure spot market model.

As these results point to a more general wage setting that contains features of both spot and history dependent wages, we continue our analysis in a framework that allows for these features. Hagedorn and Manovskii (2013) (henceforth HM) provide an OJS-model that is able to reconcile the empirical findings of history dependence in wages without abandoning the assumption of spot wages. In their model, workers may quit their jobs in favour of jobs with higher quality, leading to selection of more productive matches over time. The distribution of match quality is affected by the history of aggregate labor market conditions. These conditions influence a worker's outside option, leading to wage changes, either directly through renegotiation or indirectly by triggering quits. One of the main contribution of HM is that they develop a method that measures the quality of job matches in the data. The expected job match quality is approximated by the expected number of job offers, which is measured by the sum of market tightness over the course of a match. HM use NLSY data and include their match quality controls in the typical BDN regressions. They find that the indicators of past unemployment lose both their economical and statistical significance. Furthermore, they find that the wages of new hires are no longer more cyclical than those of workers in ongoing jobs. They conclude that period-by-period Nash bargaining is a suitable description of the wage setting. We follow HM and use our administrative data for Germany to construct the match quality controls in a similar manner. Subsequently, we augment our previous regression, where we find support for history dependence, with these controls.

Interestingly, unlike HM, we again find an economical and statistical significant relation between past labor market conditions and contemporaneous wages, even after controlling for match quality. We argue that part of their impact on wages works indeed through the selection of better match qualities as the inclusion of the selection controls decreases the magnitude of the coefficients on the indicators for past labor market conditions. However, our results show that past labor market conditions carry independent information for current wages and hence deliver empirical support for models with history dependence in wages - an observation that might be driven by institutional country-specific settings.

The literature has usually interpreted the incidence of history dependence as evidence of wage flexibility for new hires. These results were supported by additional panel data evidence, where incremental effects for new hires as compared to workers in ongoing jobs were directly estimated (starting with Bils, 1985). In the second part of this paper, we build upon these results and take up the recent critique by the literature stating that excess wage cyclicality is mainly driven by composition effects due to the selection of workers into better matches. We start by replicating the typical result from panel data evidence that finds that entry wages of new hires are substantially more cyclical than the wages of existing workers. Gertler et al. (2016) (henceforth GHT) make the point that pooling all sorts of new hires conflates the wage flexibility of new hires from unemployment with procyclical improvements of match quality of new hires from employment. Therefore, we then disentangle the relative contribution of cyclical composition and wage cyclicality to estimates of excess wage cyclicality of new hires. Our estimates show that wages of new hires from unemployment and those of workers in ongoing jobs are equally responsive to the cycle, while those of job changers are significantly more responsive. To test by how much the greater cyclicality of wages for new hires reflects cyclicality in the composition of match quality across new hires from employment, we again use the HM selection controls. We apply them separately to job stayers, new hires from unemployment, and job changers to measure how our previous estimates are affected by potential composition effects. We find that all our previous estimates appear to be biased procyclically, with the largest selection effects for job changers. Interestingly, controlling for cyclical match quality makes the observation that wages of new hires from unemployment are not more cyclical than those of stayers even clearer. These results are aligned with recent evidence that wages are more sensitive to changes in new job opportunities for employed workers than they are for unemployed workers (Karahan et al., 2017). However, these results are in contrast to Haefke et al. (2013) who find excess wage cyclicality for new hires from unemployment.

In the last part of the paper, we propose a refinement of HM's OJS-model and their method to measure match quality. While HM and most of the empirical literature focus on employer-employee contracts, there exists evidence that states that much of the labor market may be governed by job-specific arrangements rather than employer-specific contracts. The general idea is that firms adjust their labor costs over the cycle not by altering wages for particular jobs, but rather by changing the assignment of workers to those jobs (see among others Reynolds, 1951; Reder, 1955; Hall, 1974). This literature is aligned with empirical evidence that cyclical up- and downgrading of workers within the company can result in large wage changes (see Hart and Roberts, 2011; Büttner et al., 2010). To test whether job-specific arrangements matter for our results, we include match quality measures that are job-specific to our regressions. Thus, we change the observation unit from the employee-employer-level to the job-level, that is the employee-employer-occupation interaction. We construct the match quality measures in a symmetric manner to the ones in HM. The argument is that even within employer-employee matches, workers might select into better matches during good times through internal promotions. This refinement is important because the cyclical implications of implicit contracts, especially those of models with worker mobility, are observationally equivalent to the implications of cyclical intrafirm up- and downgrading. With our refinement, we both clean the reference group of job stayers and exploit an additional source of cyclical variation that might confound previous results. Interestingly, we find that the largest selection effects go along the occupational dimension as workers who change occupations at the same employers are responsible for the largest portion of the procyclical bias in the estimated wage cyclicality. These results are consistent with Carrillo-Tudela et al. (2016) who find that procyclical wage improvements are larger for workers who change careers (e.g. occupation changes) than for workers who do not. Furthermore, they are aligned with Kambourov and Manovskii (2009) who show that workers who switch occupations are particularly cyclically sensitive.

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

2 Theoretical framework

In this section, we recapitulate the theoretical frameworks that guide our analyses. Specifically, we review and contrast outcomes of (implicit) contract models with the OJS model that incorporates cyclical selection developed by HM.

2.1 Contract models

In spot labour 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, contract models allow the insurance of risk-averse workers against aggregate fluctuations and, hence, the focus lies on the engagement of workers and firms in long-lasting relationships.

BDN present two versions of contract models from which they derive implications about the potential link between wages and past labour market conditions. In the first specification, both the risk-neutral employers and the employees fully commit to the wage contract (two-sided commitment). Hence, the optimal contract in this environment implies a constant wage that is equal to the initial wage negotiated when the worker and employer formed the match. In the second specification, employers commit to contracts, while workers do not (one-sided commitment). When workers are completely mobile, the wage is only revised infrequently. Whenever labor market condition improve sufficiently, the employer is willing to adjust the wage upward to prevent the worker from separating into unemployment or moving to another employer. In the same vein, when the worker receives an offer from another employer the current employer is willing to rebargain with the worker. Thus, in this model, a worker's current wage is a function of all historical maxima of the worker's outside option.

The BDN specifications are representative for richer models that incorporate the same wage patterns as they are consistent with the general ideas in OJS-models that incorporate wage posting (two-sided commitment) and wages that change during a job spell due to credible counter offers (one-sided commitment). Postel-Vinay and Robin (2002) and Cahuc et al. (2006) are examples for these models.

BDN test the implications of the 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 labour market conditions compete against a spot wage model that is represented by the contemporaneous unemployment rate and 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 labour 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 idiosyncratic match component. $C(t, s)$ is a link variable distinguishing between the different model predictions about the relationship of current wages and labour market conditions. U_{t+s}

represents the contemporaneous unemployment rate and is treated as an indicator of current labour market conditions. $U^{min}_{t+s,t}$ denotes the minimum unemployment rate since the start of the job, and U^{begin}_{t} denotes the unemployment rate when the job started.

BDN separately estimate this equation for every combination of the unemployment variables using CPS and PSID data. All their specifications (pooled and fixed effects) result in significant and negative coefficients for the unemployment variables, except when nesting all three variables in one regression. In this case, the minimum unemployment rate variable dominates the other two. 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 labour market conditions, even long after the match has been formed.

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.

2.2 On-the-job search model with cyclical selection

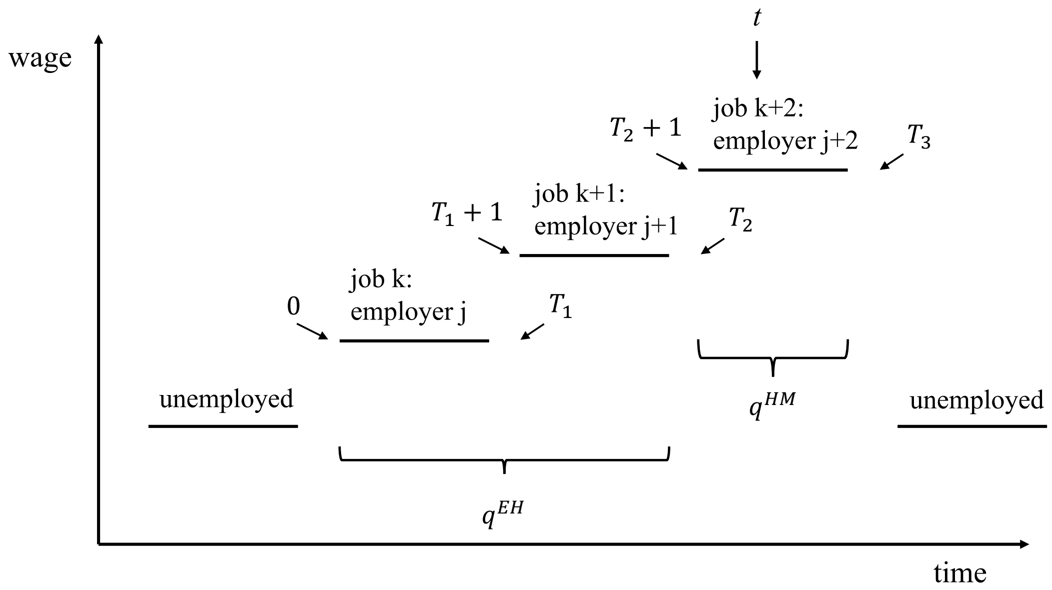
HM question the direct influence of historical labour market conditions on contemporaneous wages. The authors propose a matching model with on-the-job search, in which wages are determined by current labour market conditions and current idiosyncratic match quality only. However, the current match quality carries information about the evolution of past match qualities over a worker's employment career. Through this evolution, the past affects contemporaneous wages. The main argument is that the link between past conditions and contemporaneous wages is visible in the BDN regression because they do not account for any measures of match quality.

In this model 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 took up a job from unemployment, then switched employers at times $T_1 + 1$ and $T_2 + 1$.

Figure 1: Definition of an employment cycle with three jobs



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 wage component that varies across different jobs. On the one hand, if 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 summarise the probabilities of a job offer within each job spell which correspond 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 summarise the employment history and thereby the evolution of match quality. The second summarises the selection of workers into better matches from the most recent previous job to the current one.[1] 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.[2]

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 labour market tightness, HM use the sum of labour market tightness to define q^{HM} and q^{EH}. The idea is that in tight labour 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.

Adding the match quality measures to BDN-type regressions, 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 labour 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 labour 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 is increasing 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.

In the HM 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

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

[2] They first set up the conditional expected value of m_{ijt} for workers that have not been separated exogenously. Given that, they derive the distribution of m_{ijt} using the job switching rule from above. After further derivation, linearisation 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.

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. In their empirical application, HM show that without controlling for cyclical match quality by their indirect measures, the wages of job changers are more cyclical than those of existing workers. However, when they include their measures, the wages of the former are no longer more cyclical than the wages of the latter. They conclude that wages are set through period-by-period bargaining and all excess cyclicality arises from cyclical match quality.

3 Empirical methodology

3.1 Data

Our 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, the 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 homogeneous 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.[3] 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. According to the re-

[3]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).

porting 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 31st 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 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 HM measures of match quality, we calculate the nationwide labour 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 labour market tightness before the last job, and q^{HM} summarises the labour market tightness of the last job in the employment cycle.[4] After our data preparation and keeping only complete employment cycles, we are left with 111,847 workers and 944,937 observations.

