Wages, Workers and Vacancy Durations: Evidence from Linked Data

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Abstract

This paper provides new evidence on the relationship between the duration of a vacancy, the characteristics of workers matched to the vacancy and their re-employment wages, using a novel data set that links vacancy data and matched employer-employee data. Our analysis generates two main findings: *First*, we decompose re-employment wages into fixed worker and firm effects, and find that there is a strong positive relationship between the duration of a vacancy and the worker wage-effect and robust negative association between the duration of the vacancy and the firm wage-effect. The latter finding is consistent with theories of directed search, where more job seekers apply to more productive firms. *Second*, we provide evidence that the longer a worker remains unemployed the more likely she is to be matched to a newly available vacancy rather than an existing vacancy. This finding directly supports the main prediction of theories of stock-flow matching and implies negative duration dependence in the set of job opportunities available to unemployed workers.

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1   Introduction

A central question in search-theoretic models of the labor market is how firms and workers form employment relationships. The canonical search and matching model posits the existence of a matching function, which randomly matches workers and firms, given the number of vacancies and job seekers in the labor market. Recent evidence by Davis, Faberman, and Haltiwanger (2013) (DFH), however, shows that the number of vacancies as measured in JOLTS survey data is an imperfect predictor of hiring outcomes across firms. Their evidence strongly suggests that firms rely heavily on additional instruments to attract and recruit workers, which has important implications for aggregate labor market dynamics. Despite DFH's important contribution, many aspects of vacancy-posting and -filling behavior are still poorly understood, mainly due to the lack of appropriate data.

The main purpose of our paper is to document empirical regularities on vacancy posting and filling behavior and to evaluate the relevance of alternative theories of matching, such as (1) theories of directed search where workers and firms direct their search towards the more desirable sub-markets and (2) the theory of stock-flow matching (Coles and Smith (1998)). These theories have potentially important implications for the evolution of aggregate matching efficiency over the business cycle as well as duration dependence in the unemployed worker's job finding rate.

We use a unique combination of (i) individual vacancy data, (ii) individual unemployment register data, and (iii) firm-worker data from the various administrative sources from Austria.[1] Linking data on individual vacancies to matched firm-worker data allows us to study the process how firms fill vacancies in more detail than previous papers. The data do not only allow us to connect information on individual vacancies to firm-level outcomes but also to the characteristics of the worker filling that vacancy (e.g. the duration of the worker's current unemployment spell and the characteristics of the new match, such as starting wage, subsequent wage increases and tenure of the match).

We argue that an empirical analysis of the Austrian vacancy data is relevant for improving our understanding of the vacancy posting and filling behavior of firms more generally. *First*, the vacancy data cover a large number of postings shedding new light on incidence and duration of vacancies both in a cross-section of firms and over the business cycle. The data cover all vacancies posted by Austrian firms through the

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[1]Data from the Austrian unemployment and social-security register have been used to study the effect of unemployment insurance on unemployment and post-unemployment outcomes (see e.g. Lalive, van Ours, & Zweimüller, 2006; Card, Chetty, & Weber, 2007; Card, Lee, Pei, & Weber, 2015; Lalive, Landais, & Zweimüller, 2015; Alvarez, Borovickova, & Shimer, 2015). The present paper combines the above data sources with information on individual vacancies collected by the Austrian labor market administration (AMS).

Austrian Public Employment Service (AMS) over the period 1997-2014 which amount to roughly 9.6 million job postings. While not all firms post their vacancies via the AMS, the AMS data encompass between 35 and 50 percent of all vacancies posted in Austria. Moreover, vacancies posted through the AMS are representative for job openings relevant for currently unempoyed workers.[2] *Second*, the vacancy filling rate observed in our data exhibits business-cycle patterns similar to those of other countries, with an elasticity with respect to the labor market tightness of 0.66, which is in the ballpark of other empirical studies. *Third*, we document that, similar to the US and other countries, the Austrian Beveridge Curve has recently shifted outward, particularly over the period 2007-2014. This suggests that the Austrian labor market exhibits similar patterns in terms of vacancy posting as in other countries. *Finally*, we show that duration patterns of Austrian vacancies are similar to those for the US and that recruiting intensity patterns (fillings per vacancy) in the Austrian data are similar to those observed by DFH in the JOLTS data.

We start with a desriptive analysis of the data. One main finding is that nearly a quarter of all vacancies have zero duration, i.e. appear to be filled on the first day. A closer look at the data, however, reveals that many of these vacancies are posted and filled well before the date when the job is available. We also examine the composition of vacancies over the business cycle. We find that firms post vacancies requiring higher educational attainment in recessions, in line with the findings in Modestino, Shoag, and Ballance (2015) who interpret this finding as opportunistic "upskilling". At the same time, we also find that that firms create fewer jobs involving routine tasks during recessions. This suggests that firms, rather than increasing job requirements for the same jobs, actually create different jobs during recessions. The latter finding is consistent with a model where firms direct their search toward workers of different types, if the pool of the unemployed tilts toward the more productive workers in recessions (see, e.g., Mueller, 2015).