3.2 Estimation approach

We use the BDN methodology augmented with the HM match quality controls for studying the response of individual wages to changes in past and contemporaneous labour market conditions. The following measurement equation is the basis of our analysis:

$$\begin{aligned}\ln w_{i,t+s,t} = \beta_0 X_{i,t+s} + \beta_1 U_{i,t+s} + \beta_2 U^{min}_{i,t+s,t} + \beta_3 U^{begin}_{i,t} \\ + \beta_4 ln(q^{EH}_{i,t+s-1,t}) + \beta_5 ln(q^{HM}_{i,t+s,t+s-1}) + \alpha_i + \eta_{i,t+s}\end{aligned} \tag{4}$$

$\ln w_{i,t+s,t}$ 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

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

a worker fixed effect. $U_{i,t+s}$ is the current unemployment rate – our primary indicator of current labour 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 general class of contract models with mobile workers and one-sided commitment. $U^{begin}_{i,t}$ denotes the unemployment rate in period t, the start of a job, representing the implicit contract model with full commitment. $q^{EH}_{i,t+s-1,t}$ and $q^{HM}_{i,t+s,t+s-1}$ 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.

To test the model implications with respect to wage volatility of job stayers and job switchers, we make use of the definition of employment cycles. We suppose that each lth employment cycle starts at period t^{UE}_l and ends in period t^{EU}_l. 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^{k+s}_l. The employment cycle can be defined as the vector

$$z_l = (t^{UE}_l, t^{k+1}_l, t^{k+2}_l, ..., t^{k+s}_l, t^{EU}_l) \tag{5}$$

and consolidated in a sequence of employment cycles, defined as

$$z_l = (z_1, z_2, ..., z_L). \tag{6}$$

In the 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^{UE}_l period(s). We collect each of these periods for every worker. To identify job stayers, we collect any period that is neither a t^{UE}_l nor a t^{k+s}_l 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 $t^{k+1}_l, t^{k+2}_l, ..., t^{k+s}$. 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 labour market

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

tightness within an employment cycle. For new hires from unemployment, q^{EH} is, by definition, zero. When analysing the volatility of wages for job stayers and switchers, we follow the methodology in GHT and Carneiro et al. (2012) to estimate the following regression considering the HM model:

$$\begin{aligned}\ln w_{i,t+s,t} &= \beta_0 X_{i,t+s} + \beta_1 U_{i,t+s} + \ \beta_4 ln(q^{EH}_{i,t+s-1,t}) + \beta_5 ln(q^{HM}_{i,t+s,t+s-1}) \\ &+ \beta_{NH} I^{NH}_{i,t+s} + \beta_{NHU} I^{NH}_{i,t+s} U_{i,t+s} + \beta_{SW} I^{SW}_{i,t+s} + \beta_{SWU} I^{SW}_{i,t+s} U_{t+s} \\ &+ \alpha_i + \eta_{i,t+s}\end{aligned} \tag{7}$$

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. The coefficient in front of each interaction term measures the incremental effect of a new hire/job switcher in the wage responsiveness to changes in the unemployment rate.

4 Results

4.1 Implicit contracts and cyclical selection

Table 1: BDN replication

	(1)	(2)	(3)	(4)
U	-0.0116***	-0.0090***	-0.0105***	-0.0097***
	(0.0023)	(0.0019)	(0.0020)	(0.0020)
U^{min}		-0.0175***		-0.0082***
		(0.0010)		(0.0019)
U^{begin}			-0.0144***	-0.0093***
			(0.0007)	(0.0014)
Adjusted R^2	0.8880	0.8888	0.8888	0.8889

Notes: number of obs. is 944,937; 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 and 2008. Estimation details: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); the estimation period is 2000-2014;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

We begin with a replication of the BDN approach, testing the degree of history dependence in contemporaneous wages without match quality controls. As explained above, as in BDN, we nest three wage-setting models into one regression equation. First, a spot market model, where wages co-move with the current state of the labor market, measured by the contemporaneous unemployment rate. Second, a risk-sharing model with full commitment, where wages are determined by the state of the labor market at time a worker is hired, measured by the unemployment rate at that time. Third, a risk-sharing model with one-sided commitment and worker mobility, where wages increase in a tight but do not decrease in a slack labor market. In the latter model, improving labor market conditions are measured by the lowest unemployment rate during a worker's tenure. Table 1 shows the results of the BDN replication, where we subsequently add the indicators for past labor market conditions to the indicator of the spot market and then nest all models into one regression.[6] Column 1 shows the results for the pure spot market model. We find a procyclical relation between the current state of the labor market and contemporaneous wages: A one-percentage-point decrease in the aggregate unemployment rate is associated with a 1.16 percent increase in wages. When we add the indicator for the one-sided commitment model (column 2), we find that the coefficient for the spot market model decreases, while we estimate a negative coefficient which is larger in magnitude for the lowest unemployment rate during a worker's tenure. We find a similar result when adding the unemployment rate at the time a worker was hired (two-sided commitment). When we nest all models into one regression, we find a significant procyclical relationship between all labor market indicators and contemporaneous wages. Unlike in BDN however, none of the indicators for contracts outperforms contemporaneous conditions.[7] On the one hand, these results are supportive for retention premiums indicating increasing wages when labor market conditions improve over the course of workers' tenure. On the other hand, our results point to hiring premiums as workers who started their job during periods of higher unemployment seem to experience lower wages even after long tenure. However, since we observe coefficients of about the same magnitude for all three wage-setting models, we conclude that the contract models do not supersede the pure spot market model.

Given these results point to a more general wage setting model that may contain features of both spot wages and contracts, we continue our analysis in a framework that is able to reconcile our observations. As explained above, HM cast some doubts on the interpretation of these results. In their on-the-job search model workers' match quality increases over their career as workers gradually select into better matches. The speed of this upgrading process varies with the state of the labour market. In a tight labour market, the selection process proceeds quickly as there are plenty of job offers. HM argue that the effect of past unemployment could well be due to the selection to better match qualities. Table 2 shows the results of the estimation of Equation (4), where we add controls for match quality to the BDN regressions. Recall that 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 the log of q^{HM} and q^{EH} to the regression. If 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 over the course of the employment cycle - a key feature of HM's OJS model. In column 2, we indeed find that the coefficient on the contemporaneous unem-

[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.

[7] See Grant (2003) for similar results in NLSY data.

Table 2: HM replication

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0116***	-0.0074***	-0.0090***	-0.0064***	-0.0105***	-0.0069***
	(0.0023)	(0.0015)	(0.0019)	(0.0015)	(0.0020)	(0.0014)
$ln(q^{EH})$		0.0374***		0.0358***		0.0343***
		(0.0011)		(0.0011)		(0.0010)
$ln(q^{HM})$		0.0502***		0.0489***		0.0491***
		(0.0008)		(0.0009)		(0.0008)
U^{min}			-0.0175***	-0.0071***		
			(0.0010)	(0.0011)		
U^{begin}					-0.0144***	-0.0073***
					(0.0007)	(0.0004)
Adj. R^2	0.8880	0.8941	0.8887	0.8942	0.8888	0.8943

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

ployment rate falls by about 35% after we include the match quality proxies, however, it is still negative and significant.[8]

In columns 4 and 6, we include the match quality measures in the regressions that 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, rather than pure spot wages. We observe that the coefficients on q^{HM} and q^{EH} are relatively similar compared to the regressions without past unemployment variables. Again, like in the BDN regressions, the coefficient of the contemporaneous unemployment rate declines in magnitude. Interestingly, using our administrative data from Germany, we cannot confirm HM's results with respect to U^{begin} and U^{min}. Although the coefficient of U^{begin} decreases by approximately 60 percent, it still is negative and significant. Even after controlling for match quality, we find independent predictive power of U^{begin}. In addition, we observe the same pattern for U^{min}. We take this as evidence that the predictions of the contract models are not ruled out entirely by the measures of match productivities. U^{begin} and U^{min} are correlated with the match quality proxies; however, our results show that the past labor market conditions carry independent information about contemporaneous wages.[9]

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

[9]We applied a Davidson and MacKinnon (1981) J-Test to test the OJS model against the contract models. The idea of the test is to first estimate both models separately and then include the fitted values of one model in the other and test whether the coefficient of the included fitted value is different from zero. If it is different from zero, the first model is rejected in favor of the second. The same procedure is then done reversely to check whether the fitted values of the second model is different from zero when introduced in the first model. When considering the contract models (column (3) and (5)) and the selection model (column (2)), the test rejects the contracts models in favor of the OJS model but also the OJS model in favor of the contract models, with large t-values in both estimations. We take this as further evidence that

4.2 New hires and job stayers

Table 3: Bils vs HM

	(1)	(2)
U	-0.0107***	-0.0072***
	(0.0023)	(0.0015)
$I_{all}^{NH}U$	-0.0045***	-0.0010
	(0.0009)	(0.0007)
$ln(q^{EH})$		0.0373***
		(0.0011)
$ln(q^{HM})$		0.0501***
		(0.0008)
Adjusted R^2	0.8881	0.8941

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness; I_{all}^{NH} is a dummy equal to one for all types of new hires;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

The literature has usually interpreted the evidence for history dependence in wages as wage flexibility for new hires. These results were supported by additional panel data evidence. Starting with Bils (1985), there have been many applications that studied the cyclicality of wages of new hires as compared to workers in ongoing jobs. Pissarides (2009) surveys several empirical studies on wage cyclicality and concludes that most studies find that the wages of new hires are more responsive to the business cycle than those of job stayers. In line with the results from our previous section, all these findings are indicative that a model, where wages respond only to contemporaneous conditions might not be appropriate to understand the actual wage dynamics over the business cycle, while models that incorporate history dependence in wages seem to describe the wage setting better.
Thus, in this section, we first review previous evidence of new hire wage cyclicality and the associated implications for aggregate unemployment fluctuations using our German administrative data. We start with a replication of the usual Bils-type regression, where we estimate equation (7) but pool all sort of new hires (from unemploment and different employers) into one indicator variable that takes on the value one if the worker is a new hire and zero otherwise. In a second step, we add the match quality controls to this regression and focus on the incremental effect for new hires. Including the match quality controls is a direct test of composition bias due to procyclical match quality improvements. If, after including the match quality controls, the incremental effect becomes smaller (larger), this would be indicative for a procyclical (countercyclical) bias in the regression without match quality controls.

the German labor market could be described by some mixture of both models.

Column 1 of Table 3 shows the results for the Bils-type regression. In line with the previous evidence in the literature, we find that wages of new hires appear to be significantly more cyclical than those of workers in ongoing jobs. More precisely, we find that the semi-elasticity of job stayers (line 1) is -1.07 while it is -0.45 percentage points higher (i.e., -1.52) for new hires. In column 2 of Table 3, we add the HM controls. Interestingly, the incremental effect for new hires decreases by more than 70 % and becomes statistical insignificant, indicating composition effects that bias the wage cyclicality of new hires' wages downwards in the regression without match quality controls. At first glance, this result appears to contradict our previous evidence for history dependence because according to the theory of contract models, new hires' wages should respond more strongly to the business cycle than those of job stayers. However, we will see in the next section that wages of new hires from unemployment and wages of job switchers react very differently to aggregate labor market conditions.

4.3 New hires from unemployment vs. job switchers

In a recent paper, GHT emphasize the bias in estimates of excess new hire wage cyclicality through improving match quality of job changers. These authors disentangle the relative contribution of cyclical composition and contractual wage cyclicality of new hires and find that wages of new hires from unemployment are about as cyclical as wages of workers in ongoing jobs, while wages of job changers are more cyclical. Key to their conclusion is the distinction between new hires from unemployment and new hires from employment-to-employment transitions. In this section, we follow GHT and make the distinction between new hires coming from unemployment and workers changing jobs, to test for excess wage cyclicality of new new hires relative to workers in ongoing jobs. Column 1 of Table 4 shows the results from a regression in the spirit of GHT, where we include two new hire indicators, one for new hires from unemployment and one for workers who switch employers.

We observe a clear picture: The incremental effect for new hires from unemployment is virually zero and insignificant, while it is negative for job changers. In line with GHT, this is evidence that the estimates of new hire wage cyclicality from column 1 in Table 3 is identified only from job-changers and not from new hires from unemployment. GHT emphasize that the finding of excess cyclicality for only new hires from employment is already supportive of composition effects.

In column 2, we provide a complementary but more direct test for composition effects by adding the HM match quality controls to our regressions. We observe that the incremental effect for job changers decreases from -0.61 to -0.25, supporting the cyclical selection hypothesis, indicating that indeed the estimates from column 1 are overstating the true wage cyclicality of job switchers. Interestingly, the incremental effect for new hires from unemployment increases from zero to 0.17, indicating that even for new hires from unemployment, cyclical selection might bias the estimates without match quality controls.

Table 4: GHT vs HM

	(1)	(2)
U	-0.0107***	-0.0072***
	(0.0022)	(0.0015)
$I^{NH}U$	0.0000	0.0017**
	(0.0009)	(0.0008)
$I^{SW}U$	-0.0059***	-0.0020*
	(0.0013)	(0.0011)
$ln(q^{EH})$		0.0364***
		(0.0012)
$ln(q^{HM})$		0.0493***
		(0.0008)
Adj. R^2	0.8888	0.8945

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

4.4 Evaluation of results

In this section we evaluate our results and compare them to previous results from the literature. Furthermore, we discuss some potential limitations that might influence our results.

First, in a BDN-type regression, we find evidence for history dependence which is consistent with contract models. These results appear to be immune to the recent criticism about the potential misspecifcation error as they are mostly unaffected to the match quality controls. These results are consistent with Bellou and Kaymak (2012) and Grant (2003) who also find evidence for history dependence in contemporaneous wages.

This result is clearly in contrast to HM, who do not find any history dependence in contemporaneous wages in their US data once they control for cyclical selection by their match quality proxies. In this context, it is important to know that in Germany, wage formation is very diverse. On the one hand, firms can select themselves into collective bargaining agreements at the sectoral level, where wages are bargained between employers' associations and trade unions. Firms can also choose to directly bargain with a union at the firm level. The collective bargaining coverage is about five times higher than in the US.[10] Labour unions play an important role in enforcing employment agreements. By monitoring the employment relationships between the firm and its workers, the labour union allows workers to discipline the firm for a breach of the implicit contract (Hogan,

[10] According to the OECD database, in 2010, the collective agreement coverage was about 60 % in Germany and only 13 % in the U.S.. The union density was about 19 % in Germany and about 11 % in the US.

2001).[11] On the other hand, wages may be determined on the individual level between workers and firms without the involvement of unions. It is also important to know that firms are always allowed to voluntary pay higher wages than fixed in the agreement.

Second, we perform a Bils-type regression to disentangle our estimates into new hires and job stayers. We observe that composition effects affect our results: when we pool all sorts of new hires in one regression, the cyclical match quality controls appear to eliminate the estimated excess wage cyclicality for new hires as compared to job stayers. This result is confirmative to recent evidence by Stüber (2017), who uses a full-set of job fixed-effects to account for composition effects. Similar to us, he finds no evidence for new hire excess wage cyclicality.

However, and this is our third result, we show that the disappearing excess wage cyclicality is due to pooling new hires from unemployment and job changers into one coefficient. As GHT, we argue that, what previous literature has identified as excess wage cyclicality for new hires, stems entirely from workers changing jobs and not from new hires from unemployment. This result is indicative for cyclical selection bias that comes from job changers who improve their match quality in booms. It is also consistent with previous evidence that workers experience large wage gains from switching jobs (Topel and Ward, 1992).

Our results even go one step further than separating the two sorts of new hires as we combine the GHT distinction with the HM controls. We interpret this combination as a direct test of how cyclical selection affects all sorts of new hires. For job changers, the picture is clear: we find that large parts of the estimated wage cyclicality is indeed due to composition effects, indicating that not controlling for cyclical selection results in an overestimation of wage flexibility for job changers. Nevertheless, the match quality controls are not eliminating the entire excess cyclicality like in HM. This picture is well in line with our previous results for history dependence - particularly with the model with one-sided commitment. For new hires from unemployment, taking into account HM's cyclical selection decreases the wage cyclicality, indicating that previous estimates are overstating the wage flexibility for new hires from unemployment as well. This result is interesting because for new hires from unemployment OJS usually do not offer a clear-cut prediction. In these models, the usual assumption for unemployed job seekers is that they accept any job offer that includes a wage at least as high as their reservation wage (see for example Postel-Vinay and Robin, 2002). The literature discusses different sources of selection that might affect the estimates results for new hires from unemployment. Karahan et al. (2017) find that the reservation wage of unemployed job seekers is unlikely to be very cyclical. Mueller (2017) finds that in recessions, more previously high paid workers enter the pool of unemployed workers. He argues that these shifts result from a higher cyclicality of separations for high-wage workers. However, since our estimates for new hires from unemployment are identified from changes in wages across different entry

[11] There is also theoretical evidence that under collective wage bargaining, the worker share is counter-cyclical, directly inducing wage rigidities (Morin, 2017).

jobs, this source of selection is unlikely to play a role in our estimates (recall Section 3.2).

How to reconcile our results? What kind of model would have such predictions? We think it is plausible to conclude that in Germany wages depend on past labor market conditions - even after controlling for current labor market conditions and match quality controls. A model which is most closely related to our findings might be a business cycle version of the Cahuc et al. (2006) model. In this OJS model, unemployed workers receive a wage upon hiring that reflects current aggregate conditions but can be rebargained when the business cycle is catching up. Employed workers might receive outside offers from other firms. If the offered job is more productive, the worker switches employers, and receives a higher wage. If the job is not more productive but better paid, the worker stays in his current match but renegotiates the wage up to the counteroffer. If the new job would result in lower wages, the worker stays in his current match and the wage remains unchanged.[12] As HM point out, in the HM model knowing the match quality is sufficient to know the wage as match quality is assumed to be constant within a job spell (see equation 8). Hence, it is sufficient to add q^{EH} and q^{HM} to the wage regression which measure match quality. In Cahuc et al. (2006) however, as wages can increase within job spells due to bargaining, knowing the match quality is not sufficient to predict the wage. HM show in their appendix that a reasonably calibrated simulation of Cahuc et al. (2006) generates exactly the patterns we observe with our German data. That is a loss of predictive power of the contemporaneous unemployment rate once we control for unobserved match quality, and a significant additional influence of U^{min} and U^{begin} which also loses some power but not its significance upon adding match quality controls. Furthermore, more cyclical wages of job switchers as compared to job stayers. When we introduce an additional regressor, the expected number of offers since the beginning of the job, call it $q^{contract}$, to our regressions, we observe that it has additional explanatory power in this model. The logic behind is that offers during a match arise due to counteroffers which are matched by the employer, and hence, there is wage growth due to further offers. As q^{HM} and q^{EH} are constant across the job, they are not informative about the job offer arrival rate, but $q^{contract}$ is. If $q^{contract}$ shows significance – as it does – it is an indication that wages in a current match are adjusted. In Appendix C, we provide the results which include $q^{contract}$.

5 Model extension – occupational refinement

5.1 Motivation

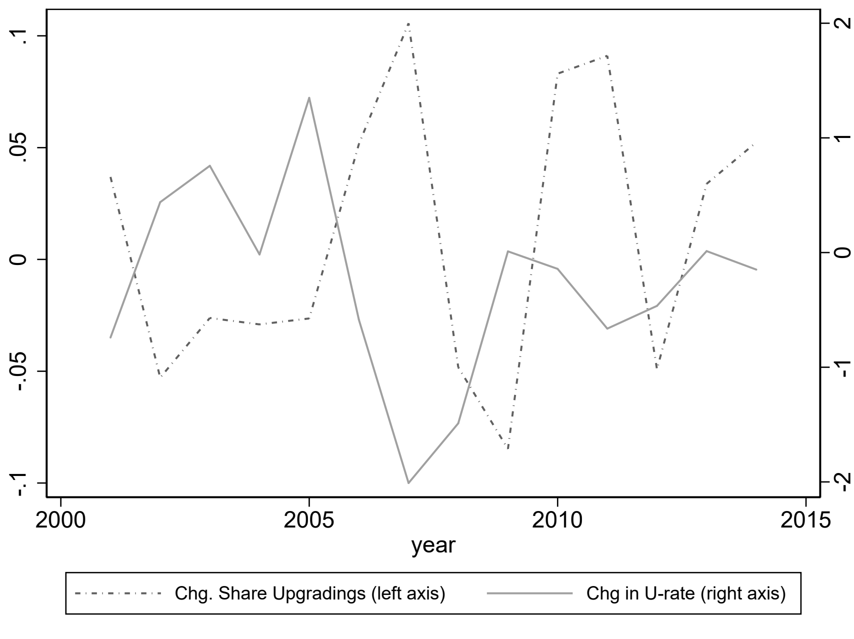
While most of the theoretical and empirical literature focus on employer-employee contracts, it seems plausible to think that wages within firms are related to job titles rather than to an unified "job" at heterogeneous employers.

[12]Through the dependency on the productivity of the match on the one hand side and the wage paid on the other hand side, the model can generate a situation in which the worker switches though he receives a lower wages because he expects a future higher wage growth by moving to a more productive firm.

The idea dates back to Reynolds (1951), Reder (1955), and Hall (1974), who emphasize the importance of within firm "re-assignments". The intuition is that during booms, employers react to labor shortages through internal job re-assignment (e.g. promotions). Existing workers might 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 "re-assignment"-model predicts that a significant proportion of overall wage cyclicality results from workers changing occupations rather than wage changes within occupations. This arises either because the rate of occupation changing is procyclical or because the wage changes of internal movers are more procyclical than the wage changes of stayers. The implication of these internal job moves are that at each firm can be a mixture of rigid wages of job stayers and procyclical wages because internal job regrading. Among others, Devereux and Hart (2006) show that these ideas are in line with empirical findings in UK data. They argue that the proportion of internal and external job moves varies over the business cycle and that the wages of internal (and external movers) are considerably more procyclical than those of stayers (see also Hart and Roberts, 2011; Büttner et al., 2010).

How could occupational switching affect our, and previous results from the literature? If internal job switches are in fact procyclical, neglecting these would lead to an overestimation of the wage cyclicality of job stayers because these internal job switches would be erroneously counted as stayers. As much of the empirical methodology relies on identifying incremental effects, this would additionally confound the estimated effects for new hires and job switchers.