A central assumption in many search models of equilibrium wage dispersion (e.g., Burdett and Mortensen (1998)) is that firms post wages, which is associated with a trade-off between the cost of posting a higher wage and the benefit of a higher arrival rate of job applicantions or a higher acceptance rate of the job offer. This mechanism can lead to an equilibrium where firms are equally well off by either posting a high- or a low-paying wage for the same type of job. Despite the central importance of this mechanism in many models, the evidence on the relationship between the vacancy-filling rate and the starting wage remains scarce. An important exception is Faberman

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[2]The data are less representative of those vacancies that are eventually filled by employed workers moving from job to job. As the AMS platform is mainly used by unemployed workers, firms searching on labor markets where the pool of potential new hires consists predominantly of employed workers are more likely to use other search channels.

and Menzio (2015) who use data from the Earnings and Opportunities Pilot Project (EOPP) in the U.S. for the years 1980 and 1982. They find that the starting wage shows a positive association with the duration of the vacancy, which is in the opposite direction of what models with wage posting would predict.[3] They point out, however, that a key empirical challenge is to control for worker-level heterogeneity in the starting wage, which is likely an important confounding factor in the analysis.

In our empirial analysis, we can go one step further. We study the relationship between vacancy duration and the starting wage by implementing the following two-step procedure. First, we decompose wages into fixed worker- and firm-characteristics using the technique proposed by Abowd, Kramarz, and Margolis (1999). This allows us to look at the association between the vacancy duration to the firm- , worker- and residual-components of the starting wage. It turns out that vacancy durations do not show any clear correlation with the raw starting wage. However, this is likely to mask two underlying opposing forces: On the one hand, it may take longer to fill a vacancy for firms targeting a high productivity worker. On the other hand, all else equal, vacancies promising a higher wage are filled more quickly when workers direct their search towards high-paying job openings.

Our empirical analysis, indeed, suggests that worker fixed effects in the starting wage show a strong positive association with vacancy duration, suggesting that it takes longer to find a suitable worker for firms when targeting high productivity segments of the labor market. On the other hand, we also find that firm fixed effects in the starting wage are negatively correlated with vacancy duration. This is in line with directed search theories of the labor market: workers' search efforts seem to be more strongly concentrated towards firms posting high wages leading to shorter vacancy durations.

Finally, our paper evaluates the relevance of theories of stock-flow matching (e.g., Coles & Smith, 1998). The primary implication of these theories is that the stock of unemployed workers is more likely to match to the inflow of new vacancies than to the stock of existing vacancies. We provide direct evidence on this mechanism, by merging information on the workers' unemployment duration at the time of the match to the AMS vacancy data. We show that – compared to short-term unemployed workers – long-term unemployed workers are more likely to match to newly available vacancies, directly supporting the main prediction of theories of stock-flow matching. This finding also implies negative duration dependence in the set of job opportunities available to unemployed job seekers. We also derive a non-parametric test to quantify these forces and reject the null hypothesis of random matching for nearly all periods

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[3]Interestingly, Holzer, Katz, and Krueger (1991) find in the same data set that vacancies from firms in high-wage industries and larger firms attract a higher number of job applications.

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in our sample.

Our paper proceeds as follows: Section 2 discusses the related empirical literature. Section 3 provides a summary of the data and discusses the concept of vacancy. Section 4 provides an analysis of the vacany filling rate over the duration of the vacancy spell and documents patterns in vacancy filling across industries and firms. Section 5 analyses the relationship between vacancy duration and starting wages in the new job. Section 6 evaluates the extent of stock-flow matching by using information on the duration of unemployment at the time of the match and relating it to the characteristics of the vacancy (i.e., whether the vacancy was newly available). Section 7 concludes.

2   Related Empirical Literature

Our contribution relates to a number of studies of vacancy behavior, the latest and arguably most influential being DFH. With data from the Job Openings and Labor Turnover Survey (JOLTS) for the US, they show that faster growing firms not only post more vacancies but also exhibit a higher vacancy yield, i.e. a higher number of realized hires per vacancy. The latter finding has attracted considerable attention as it suggests that firms use other channels to recruit workers if they quickly expand their workforce, and a reduction in aggregate recruiting intensity may be responsible for the shift of the U.S. Beveridge Curve during the Great Recession. We replicate the findings of DFH in our vacancy data from Austria. We find that the relationship between firm growth and the vacancy yield is surprisingly similar to the one documented by DFH with the JOLTS. Since the JOLTS has only been available since December 2000, many earlier studies focused on the Help Wanted Index (Abraham, 1983; Abraham, 1987; Blanchard & Diamond, 1989). While Shimer (2005) and Barnichon (2010) note that the Help Wanted Index tracks the movements in the JOLTS quite well when accounting for the negative long-term trend in newspaper advertising, it does not allow for an analysis at the micro level.

Micro studies of vacancy posting behavior are mainly based on survey (e.g. DFH; van Ours & Ridder, 1991; van Ours & Ridder, 1992; Holzer, 1994; Gorter, Nijkamp, & Rietveld, 1996; Burdett & Cunningham, 1998; Dickerson, 2003; Valletta, 2005; Hall, 2006; Shimer, 2007) or online job board data (e.g. Barron, Berger, & Black, 1999; Marinescu, 2015; Modestino et al., 2015).[4] A few earlier studies also use administrative data on vacancies, e.g. Coles and Smith (1996) use Job Centre data recording the stock of vacancies for 257 regions in the UK. Berman (1997) and Yashiv (2000) analyze Israeli administrative data on vacancies, which record stocks and flows of vacancies. Andrews, Bradley, Stott, and Upward (2008) analyze administrative data for one

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[4]See Kuhn (2014) for a general discussion of internet job search.

labor market in the UK on vacancies intended for youths (aged between 15 and 18). Sunde (2007) uses German administrative data on yearly stocks of vacancies that are disaggregated according to 40 occupation groups.