Figure 2: Change in unemployment rate vs. change in share of promotions



In Figure 2, we examine the cyclicality of intra-firm promotions in our data. Hence, we plot the change in the share of workers who change occupations within the same employer and improve their wages (promotions) against the change in the unemployment rate. We indeed observe that an decrease (increase) in the unemployment rate is associated with a increase (decrease) of internal promotions, supporting the job re-assignment hypothesis. It is worth noting that the cyclical implications of contract models are observationally equivalent to the implications of cyclical re-assignments. Devereux and Hart (2007) argue that if promotions are procyclical, the functions of the past unemployment rate would be negatively correlated with the current wage because the lower the functions of unemployment are, the more likely it is that a promotion has taken place during the spell.

5.2 Model extension – framework

Following the argumentation from the previous section, the main objective of this section is to develop a framework that accounts for both cyclical job re-assignment within companies and cyclical selection across employers. By using detailed data on occupational labour market conditions, we are able to control for both types of selection.[13]

We start by redefining the wage equation:

$$log\, w_{ijot} = log\, C_t + log\, m_{ijot}, \tag{8}$$

where m_{ijot} is the idiosyncratic match productivity, which is now specific to an employer-employee-occupation match, i.e. a job is now a unique combination of the worker (i), firm (j) and occupation (o) identifier. Following HM (page 777 seq), during job k a worker receives N_t^k offers. The total number of job offers received during job k equals $N_{T_k}^k$. The number of offers received since the start of the employment cycle T is given by N_t. Note that, in our refined setting, a worker can also receive job offers from her current employer but for jobs in a different occupation. For a given employment cycle, we can define

$$q_{t,o}^{HM} = q_{1+T_{j-1}}^o + \cdots + q_{T_j}^o \tag{9}$$

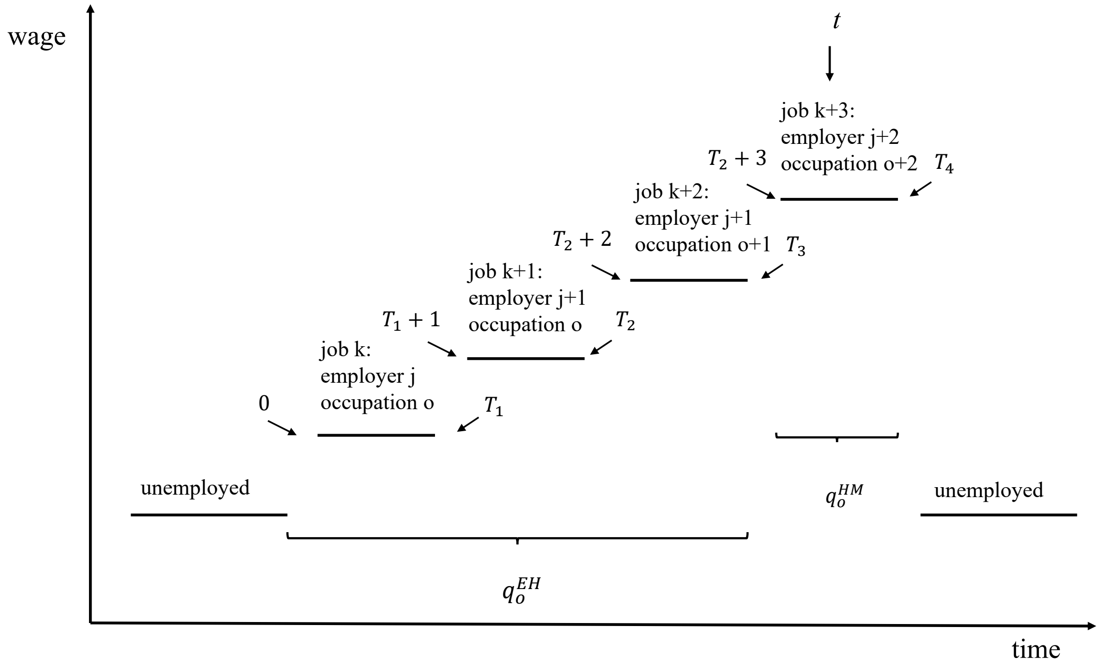
and

$$q_{t,o}^{EH} = q_0^o + \cdots + q_{T_{j-1}}^o \quad for \quad 1 + T_{j-1} \leq t \leq T_j. \tag{10}$$

$q_{t,o}^{HM}$ equals the sum of all qs from the start of the current job spell until the last period of this job spell (employer-occupation-interaction). $q_{t,o}^{EH}$ describes the employment history

[13] 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 3: Definition of an employment cycle with four jobs



in the current employment cycle until the start of the current job spell. Given the new definition of a job, switching jobs means either (i) changing the employer but staying in the previous occupation, (ii) changing occupations but staying with the previous employer or (iii) simultaneously changing occupations and employers. Figure 3 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 illustrated, corresponds to (iii).

The job switching rule follows the same logic as in the original model: The worker will change jobs (i, ii, iii), if and only if she receives a job offer that incorporates a higher match productivity. The expected value of m_k conditional on m_{k-1} is

$$E_t(m_k|m_{k-1}, N_t^k) = \int_{m_{k-1}}^{\bar{m}} md\tilde{F^k}(m|N_t^k) \tag{11}$$

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 productivity is drawn from an exogenous distribution. HM show that after linearisation equation 11 yields approximately

$$E_t(m_k|m_{k-1}) = c_0 + c_1 \sum\nolimits_{1+T_{k-1}}^{T_k} q_{1+T_{k-1}} + c_2 m_{k-1}, \tag{12}$$

where the coefficients c_0, c_1, and c_2 are the first derivatives and shown to be positive (see HM, Online Appendix IB). Plugging in 9 yields

$$E_t(m_k|m_{k-1}) = c_0 + c_1 q_{t,o}^{HM} + c_2 m_{k-1}. \tag{13}$$

For the unconditional expectation it holds that

$$E_t(m_k) = c_0 + c_1 q_{t,o}^{HM} + c_2 E_{T_{k-1}}(m_{k-1}). \tag{14}$$

Iterating for would inflate the number of regressors. Thus, the iteration can be truncated and be approximated by only one variable, which captures the entire employment history.

$$E_{T_{k-1}}(m_{k-1}) = c_3 + c_4 q_{T_{k-1},o}^{EH}. \tag{15}$$

Combining 14 and 15 gives

$$log(m) = \tilde{c_0} + \tilde{c_1} q_o^{HM} + \tilde{c_2} q_o^{EH}. \tag{16}$$

We define the measures of job quality in the same manner as above, namely as the sum of the job offer probabilities. 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 $q_{HM,o,t} = q_{j+2,o+2,t}$.

5.3 Discussion

HM provide a theoretical foundation for their employer-specific match quality controls. Workers receive job offers which come from a time-invariant match quality distribution. Workers accept an offer whenever the new match has higher match quality than their current one. The expected number of job offers increases in labour market tightness. The match quality controls sum up the national labour market tightness over the jobs in a given employment cycle and, hence, has predictive power for the wage.

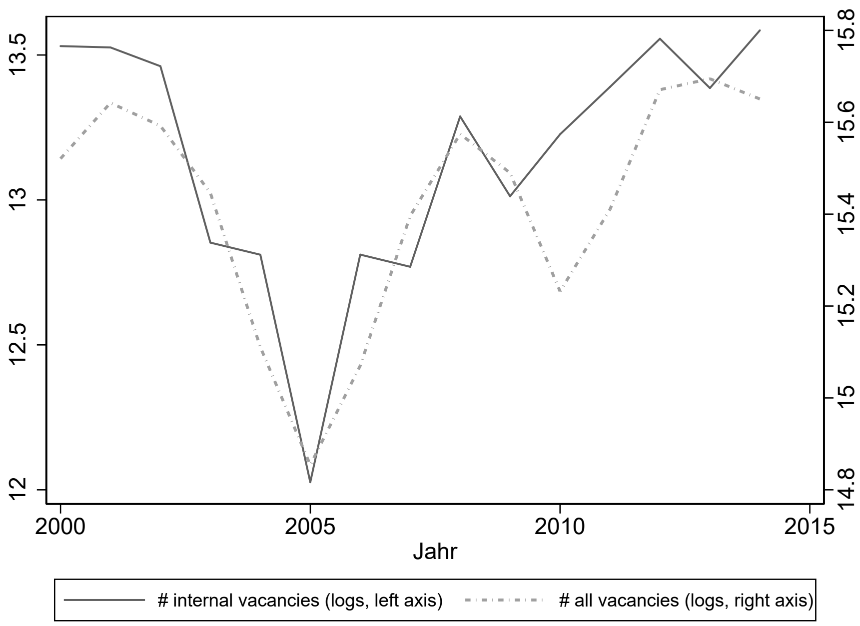
Our model extension provides a generalization of the HM model. We add an occupation-employer-interaction dimension in a completely symmetric manner to the pure employer dimension. Hence, we assume that job offers come from an occupational specific match quality distribution and sum up occupational labour market tightness to construct the match quality controls.

How is our refinement related to contract models? In contract models with two-sided commitment without our occupational refinement, there is no wage change at all at the time of the job re-assignment. With our refinement however, we argue that the contract is renegotiated from scratch at the time of the occupational change with the same employer. Consider the following example: a mechanic is employed at a large car producer. It happens that there is once an open manager position and the mechanic is promoted. In our refined model, we view these two employment relationships as separate jobs and that at the time of the re-assignment the wage contract is re-bargained. For new hires from unemployment and workers who switch employers and occupations, the intuition is straightforward. Firms post occupation-specific vacancies which might result in a contact with a potential hire. These open vacancies show up in the number of registered vacancies and we can construct the match quality controls, that is the sum over the ratios of the number of registered vacancies and the number of unemployed workers in a given occupation. For workers who stay at their employer but change their occupations, it might however be the case that the pool of open vacancies consists of registered vacancies and vacancies that are only advertised within the firm. If certain jobs are only advertised within a firm they might not show up in the number of registered vacancies, which we use to construct the match quality controls. Unfortunately very little is known whether employed workers search differently for internal and external jobs. In our admin data we have no information on the exact hiring mechanism of a match. What matters for the match quality controls is whether they proxy the positive correlation between labor market tightness and the expected number of job offers, hence carry information on the quality of a match. To document that vacancies that are only advertised within the firm behave very similar to all vacancies over the business cycle, we use additional information on the source of vacancies from the IAB Job Vacancy survey. This survey directly asks firms about the type of vacancy the use. Figure 4 validates that the number of internally advertised vacancies and the number of all vacancies and are highly correlated (the pearson correlation coefficient is 0.86) and are, hence, appropriate to construct the match quality controls.

5.4 Data and empirical methodology

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 (after refinement). Since monthly 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 primarily search for a job in the occupation they will take up in their subsequent job. In Appendix D.2, we show that assuming instead that the unemployed workers search for a job in their previous occupation does not substantively alter the results of our analyses. We merge occupation-specific vacancy data from the Federal Employment Agency to our sample, which allows us to compute an occupation-specific labour market tightness and, given that, q_o^{HM} and q_o^{EH}. To fully exploit all the advantages of

Figure 4: Number of internally advertised and all vacancies



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. Since in the exercises that take into account the occupational dimension the starting/ ending periods of "jobs" may change, we recalculate the unemployment measures (U, U^{begin}, U^{min}).

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.

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

$$\begin{aligned}\ln w_{i,t+s,t} = {} & \beta_0 X_{i,t+s} + \beta_1 U_{t+s} + \beta_4 q^{EH}_{i,t+s} + \beta_5 q^{HM}_{i,t+s} \\ & + \beta_{NH} I^{NH}_{i,t+s} + \beta_{NHU} I^{NH}_{i,t+s} U_{t+s} + \beta_{OSW} I^{OSW}_{i,t+s} + \beta_{OSWU} I^{OSW}_{i,t+s} U_{t+s} \\ & + \beta_4 ln(q^{EH}_{i,o,t+s-1,t}) + \beta_5 ln(q^{HM}_{i,o,t+s,t+s-1}) + \beta_{OESW} I^{OESW}_{i,t+s} \\ & + \beta_{OESWU} I^{OESW}_{i,t+s} U_{t+s} + \alpha_i + \eta_{i,t+s}\end{aligned} \tag{17}$$

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.

5.5 Results

Table 5: Refined model

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0116***	-0.0076***	-0.0092***	-0.0064***	-0.0105***	-0.0070***
	(0.0023)	(0.0015)	(0.0019)	(0.0015)	(0.0020)	(0.0014)
$ln(q_o^{EH})$		0.0211***		0.0196***		0.0182***
		(0.0011)		(0.0011)		(0.0011)
$ln(q_o^{HM})$		0.0347***		0.0341***		0.0346***
		(0.0016)		(0.0016)		(0.0015)
U^{min}			-0.0152***	-0.0083***		
			(0.0009)	(0.0013)		
U^{begin}					-0.0116***	-0.0065***
					(0.0006)	(0.0008)
Adj. R^2	0.8880	0.8931	0.8886	0.8933	0.8887	0.8933

Notes: number of obs. is 944,937; 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 labour market tightness; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 5 displays the results from estimating the refined HM model. Please recall that in this model, the match quality measures are occupation specific, as explained above. Furthermore, please recall that due to the finer segmentation of the job definitions, U, U^{begin}, and U^{min} are calculated differently as in the original setup. 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. Even after including the match quality proxies at the occupational level, we again find support for both implicit contract models (significant and negative coefficient on U^{min} and U^{begin}).[14] In terms of magnitude, we find that the coefficent on U is slightly higher (0.76 compares to 0.72) in the refined model when we add the match quality control (column 2). 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 (2). Since the refined model takes into account occupational selection within employer-employee matches, we identify more switches than the original model

[14] 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 labour market tightness over all durations of all jobs before the current job.

does.[15] 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 later 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.

In Table 6, we compare the estimates of the wage cyclicality for new hires from unemployment, job stayers and job switchers using the refined model which adds the occupational dimension.[16] The first important insight is that in column 1, that is the estimation without match quality controls, we observe coefficients that are qualitatively similar to those from the original model. In terms of magnitude, we estimate a slightly smaller coefficient on U, which represents the wage cyclicality of workers who stay at their employer and in their occupation. Intuitively, by applying the refined model, we remove cyclicality in wages that is due to workers who switch occupations but stay at the same employers. Hence, we clean the reference group, that is job stayers, from cyclical occupational selection.

Table 6: Refined model – stayers, new hires from unemployment, and job switchers

	(1)	(2)
U	-0.0106***	-0.0071***
	(0.0023)	(0.0015)
$I^{NH}U$	-0.0002	0.0009
	(0.0009)	(0.0008)
$I^{SW}U$	-0.0055***	-0.0045***
	(0.0013)	(0.0013)
$ln(q_o^{EH})$		0.0195***
		(0.0012)
$ln(q_o^{HM})$		0.0345***
		(0.0015)
Adj. R^2	0.8888	0.8936

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

The incremental effect of all job changers, that are those workers who either switch

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

[16] 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.

employers and occupations at the same time or only employers or only occupations, is negative and significant. Adding match quality controls decreases the incremental effect, but interestingly less than in the original model. Similar to our previous result, we find that wages of new hires from unemployment are about as cyclical as those of stayers. This is also true when we add the refined match quality controls.

To obtain deeper insights into which worker types are affected and how by adding match quality controls, we now distinguish the source of job switching in greater detail. This differentiation allows us to analyse 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 7 presents the results of distinguishing the source of every job switch. Column 1 shows the results without controlling for match quality.

Table 7: Refined model – full decomposition

	(1)	(2)
U	-0.0104***	-0.0070***
	(0.0022)	(0.0015)
$I^{NH}U$	-0.0002	0.0008
	(0.0009)	(0.0008)
$I^{ESW}U$	-0.0043***	-0.0049***
	(0.0013)	(0.0011)
$I^{OSW}U$	-0.0061***	-0.0014
	(0.0012)	(0.0019)
$I^{OESW}U$	-0.0102***	-0.0091***
	(0.0017)	(0.0014)
$ln(q_o^{EH})$		0.0205***
		(0.0009)
$ln(q_o^{HM})$		0.0344***
		(0.0015)
Adj. R^2	0.8888	0.8937

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{ESW} is a dummy equal to one for workers who switch employers but stay in their occupation, I^{OSW} is a dummy equal to one for workers who switch occupations but stay at their employer, I^{OESW} is a dummy equal to one for workers who switch occupations and employers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

For new hires from unemployment, we find that there is no significant incremental effect, so their wages are equally cyclical as those of job stayers. For all other workers, we observe significant procyclical incremental effects. This effect is highest (almost 100% higher compared to job stayers) for those workers who simultaneously change their employers and occupations. For workers who only change occupations but stay in their previous employers, we estimate an incremental effect of -0.61, which is the second largest incremental effect. For those workers who only change their employer, but stay in their previous occupation, the incremental effect is -0.43.

In column 2, we add the refined match quality controls. Again we interpret these controls as a direct test for cyclical selection. If after their inclusion, the incremental effects change, this is indicative for selection bias that effects the coefficients in column 1. Two important insights stand out: First, our refinement does not affect the coefficients for new hires from unemployment. For those workers, we observe a similar pattern as in the original model, albeit smaller in magnitude. The incremental effect remains insignificant. Second, occupation switches appear to be responsible for all the procyclical selection bias of job switchers. This is most striking for workers who switch the occupation but stay at the same employer. For these workers, we find that the incremental effect shrinks from -0.61 to -0.14 and turns insignificant after we include the refined match quality controls. For worker simultaneously changing occupations and employers, we find that the incremental effect decreases from -1.02 to -0.91. Interestingly, we observe an inverse pattern for workers who switch their employer but stay in their previous occupation. For these workers, including the refined controls slightly increases the incremental effect from -0.43 to -0.49, which indicates a small countercyclical bias in their incremental effect in column 1, indicating that the procyclicality of job switching stems from switching occupations, not employers.

6 Summary and Conluding Remarks

Using German administrative data, this paper studies the linkage between real wages and past and contemporaneous labour market conditions. Our results are, at least, fivefold:

First, we find that indicators of both past unemployment and contemporaneous unemployment are important predictors of the contemporaneous wage. This result is in line with results from other labour markets, e.g., by Grant (2003) using U.S. survey data and by Devereux and Hart (2007) using British survey data, and Bellou and Kaymak (2012) using a panel of various European countries.
Second, we test the implications of HM's OJS search model. The key feature of the HM method is that it allows 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 important predictors of contemporaneous wages. We can confirm that after controlling for the match quality proxies, the indicators for contracts lose predictive power for contemporaneous wages. However, we find independent predictive power of the initial unemployment rate and the minimum unemployment rate for contemporaneous wages. This observation is consistent with many contract models. It is also consistent with Bellou and Kaymak (2012) who find that institutional wage setting mechanisms like collective bargaining agreements favor the result of history dependence in wages.

Third, we investigate whether wage cyclicality differs across job stayers and new hires.

When we pool all new hires into one coefficient, we observe that wages of new hires appear to be more cyclical than those of job stayers. However, once we control for cyclical match quality improvements as in HM, the excess wage cyclicality disappears. This result is consistent with Stüber (2017), who uses a different approach to account for composition effects, but reaches a similar conclusion. When we disentangle job switchers and new hires from unemployment, we show that the previous evidence for new hires excess wage cyclicality stems entirely from job changers. As GHT, 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. Without match quality controls, the wages of new hires appear to be more volatile than those of stayers. When we add HM's match quality controls, we observe that large parts of the wage cyclicality of job changers can be explained by HM's OJS model, where workers select into better matches during booms. However, even after controlling for match quality, we find that wages of job changers are more cyclical than those of job stayers. These results contrast with the conclusion of HM, who find that, after controlling for match quality, the wages of stayers and switchers are equally cyclical.[17]

Fourth, we find that, once we control for match quality, the wages of new hires from unemployment are about as cyclical as wages of job stayers. This result is supportive for GHT. However, it clearly contrasts the results in Haefke et al. (2013), who find excess wage cyclicality for new hires from unemployment in U.S. data.

Fifth, we augment the original HM model by taking occupational job re-assignments into account. 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 observe wages of new hires from unemployment that are approximately as cyclical than those of job stayers. In our refined model, occupational mobility, both within the firm and across firms, is the biggest source of cyclical selection. Wages of workers who simultaneously change employers and occupations respond strongly to the cycle - even when we control for our refined match quality proxies. These results are confirmative to Devereux and Hart (2007) and Devereux and Hart (2006), who emphasize the cyclicality of job re-assignments.

We think that any single model will have a hard time to fully explain all the empirical patterns of job-to-job transitions and wage-dynamics over the business cycle. Too many mechanisms interact, in particular in Germany where the institutional wage settings are very diverse. However, we think that our results show that an appropriate wage setting model for Germany would be an OJS model which features some degree of history dependence in wages. This could be a version of Cahuc et al. (2006) with wage posting and sequential bargaining. It might also be appropriate to extend this model with an occupational dimension as we sketched in our model refinement. This would include job-specific wage postings and competition between different jobs at the same firm.

[17]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.

References

Bellou, Andriana and Baris Kaymak (2012) "Wages, implicit contracts, and the business cycle: Evidence from a European panel," *Labour Economics*, Vol. 19, pp. 898 – 907.

Bils, Mark J. (1985) "Real wages over the business cycle: evidence from panel data," *Journal of Political economy*, Vol. 93, pp. 666–689.

Burdett, Kenneth and Dale T. Mortensen (1998) "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, Vol. 39, pp. 257–273.

Büttner, Thomas, Peter Jacobebbinghaus, and Johannes Ludsteck (2010) "Occupational Upgrading and the Business Cycle in West Germany," *Economics: The Open-Access, Open-Assessment E-Journal*, Vol. 4.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin (2006) "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, Vol. 74, pp. 323–364.

Carneiro, Anabela, Paulo Guimaraes, and Pedro Portugal (2012) "Real Wages and the Business Cycle: Accounting for Worker, Firm, and Job Title Heterogeneity," *American Economic Journal: Macroeconomics*, Vol. 4, pp. 133–52.

Carrillo-Tudela, Carlos, Bart Hobijn, Powen She, and Ludo Visschers (2016) "The extent and cyclicality of career changes: Evidence for the U.K.," *European Economic Review*, Vol. 84, pp. 18 – 41.

Davidson, Russell and James G MacKinnon (1981) "Several Tests for Model Specification in the Presence of Alternative Hypotheses," *Econometrica*, Vol. 49, pp. 781–93.

Devereux, Paul J. and Robert A. Hart (2006) "Real Wage Cyclicality of Job Stayers, Within-Company Job Movers, and Between-Company Job Movers," *Industrial and Labor Relations Review*, Vol. 60, pp. 105–119.

——— (2007) "The Spot Market Matters: Evidence On Implicit Contracts From Britain," *Scottish Journal of Political Economy*, Vol. 54, pp. 661–683.