Compared to existing datasets on vacancies that we are aware of, our data have several advantages: First and foremost, none of the studies match the vacancy data to either the employment history of the matched worker or to firm data. Second, while most of the mentioned studies were mainly based on survey or career services data, we have administrative data, which should decrease the extent of measurement error due both to more accurate data and a larger sample size. The mentioned studies that do use administrative data are mostly based on aggregated data. One exception is Andrews et al., 2008 who covers the labor market for teenagers for one region of the UK. Finally, datasets usually record repeated stocks of vacancies, such as the most prominent example, the JOLTS, which records the stock of vacancies at the end of the month. This poses the problem that vacancies with short durations (opened and closed between two survey rounds) are undersampled (length-biased sampling/aggregation bias), which is especially severe as vacancies with very short durations will turn out to be quantitatively relevant. This problem does not arise in our data as every vacancy is recorded, irrespective of its length.

3   The Data and Conceptual Issues

We combine three datasets, the Austrian Social Security Database (ASSD), register data on individual vacancies, and register data on unemployment spells. The two latter data sources come from the Austrian Public Employment Service (AMS), the institution administrating unemployment insurance and active labor market policies for all workers in Austria.

The ASSD, explained in detail in Zweimüller et al. (2009), covers the universe of all private sector workers (about 80% of the total workforce), providing longitudinal information from 1972 onwards. The data has been collected in order to verify old-age pension claims and records each employment spell, each spell on unemployment insurance, as well as other social insurance programs. We also observe worker and employer characteristics, as well as the workers earnings.

The vacancy register data contain information on all vacancies posted through the AMS and covers the years 1987-2014. The data quality has been improving over time, for the entire set of variables is available from 2007 onwards. The vacany register records the date when the vacancy is posted, the desired start date of the job, and the date when the vacancy is filled (or put off the system for other reasons). In addition to the timing and duration of a vacancy, the data report job characteristics and job
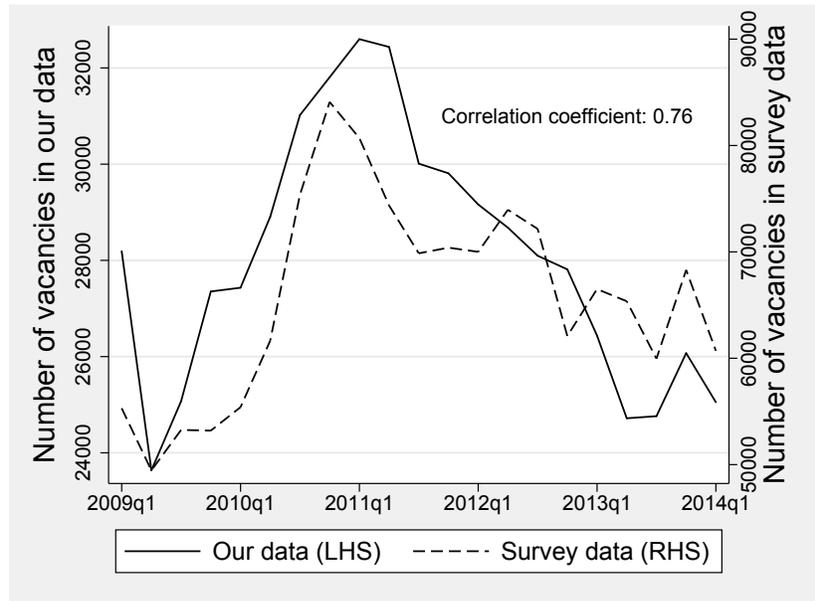
Figure 1: AMS vacancy data vs. representative survey data

requirements, as well as some characteristics of the firm posting the vacancy.

The information on timing and duration of a vacancy corresponds to three different outcomes. First, a vacancy posted at the AMS can either result in a hiring directly mediated by the AMS. In this case, a personal worker identifier is recorded in the data, which gives the identity of the worker who fills the vacancy. A second outcome is that the firm ends up hiring a worker outside the AMS system. This will happen if the firm does not only rely exclusively on the AMS as a search platform but also employs other search channels (other internet platform, newspaper ads, etc.). In the latter case, the personal identifer for the worker who fills the vacancy is unknown, but the vacancy duration is reported in the vacancy data. The third possibility is that the vacancy lapses, either because it has become obsolete or because the firm cannot be contacted any longer. Around 44% of all vacancies never result in a hire, but this drops to around 29% after 2005. Of the remaining vacancies, around 28% are hired through the AMS system while 72% are filled through a different channel.

One obvious concern is that the vacancies that firms post on the AMS platform are not a representative window of the universe of vacancies posted by Austrian firms. To assess this potential concern, we compare the number of vacancies in the vacancy register with the total number of vacancies based on a representative vacancy survey (akin to the JOLTS) and conducted by Statistik Austria.[5] Figure 1 shows that the vacancies posted at the AMS constitute a relevant submarket, making up around 35% to 50% of all vacancies, depending on the time period. Also, the movements over the

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[5]Unfortunately, the underlying micro data are not accessible.

business cycle are qualitatively very similar.[6] This makes us confident that we can make fairly general statements with the dataset at hand.