Feng, Shuaizhang, Richard V Burkhauser, and JS Butler (2006) "Levels and long-term trends in earnings inequality: overcoming current population survey censoring problems using the GB2 distribution," *Journal of Business & Economic Statistics*, Vol. 24, pp. 57–62.

Gartner, Hermann and Christian Holzner (2015) "Wage Posting as a Positive Selection Device: Theory and Empirical Evidence," CESifo Working Paper Series 5494, CESifo Group Munich.

Gertler, Mark, Christopher Huckfeldt, and Antonella Trigari (2016) "Unemployment Fluctuations, Match Quality, and the Wage Cyclicality of New Hires," Working Paper 22341, National Bureau of Economic Research.

Gottfries, Axel and Coen Teulings (2017) "Wage Posting, Nominal Rigidity, and Cyclical Inefficiencies," Cambridge Working Papers in Economics 1736, Faculty of Economics, University of Cambridge.

Grant, Darren (2003) "The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from the National Longitudinal Surveys," *Industrial and Labor Relations Review*, Vol. 56, pp. 393–408.

Haefke, Christian, Marcus Sonntag, and Thijs van Rens (2013) "Wage rigidity and job creation," *Journal of Monetary Economics*, Vol. 60, pp. 887 – 899.

Hagedorn, Marcus and Iourii Manovskii (2013) "Job selection and wages over the business cycle," *The American Economic Review*, Vol. 103, pp. 771–803.

Hall, Robert E. (1974) "The Process of Inflation in the Labor Market," *Brookings Papers on Economic Activity*, Vol. 5, pp. 343–410.

Hart, Robert A and J Elizabeth Roberts (2011) "Spot wages, job changes, and the cycle," Stirling Economics Discussion Papers 2011-11, University of Stirling, Division of Economics.

Hogan, Chad (2001) "Enforcement of Implicit Employment Contracts through Unionization," *Journal of Labor Economics*, Vol. 19, pp. 171–195.

Kambourov, Gueorgui and Iourii Manovskii (2009) "OCCUPATIONAL SPECIFICITY OF HUMAN CAPITAL*," *International Economic Review*, Vol. 50, pp. 63–115.

Karahan, Fatih, Ryan Michaels, Benjamin Pugsley, Aysegül Sahin, and Rachel Schuh (2017) "Do Job-to-Job Transitions Drive Wage Fluctuations over the Business Cycle?" *American Economic Review*, Vol. 107.

Lochner, Benjamin (2016) "Labor Market Institutions and Wage Formation in an Economy with Search Frictions," Dissertation, Friedrich-Alexander-Universität Erlangen-Nürnberg.

Lochner, Benjamin and Bastian Schulz (2016) "Labor Market Sorting in Germany," CESifo Working Paper Series 6066, CESifo Group Munich.

Morin, A. (2017) "Cyclicality of wages and union power," *Labour Economics*, Vol. 48, pp. 1 – 22.

Moulton, Brent R. (1986) "Random group effects and the precision of regression estimates," *Journal of Econometrics*, Vol. 32, pp. 385–397.

Mueller, Andreas I. (2017) "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, Vol. 107, pp. 2081–2107.

Pissarides, Christopher A. (2009) "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica*, Vol. 77, pp. 1339–1369.

Postel-Vinay, Fabien and Jean-Marc Robin (2002) “Equilibrium Wage Dispersion with Worker and Employer Heterogeneity,” *Econometrica*, Vol. 70, pp. 2295–2350.

Reder, M. W. (1955) “The Theory of Occupational Wage Differentials,” *The American Economic Review*, Vol. 45, pp. 833–852.

Reynolds, L.G. (1951) *The structure of labor markets: wages and labor mobility in theory and practice*, Labor and Management Center, Yale University, Yale Labor and Management Center Series. [Publications]: Harper.

Solon, Gary, Robert Barsky, and Jonathan A. Parker (1994) “Measuring the Cyclicality of Real Wages: How Important is Composition Bias,” *The Quarterly Journal of Economics*, Vol. 109, pp. 1–25.

Stüber, Heiko (2017) “The Real Wage Cyclicality of Newly Hired and Incumbent Workers in Germany,” *The Economic Journal*, Vol. 127, pp. 522–546.

A Descriptives statistics

A.1 Original model

Table 8: Main variables - original model

Variable	Mean	Std. Dev.	Min.	Max.
$ln(wage)$	4.31	0.39	2.20	6.89
U	9.56	1.80	7.2	14.1
U^{begin}	10.37	1.82	3.3	14.1
U^{min}	9.32	1.53	3.3	14.1
θ (tightness)	0.12	0.04	0.04	0.21
$ln(q^{EH})$	0.39	0.99	-3.61	3.75
$ln(q^{HM})$	2.10	1.13	-3.15	3.86
# employm. cycles	2.36	2.11	1	46
# jobs in cycle	1.67	1.01	1	19

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

Table 9: Shares of switches, stayings and new hirings - original model

Variable	Share
Switches/New Hirings	66.57 %
Switches/Stayings	6.29 %

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 10: Main variables - refined model

Variable	Mean	Std. Dev.	Min.	Max.
$ln(wage)$	4.31	0.39	2.20	6.89
U	9.56	1.80	7.2	14.1
U^{begin}	10.37	1.82	3.3	14.1
U^{min}	9.31	1.54	3.3	14.1
$ln(q_o^{EH})$	0.47	1.06	-3.87	4.71
$ln(q_o^{HM})$	2.20	1.27	-4.24	4.73
# employm. cycles	2.36	2.11	1	46
# jobs in cycle	1.81	1.13	1	19

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

Table 11: Shares of switches, stayings and new hirings - refined model

Variable	**Share**
Switches/ New Hirings	67 %
Switches/ Stayings	10 %

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

Table 12: Number of switches - refined model

Variable	**Total number of switches**	**% of total switches**
All Switches	84,293	100
Occup. Switcher/Empl. Stayer	21,510	25,5
Occup. Stayer/ Empl. Switcher	40,627	48,2
Occup. Switcher/Empl .Switcher	22,156	26,3

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 13: GHT vs HM

	(1)	(2)
U	-0.0107 ***	-0.0072***
	(0.0022)	(0.0015)
$I^{NH}U$	0.0000	0.0017**
	(0.0009)	(0.0008)
$I^{SW}U$	-0.0059***	-0.0020*
	(0.0013)	(0.0011)
I^{NH}	-0.0185*	-0.0348***
	(0.0099)	(0.0080)
I^{SW}	0.0929***	0.0444***
	(0.0133)	(0.0106)
$ln(q^{EH})$		0.0364***
		(0.0012)
$ln(q^{HM})$		0.0493***
		(0.0008)
Adj. R^2	0.8888	0.8945

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 14: Refined model – stayers, new hires from unemployment, job switchers

	(1)	(2)
U	-0.0106***	-0.0071***
	(0.0023)	(0.0015)
$I^{NH}U$	-0.0002	0.0009
	(0.0009)	(0.0008)
$I^{SW}U$	-0.0055***	-0.0045***
	(0.0013)	(0.0013)
I^{NH}	-0.0185*	-0.0348***
	(0.0099)	(0.0080)
I^{SW}	0.0929***	0.0444***
	(0.0133)	(0.0106)
$ln(q_o^{EH})$		0.0195***
		(0.0012)
$ln(q_o^{HM})$		0.0345***
		(0.0015)
Adj. R^2	0.8888	0.8936

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 15: Refined model – full decomposition

	(1)	(2)
U	-0.0104***	-0.0070***
	(0.0022)	(0.0015)
$I^{NH}U$	-0.0002	0.0008
	(0.0009)	(0.0008)
$I^{ESW}U$	-0.0043***	-0.0049***
	(0.0013)	(0.0011)
$I^{OSW}U$	-0.0061***	-0.0014
	(0.0012)	(0.0019)
$I^{OESW}U$	-0.0102***	-0.0091***
	(0.0017)	(0.0014)
I^{ESW}	0.0787***	0.0798***
	(0.0133)	(0.0110)
I^{OSW}	0.0731***	0.0110
	(0.0132)	(0.0218)
I^{OESW}	0.1314***	0.1127***
	(0.0172)	(0.0144)
$ln(q_o^{EH})$		0.0205***
		(0.0009)
$ln(q_o^{HM})$		0.0344***
		(0.0015)
Adj. R^2	0.8888	0.8937

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{ESW} is a dummy equal to one for workers who switch employers but stay in their occupation, I^{OSW} is a dummy equal to one for workers who switch occupations but stay at their employer, I^{OESW} is a dummy equal to one for workers who switch occupations and employers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

C Test of Cahuc et al. (2006)

Table 16: HM vs Cahuc et al. (2006), including $q^{contract}$

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0116***	-0.0065***	-0.0090***	-0.0059***	-0.0105***	-0.0061***
	(0.0023)	(0.0014)	(0.0019)	(0.0014)	(0.0020)	(0.0013)
$ln(q^{contract})$		0.0126***		0.0103***		0.0117***
		(0.0012)		(0.0012)		(0.0011)
$ln(q^{HM})$		0.0486***		0.0479***		0.0477***
		(0.0009)		(0.0009)		(0.0009)
$ln(q^{EH})$		0.0398***		0.0382***		0.0367***
		(0.0011)		(0.0011)		(0.0010)
U^{min}			-0.0175***	-0.0053***		
			(0.0010)	(0.0012)		
U^{begin}					-0.0144***	-0.0069***
					(0.0007)	(0.0004)
Adjusted R^2	0.8880	0.8942	0.8887	0.8943	0.8888	0.8944

Notes: number of obs. is 944,937; 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}, q^{HM}, and $q^{Contract}$ are calculated using the national labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 17: Refined model vs Cahuc et al. (2006), including $q_o^{contract}$

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0116***	-0.0079***	-0.0092***	-0.0068***	-0.0105***	-0.0073***
	(0.0023)	(0.0017)	(0.0019)	(0.0016)	(0.0020)	(0.0015)
$ln(q_o^{contract})$		0.0047**		0.0031		0.0049**
		(0.0020)		(0.0019)		(0.0020)
$ln(q_o^{HM})$		0.0317***		0.0318***		0.0317***
		(0.0017)		(0.0016)		(0.0017)
$ln(q_o^{EH})$		0.0309***		0.0285***		0.0279***
		(0.0017)		(0.0016)		(0.0015)
U^{min}			-0.0152***	-0.0075***		
			(0.0009)	(0.0012)		
U^{begin}					-0.0116***	-0.0058***
					(0.0006)	(0.0008)
Adjusted R^2	0.8880	0.8926	0.8886	0.8927	0.8887	0.8927

Notes: number of obs. is 944,937; 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}, q_o^{HM}, and $q_o^{Contract}$ are calculated using the occupational labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

D Robustness check

In this Section we show that none of our substantive results is sensitive to the following robustness checks:

- using detrended unemployment variables
- using workers' origin occupation to construct the occupational match quality controls

D.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.

Table 18: BDN replication, detrended unemployment rate

	(1)	(2)	(3)	(4)
U	-0.0118***	-0.0090***	-0.0105***	-0.0097***
	(0.0023)	(0.0019)	(0.0020)	(0.0020)
U^{min}		-0.0176***		-0.0082***
		(0.0010)		(0.0020)
U_{begin}			-0.0142***	-0.0092***
			(0.0006)	(0.0014)
Adjusted R^2	0.8881	0.8887	0.8888	0.8889

Notes: number of obs. is 944,937; 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 and 2008. Estimation details: fixed-effects regression for males with clustered standard errors (by beginning and end date of observation); the estimation period is 2000-2014;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 19: HM replication; detrended unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0118***	-0.0075***	-0.0090***	-0.0065***	-0.0105***	-0.0069***
	(0.0023)	(0.0015)	(0.0019)	(0.0015)	(0.0020)	(0.0014)
$ln(q^{HM})$		0.0501***		0.0489***		0.0492***
		(0.0008)		(0.0009)		(0.0008)
$ln(q^{EH})$		0.0374***		0.0358***		0.0341***
		(0.0011)		(0.0011)		(0.0010)
U^{min}			-0.0176***	-0.0068***		
			(0.0010)	(0.0012)		
U_{begin}					-0.0142***	-0.0069***
					(0.0006)	(0.0004)
Adjusted R^2	0.8881	0.8941	0.8887	0.8942	0.8888	0.8943

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 labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 20: Bils vs HM; detrended unemployment rate

	(1)	(2)
U	-0.0109***	-0.0073***
	(0.0023)	(0.0015)
$I^{NH}_{all}U$	-0.0040***	-0.0009
	(0.0008)	(0.0006)
$ln(q^{EH})$		0.0373***
		(0.0011)
$ln(q^{HM})$		0.0501***
		(0.0008)
Adjusted R^2	0.8881	0.8941

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness; I^{NH}_{all} is a dummy equal to one for all types of new hires;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 21: GHT vs HM; detrended unemployment rate

	(1)	(2)
U	-0.0109***	-0.0073***
	(0.0022)	(0.0015)
$I^{NH}U$	0.0003	0.0017**
	(0.0008)	(0.0007)
$I^{SW}U$	-0.0054***	-0.0019**
	(0.0012)	(0.0009)
$ln(q^{EH})$		0.0364***
		(0.0012)
$ln(q^{HM})$		0.0492***
		(0.0008)
Adj. R^2	0.8888	0.8945

Notes: number of obs. is 944,937; 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 and 2008. 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; and the source is SIAB-7514-V1

Table 22: Refined model; detrended unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0118***	-0.0083***	-0.0092***	-0.0073***	-0.0106***	-0.0079***
	(0.0023)	(0.0017)	(0.0019)	(0.0017)	(0.0020)	(0.0016)
$ln(q_o^{EH})$		0.0293***		0.0273***		0.0265***
		(0.0015)		(0.0015)		(0.0014)
$ln(q_o^{HM})$		0.0333***		0.0330***		0.0334***
		(0.0017)		(0.0016)		(0.0016)
U^{min}			-0.0152***	-0.0062***		
			(0.0010)	(0.0016)		
U^{begin}					-0.0109***	-0.0043***
					(0.0006)	(0.0009)
Adj. R^2	0.8881	0.8925	0.8886	0.8926	0.8887	0.8926

Notes: number of obs. is 944,937; 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 labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 23: Refined model – stayers, new hires from unemployment, and job switchers; detrended unemployment rate

	(1)	(2)
U	-0.0107***	-0.0079***
	(0.0023)	(0.0017)
$I^{NH}U$	0.0001	0.0004
	(0.0009)	(0.0007)
$I^{SW}U$	-0.0049***	-0.0039***
	(0.0012)	(0.0012)
$ln(q_o^{EH})$		0.0272***
		(0.0013)
$ln(q_o^{HM})$		0.0332***
		(0.0016)
Adj. R^2	0.8888	0.8929

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 24: Refined model – full decomposition; detrended unemployment rate

	(1)	(2)
U	-0.0106***	-0.0077***
	(0.0022)	(0.0016)
$I^{NH}U$	0.0000	0.0003
	(0.0008)	(0.0007)
$I^{ESW}U$	-0.0038***	-0.0044***
	(0.0012)	(0.0009)
$I^{OSW}U$	-0.0056***	-0.0011
	(0.0011)	(0.0018)
$I^{OESW}U$	-0.0096***	-0.0086***
	(0.0015)	(0.0013)
$ln(q_o^{EH})$		0.0283***
		(0.0011)
$ln(q_o^{HM})$		0.0332***
		(0.0016)
Adj. R^2	0.8889	0.8931

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{ESW} is a dummy equal to one for workers who switch employers but stay in their occupation, I^{OSW} is a dummy equal to one for workers who switch occupations but stay at their employer, I^{OESW} is a dummy equal to one for workers who switch occupations and employers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

D.2 Using workers' origin occupation to construct the occupational match quality controls

Table 25: Refined model, alternative construction of q_o^{EH} and q_o^{HM}

	(1)	(2)	(3)	(4)	(5)	(6)
U	-0.0116***	-0.0082***	-0.0092***	-0.0070***	-0.0105***	-0.0077***
	(0.0023)	(0.0017)	(0.0019)	(0.0016)	(0.0020)	(0.0016)
$ln(q_o^{HM})$		0.0334***		0.0329***		0.0334***
		(0.0017)		(0.0016)		(0.0016)
$ln(q_o^{EH})$		0.0293***		0.0274***		0.0263***
		(0.0015)		(0.0015)		(0.0014)
U^{min}			-0.0152***	-0.0079***		
			(0.0009)	(0.0013)		
U^{begin}					-0.0116***	-0.0058***
					(0.0006)	(0.0008)
Adjusted R^2	0.8880	0.8925	0.8886	0.8927	0.8887	0.8927

Notes: number of obs. is 944,937; 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 labour market tightness;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

Table 26: Refined model - stayers, new hires from unemployment, job switchers; alternative construction of q_o^{EH} and q_o^{HM}

	(1)	(2)
U	-0.0106***	-0.0078***
	(0.0023)	(0.0017)
$I^{NH}U$	-0.0002	0.0002
	(0.0009)	(0.0008)
$I^{SW}U$	-0.0055***	-0.0043***
	(0.0013)	(0.0013)
$ln(q_o^{EH})$		0.0273***
		(0.0013)
$ln(q_o^{HM})$		0.0332***
		(0.0016)
Adjusted R^2	0.8888	0.8929

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{SW} is a dummy equal to one for job switchers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

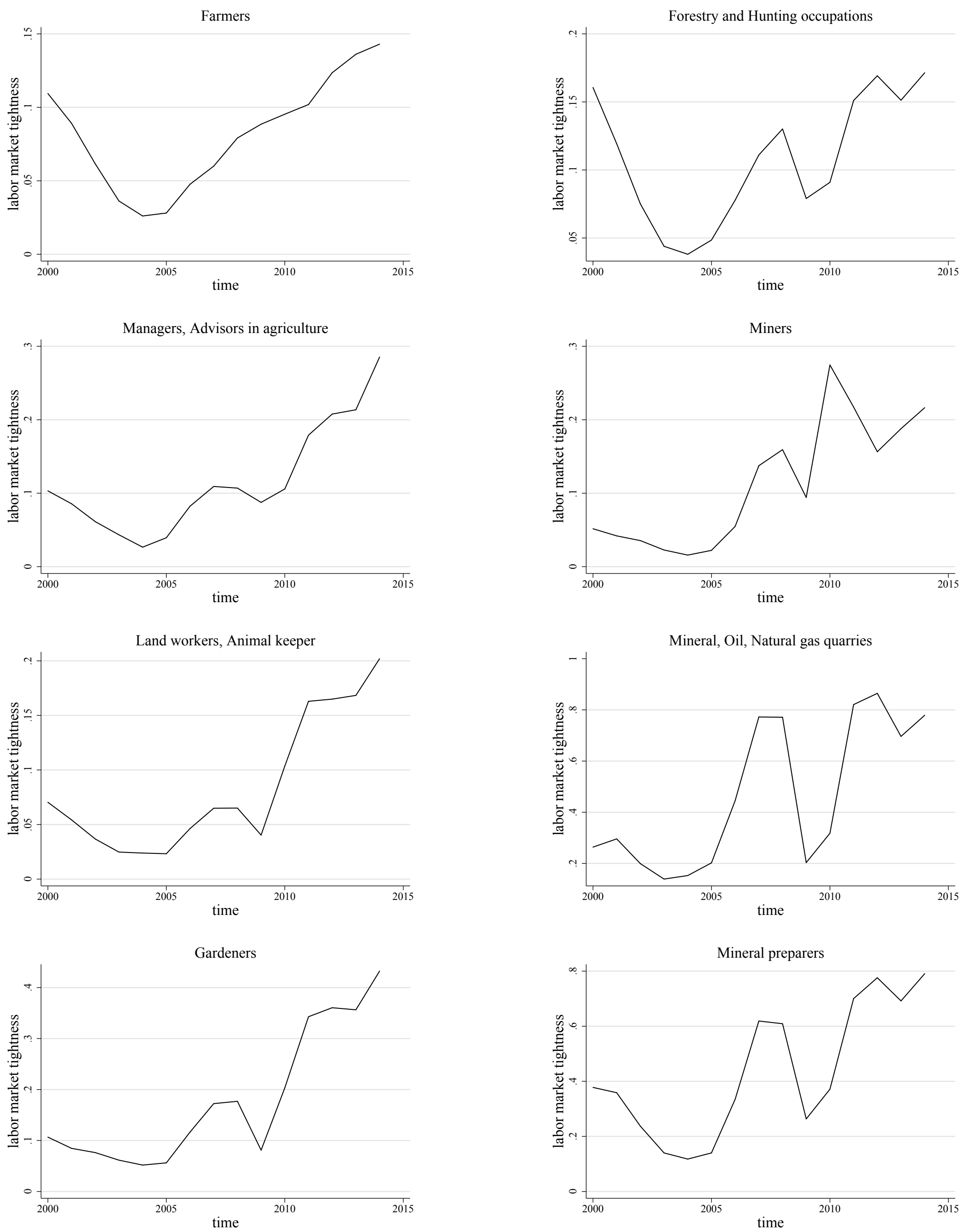
Table 27: Refined model - full decomposition; alternative construction of q_o^{EH} and q_o^{HM}

	(1)	(2)
U	-0.0104***	-0.0076***
	(0.0022)	(0.0016)
$I^{NH}U$	-0.0002	0.0001
	(0.0009)	(0.0008)
$I^{ESW}U$	-0.0043***	-0.0048***
	(0.0013)	(0.0010)
$I^{OSW}U$	-0.0061***	-0.0011
	(0.0012)	(0.0020)
$I^{OESW}U$	-0.0102***	-0.0090***
	(0.0017)	(0.0014)
$ln(q_o^{EH})$		0.0284***
		(0.0011)
$ln(q_o^{HM})$		0.0332***
		(0.0016)
Adjusted R^2	0.8888	0.8931

Notes: number of obs. is 944,937; 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 labour market tightness; I^{NH} is a dummy equal to one for new hires from unemployment, I^{ESW} is a dummy equal to one for workers who switch employers but stay in their occupation, I^{OSW} is a dummy equal to one for workers who switch occupations but stay at their employer, I^{OESW} is a dummy equal to one for workers who switch occupations and employers;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; source: SIAB-7514-V1