In the empirical analysis below, we will study alternative samples, depending on the particular question we want to address. Since the vacancy register itself contains a lot of information on the posted vacancies, many analyses will need the vacancy register only. For some questions, we will match the vacancy register to firm level observations. We observe firm identifiers both in the ASSD and in the vacancy register, and there is a mapping translating them. However, the mapping is not unambiguous. For the time being, we are working with the set of unique matches, covering around 44% of all identifiers recorded in the vacancy data. (This share can be increased by using a refined algorithm and using additional information that we have not yet exploited.) This match allows a connection of vacancy-posting behavior to all firm characteristics recorded in the ASSD, such as firm size, firm growth, and wages. Other questions require a match to the hired worker. If a vacancy is matched to firm-level ASSD data, we also observe all hires after the vacancy is posted. In principle, this allows us to connect a vacancy to any worker, even if not hired through the AMS system. On the other hand, if the hire is through the AMS, a worker identifier is recorded which coincides with the worker identifier in the ASSD.

In Table 1, we report summary statistics, comparing the universe of vacancies to our baseline sample, which is the most narrow sample which we will use for most of our analyses. In moving from the initial to the final sample, (i) we exclude vacancies that never result in a hire, (ii) we only include vacancies where a worker can be matched, (iii) we exclude vacancies for apprentices, part-time jobs, and resulting in recalls, (iv) we only keep vacancies where the firm identifier can be mapped to the firm identifier in the ASSD, (v) we exclude vacancies where a firm or worker wage effect (as explained later in the text) cannot be identified, and (vi) we only keep vacancies with positive durations. While the sample size is reduced by a large fraction, the descriptive statistics suggest that the final sample is not completely different from the original sample.

Another way of seeing that our baseline sample compares well to the universe is to compare the firms contained in the sample to the universe of firms. More specifically, we know for every firm in the ASSD, which contains the universe of firms, whether it appears in the baseline sample or not. In Figure 2, we plot firm wage effect estimated following Abowd et al. (1999) for the two groups. While we discuss this concept in more detail below, it is an estimate of the average wage paid in a firm, controlling for

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[6]It appears that the aggregate numbers lead our numbers somewhat (the fit would be much better if we lagged them by one quarter), which might have to do with a different way of allocating vacancies to time periods.

	All	Baseline Sample
At least apprenticeship (%)	48.21	48.88
Manufacturing (%)	34.92	41.94
Permanent contract (%)	79.97	83.37
Hired through system (%)	14.58	100.00
Fixed working time (%)	22.81	28.68
Small firm (%)	45.14	42.72
Vienna (%)	16.23	11.09
Full time (%)	80.55	100.00
Start of observation period	1997.00	1997.00
Observations	9.60e+06	278434.00

Table 1: Full vs. baseline sample

observed and unobserved worker characteristics. Clearly, the distributions look very similar. It turns out hat firms included in the baseline sample pay around 5% lower wages c.p. on average. However, this is to be expected as these are firms posting vacancies intended for the currently unemployed.

3.1 The Concept of a Vacancy in the AMS Data

A conceptual issue to be clarified at this point is the definition of a vacancy and vacancy duration. For all observations after 2007, the vacancy data record the date when the vacancy is opened and closed by the AMS, t_0 and t_1. The data also record the date when the job becomes available, t_0^*, and when the vacancy is filled, t_1^*. One can think of t_1 as a proxy of the starting and closing date of the match, t_1^*, though the two do not necessarily coincide with each other. The AMS calculates a vacancy duration for all vacancies in the data based on the date of the match, defined as,

$$d \equiv \max\left\{t_1^* - t_0^*, 0\right\}.$$

Therefore, for vacancies with positive measured duration d, we can infer the time of the match from the vacancy duration reported by the AMS. The AMS vacancy duration is zero by definition when a vacancy is filled before the desired start date, i.e. before it is available. Note that this definition of vacancy duration is loosely consistent with the definition of a vacancy employed in the JOLTS, which requires that a job could start within 30 days (see Elsby, Michaels, and Ratner (2015) for a more detailed discussion of the concept of a vacancy in the JOLTS).
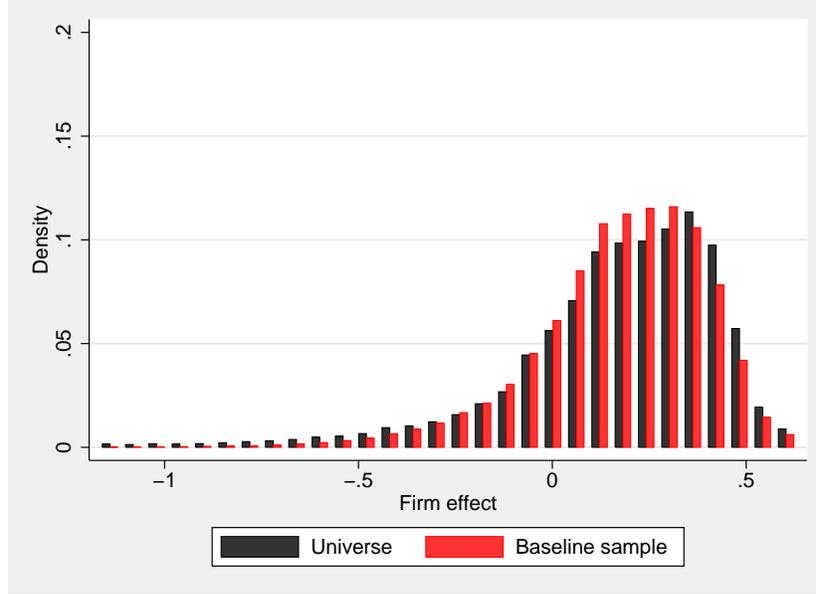
Figure 2: Distribution of firm wage effects, universe vs. in baseline sample (weighted by average employment)

3.2 The Vacancy Filling Rate

Previous studies, such as DFH, relying on repeated observations of the vacancy stock cannot observe the vacancy-filling rate directly but have to impose assumptions to infer this rate from stock-samples. An advantage of our data set is that we can exploit our longitudinal information to accurately calculate the daily vacancy-filling rate without imposing any assumptions.

Denote by $\tau(m)$ the time a vacancy is "at risk" of being filled in calendar period m. That is, assuming a monthly periodicity, if a vacancy is opened on March 15 and filled on April 7, it was at risk for 16 days in March (until March 31) and for seven days in April. Also, $q_j(m)$ takes the value one if vacancy j is filled in period m and zero otherwise. If we assume that the daily vacancy-filling rate is constant within a period and denoted by $\lambda(m)$, the average vacancy-filling rate in period m is estimated as

$$\hat{\lambda}(m) = \frac{\sum_j q_j(m)}{\sum_j \tau_j(m)},$$

where $q_j(m)$ takes the value one if vacancy j is filled in period m and zero otherwise.[7]

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[7]The likelihood contribution of one observation j in period m is given by

$$\left[\exp(-\lambda(m)\tau_j(m))\lambda(m)\right]^{q_j(m)} \left[\exp(-\lambda(m)\tau_j(m))\right]^{1-q_j(m)}.$$

The estimator is obtained by maximizing the log likelihood.

That is, the average daily vacancy-filling rate is identified by the number of vacancies filled divided by the total time at risk. For our main analysis, we use a monthly periodicity and thus effectively compute the average daily vacancy filling rate in a given calendar month. It is also possible to directly compute the daily filling rate for each day during a calendar month and then to take the average over the month. This approach, however, does not work well in practice due to the presence of many small cells, which makes the daily filling rate much more noisy.

4 Empirical Patterns

4.1 Behavior along the Business Cycle

How does the vacancy-filling rate change over the business cycle? In Figure 13 in the Appendix, panels (a) to (c), we plot the average daily vacancy filling rate against the average number of vacancies, the average number of unemployed measured in the ASSD, as well as against the ratio of the two measures (labor market tightness). Interestingly, the cyclical patterns fit the theoretical prediction of the standard theory quite precisely. The vacancy-filling rate is strongly negatively correlated with the number of vacancies and with labor market tightness, and is positively correlated with the level of unemployment. This suggests that that the set of vacancies posted through the AMS platform corresponds to the set of vacancies that is relevant for the unemployed. If we estimate the elasticity of the vacancy-filling rate with respect to the labor market tightness, we obtain a point estimate of around 0.66, which is in the ballpark of the usual findings. Looking at the Beveridge curve in 13(d),[8] our data suggest that Austria has had similar experiences to the US, with the Beveridge curve appearing to shift out recently.

The data also yield interesting insights on vacancy posting along the business cycle, as it records information on required education and the type of work on the vacancy level.[9] In Figure 3, we plot required education and job characteristics on the vacancy level along the business cycle. Two observations emerge: On the one hand, it seems that firms require higher education during downturns. This holds irrespective of whether we look at the share of vacancies requiring at least an apprenticeship or at least an academic education. On the other hand, it seems that jobs are less likely to involve routine tasks if created during recessions, as indicated by a lower share of jobs involving shift work and a higher share of jobs characterized by a free disposal of time.

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[8]Strictly speaking, this is not the Beveridge curve, as we do not standardize by the working population.

[9]Since this information is less precise for earlier years, we will restrict attention to the time after 2007.
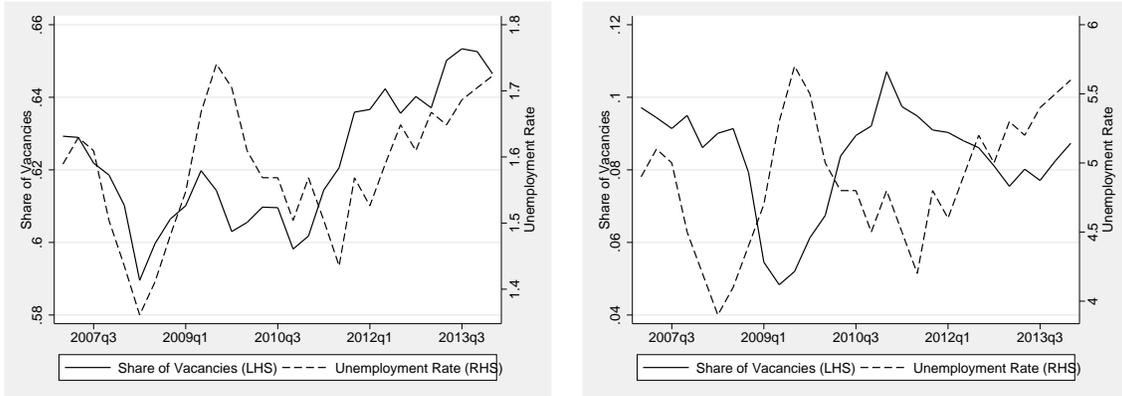
(a) Share requiring at least apprenticeship　　　　(b) Share involving shift work