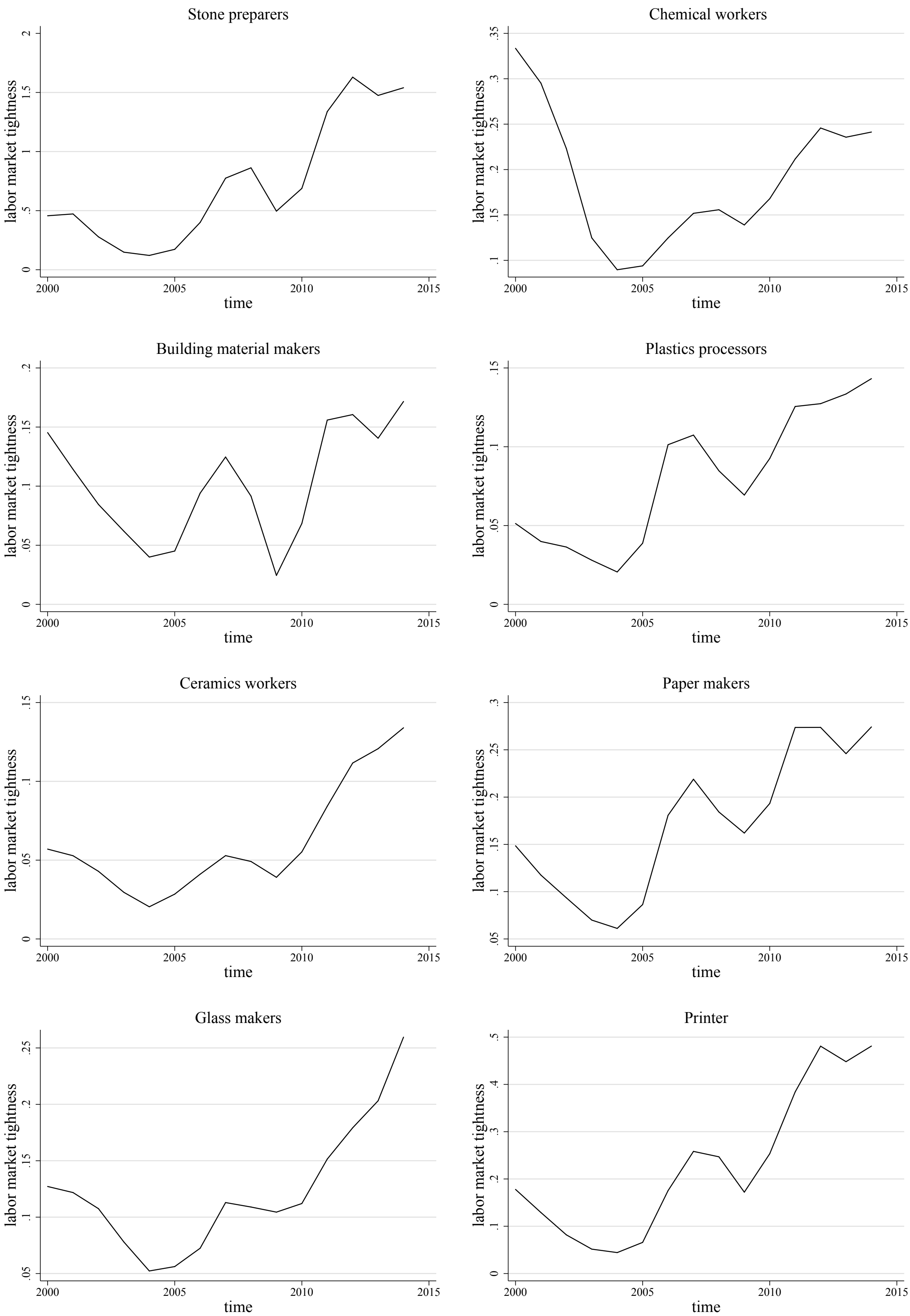
E Occupational labour market tightness

Figure 5: Occupational labour market tightness – 2000-2014



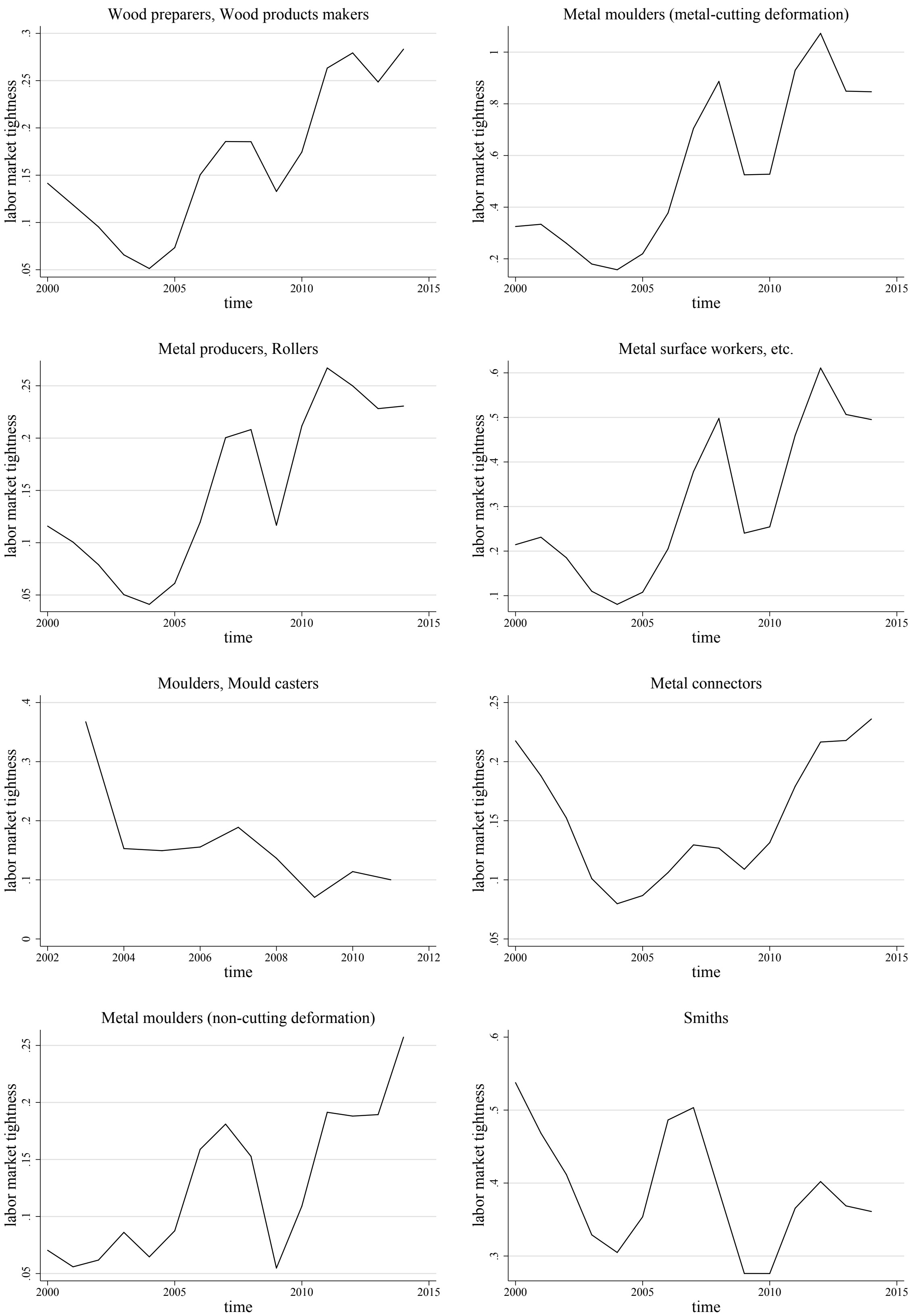
Note: Yearly average of the occupational labour market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)

Occupational labour Market tightness – 2000-2014



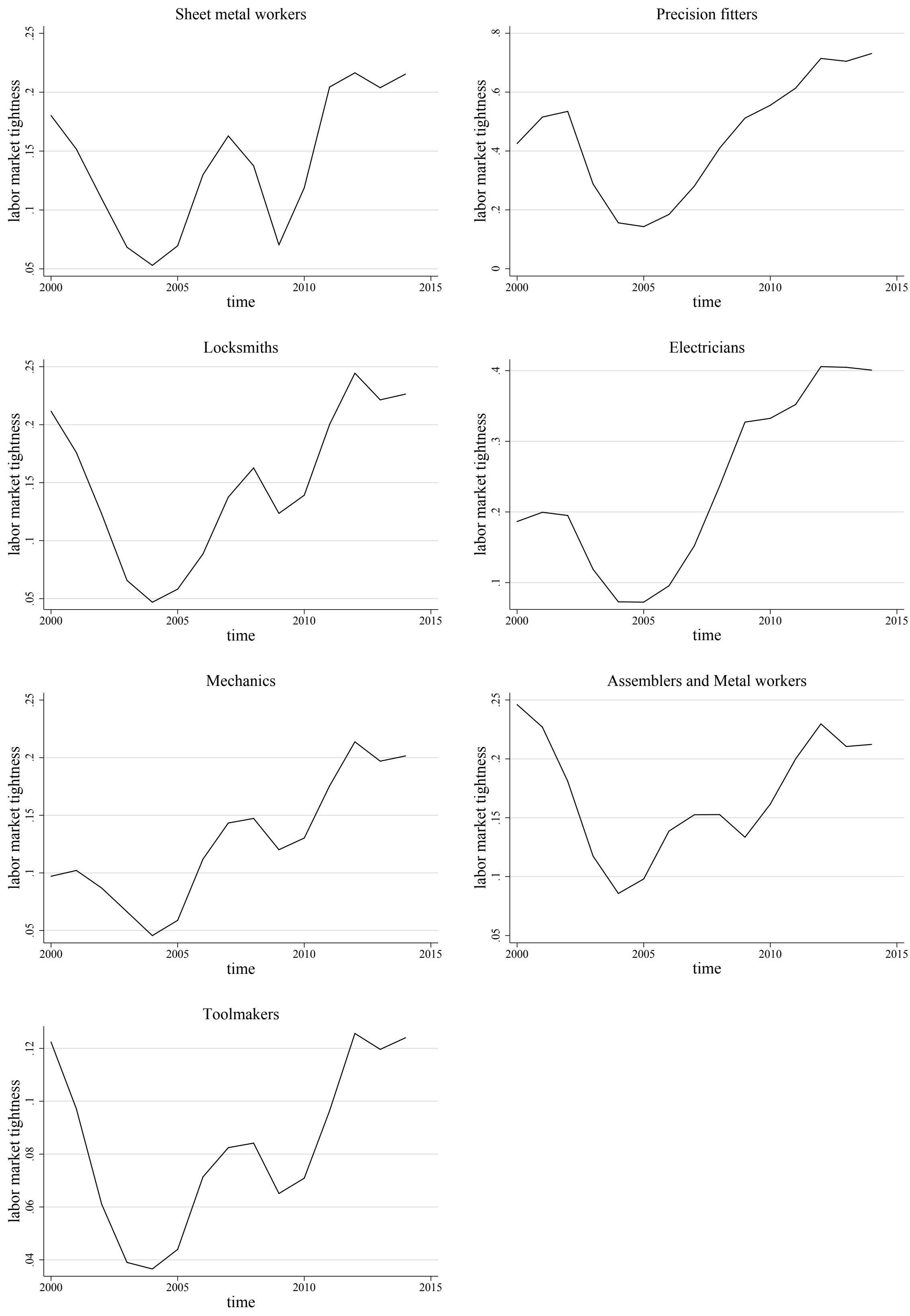
Note: Yearly average of the occupational labour market tightness. 2-digit occupational classification of the German Classification of Occupations (KldB88)

Occupational labour market tightness – 2000-2014



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

Occupational labour market tightness – 2000-2014



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