Figure 3: Vacancy characteristics over the business cycle

The first observation has been documented for the US as well (Modestino et al., 2015) and interpreted as opportunistic "upskilling": Given the higher arrival rate of workers during times of high unemployment, firms react by setting higher standards for the same jobs. However, the observation that firms create fewer jobs involving routine tasks during recessions seems to suggest that firms, rather than increasing job requirements for the same jobs, actually create different jobs during recessions. While the "upskilling" conjecture arises from a random search model (i.e. all workers compete for all jobs whose requirements they meet), the two findings together are consistent with a model where firms direct their search toward workers of different types, if the pool of the unemployed tilts toward the more productive workers in recessions (this has been demonstrated for the US by Mueller (2015)).

4.2　Vacancy Filling over the Duration of the Vacancy Spell

The average AMS vacancy duration, as measured by the conventional concept, d, is about one month. However, vacancy durations show substantial variance and are also considerably skewed. About two third have been filled one month after the desired starting date while 15 percent are open for longer than two months. Interestingly, one fourth of all vacancies have been filled by the desired start date, as shown in Figure 4.[10] According to the definition explained above, this means that the vacancy is opened and filled before the desired start date indicated by the firm. It is also worth noting that about two thirds of all vacancies are posted before the desired start date, and over 20 percent are posted at least one month before that date. Moreover, among all

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[10]Figure 16 in the Appendix depicts the daily vacancy filling hazard. It spikes for vacancies with zero duration and then drops right afterwards and slowly decreases over time.

(a) Distribution of vacancy duration   (b) C.d.f. for vacancy duration ≤ 90 days
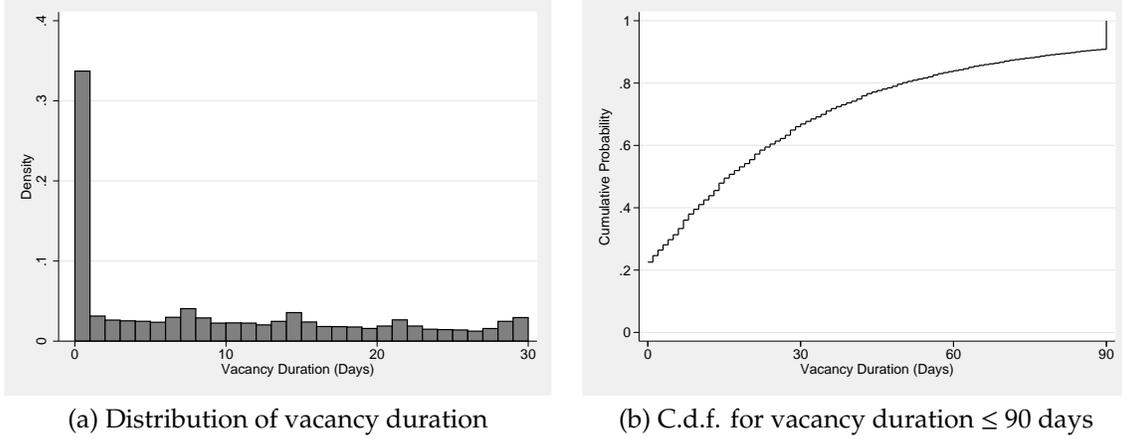
Figure 4: Observed distribution of vacancy duration

vacancies posted, almost 20 percent are already filled prior to the desired start date of the job.

It is particularly interesting to look at the duration pattern of the vacancy-filling rate and how it evolves before, at, and after the desired starting date. To answer this question, we will analyse the vacancy filling hazard over the duration of the vacancy before and after the desired start date of the job. To this purpose, we set vacancies with $d = 0$ to negative duration if the vacancy was opened and closed in the system before the desired start date.[11]

Figure 5 plots the resulting hazard rates, both for daily and weekly periodicity. The figure starts six months before the desired start date and shows that the filling rate increases gradually as we move toward the desired start date. The filling rate spikes at the desired start date and gradually falls thereafter. It is worth noting that the dynamic patterns of the vacancy-filling hazard are a mixture of heterogeneity and duration dependence and it is not possible to disentangle these two factors. Dynamic selection due to unobserved heterogeneity arises when there are vacancies with an intrinsically high filling rate that leave the sample early while the "surviving" vacancies at longer

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[11]To be precise, we define the vacancy duration as

$$\tilde{d} = \begin{cases} d & \text{if} \quad d > 0 \\ \min\{t_1 - t^*, 0\} & \text{if} \quad d = 0. \end{cases}$$

In order to calculate a meaningful hazard rate, we have to take into account that different vacancies start out at different points in time. Specifically, the vacancy-filling hazard after τ periods relative to the desired start date is given by

$$\lambda(\tau) = \lim_{h \to 0} \frac{\Pr\left(\tau \leq \tilde{d} \leq \tau + h\right)/h}{\Pr\left(\min\{t_0 - t_0^*, 0\} \leq \tau \leq \tilde{d}\right)},$$

where we only count vacancies that have been opened, i.e. $\tau \geq \min\{t_0 - t^*, 0\}$, at any given time τ.
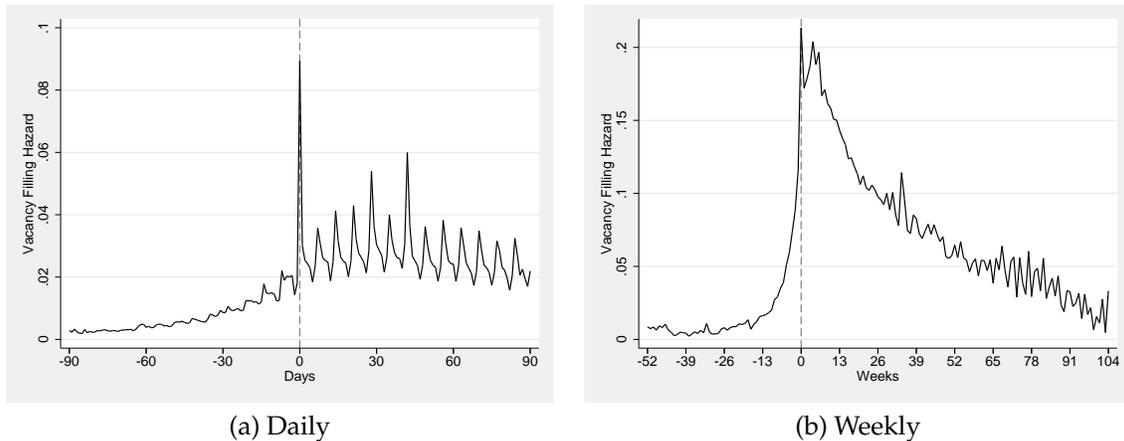
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(a) Daily   (b) Weekly

Figure 5: Vacancy-filling hazard, relative to desired start date

duration exhibit low filling rates. There could also be positive dynamic selection before the desired start date as firms expecting a low filling rate could increase the probability of filling their vacancy by the desired start date by posting early, which could explain part of the upward slope to the left of the desired start date.

The fact that early posting and filling are quantitatively relevant is interesting per se. It points to a margin of employment adjustment that has so far not been recognized. For instance, early posting may be seen as part of the search effort by firms. If this is a realistic description, then the relationship to the filling rate could either be positive or negative, depending on whether search effort and the firm's hiring efficiency are complements or substitutes. The previous empirical literature has not brought up the issue of early filling and posting. The main data set, the JOLTS survey, defines a vacancy as a position where work could start within 30 days, a concept which does not allow for early posting and filling. Moreover, there are no search models of the labor market in which the vacancy-posting behavior of firms is explictly modeled.[12]

4.3 Patterns in Vacancy Filling across Industries and Firms

As in DFH, our data show a large dispersion in the vacancy-filling rate across industries.[13] Much of the inter-industry dispersion in vacancy filling rates appears to be

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[12]To assess whether early posting is related systematically to the vacancy-filling rate, we compute firm averages of early posting, $\min\{t_0 - t_0^*, 0\}$, and the vacancy-filling rate. Because a vacancy-filling rate could be low mechanically due to early posting, we calculated the vacancy-filling rate only using positive durations ($d > 0$). Interestingly, there appears to be a u-shaped relationship between firm-level average filling rates and early posting (see Figure 15 in the Appendix). On the one hand, firms with a very low average filling rate tend to post early, which corresponds to the intuition mentioned above. However, we also observe that firms with the highest filling rate post earlier, which seems to be harder to explain.

[13]See Appendix Table 5, where we distinguish between NACE sections (we only observe the industry class after 2004).
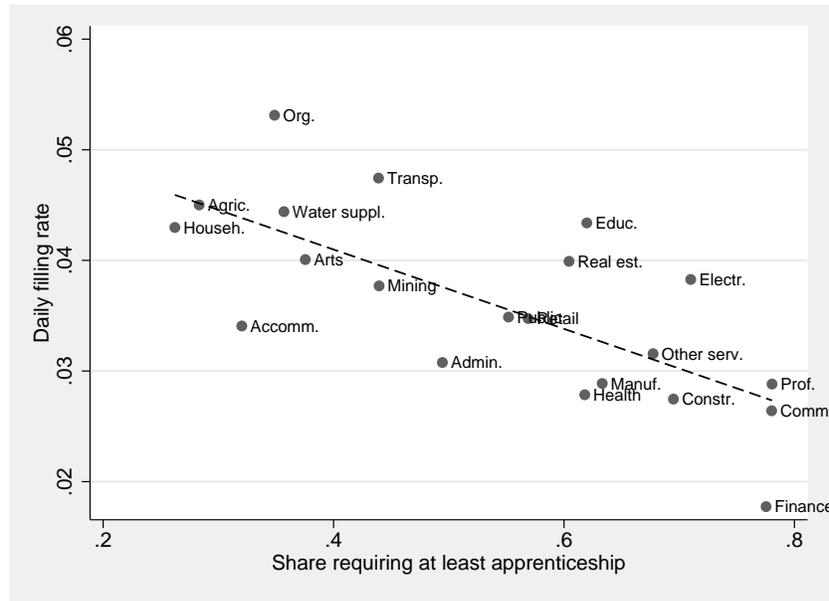
Figure 6: Apprenticeship requirement and vacancy-filling rate across industries

driven by different education requirements, as is apparent from Figure 6(a), where we relate the filling rate to the share of vacancies requiring at least an apprenticeship: Industries whose jobs typically require higher skills, such as the financial industry, have lower vacancy-filling rates compared to industries that require fewer skills, such as household services. Figure 6(b) draws the vacancy filling rate for jobs where an apprenticeship certificate is required (high eduation) and jobs that do not demand apprenticeship training (low education). The vacancy-filling rates for vacancies not requiring an apprenticeship training is substantially higher.[14] This is consistent with earlier evidence (e.g. van Ours & Ridder, 1991 document in Dutch data that the vacancy duration increases with the required education level), as well as with, e.g., Albrecht and Vroman (2002), who construct a model where employers set skill requirements. In equilibrium, jobs requiring higher skills exhibit longer vacancy durations.

DFH argue that merely looking at the number of vacancies per firm may miss an important part of the picture. Over the business cycle, growing firms systematically increase their hiring intensity, leading to more hires for every posted vacancy. Their results are based on the JOLTS, a monthly survey of the vacancy stocks. As argued above, the JOLTS is subject to aggregation bias, leading to undersampling of vacancies with short durations. While they correct for this bias given some assumptions, it makes sense to reconsider their findings, as our data do not suffer from this shortcoming. Moreover, it is also interesting to analyse whether the same patterns emerge in a

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[14]We exclude observations with zero duration for better visibility, but the results do not change even looking at d_1 instead of d_0.
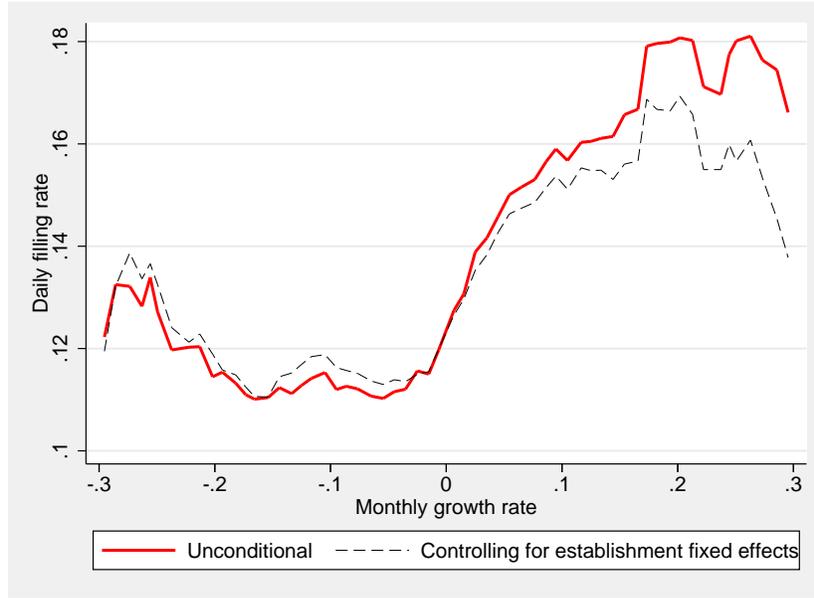
Figure 7: Establishment growth and the vacancy filling rate

different labor market setting, such as in Austria.

We calculate the monthly growth rates in establishment size using the ASSD. Following DFH, we calculate growth rates allowing for entries and exits, defined as

$$g_t = \frac{n_t - n_{t-1}}{0.5(n_t + n_{t-1})},$$

where n_t denotes the establishment size in period t. We merge these growth rates and the establishment size to the vacancy register. Following DFH, we define 195 growth rate bins, allowing for mass points at -2, 0, and 2, choosing the bins to be narrower for growth rates close to 0. We then calculate the average vacancy-filling rate within these bins. We smooth the results using a centered five-bin moving average.

The result of this exercise can be seen in Figure 7. We can confirm DFH's main finding that growing firms fill vacancies more quickly. Moreover, the patterns look qualitatively very similar to DFH's model implied vacancy filling rate. Then again, the elasticity of the vacancy-filling rate with respect to the growth rate is not as strong. One explanation could be that we only observe part of all vacancies, and predominantly those intended for the currently unemployed.[15]

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[15]Another interesting question is how early vacancy posting depends on the growth rate. There seems to be a clear tendency for shrinking firms to post vacancies prematurely, even controlling for establishment fixed effects. One explanation for this finding could be advance notice regulations, as also discussed by Burdett and Cunningham (1998): When the employer is informed of an imminent quit, she will post a vacancy right away even though the job will only become available as the worker actually leaves.

5 Vacancy Durations and Wages in New Jobs

A central assumption in many search-theoretic models of equilibrium wage dispersion (e.g., Burdett & Mortensen, 1998) is that the level of wages posted by firms affects the likelihood of either a worker applying to the job or of accepting a given wage offer and thus determines the vacancy filling rate. However, the evidence on the relationship between the vacancy-filling rate and the starting wage remains scarce, with the exception of Faberman and Menzio (2015) who use data from the Earnings and Opportunities Pilot Project (EOPP) in the U.S. for the years 1980 and 1982. They find that the starting wage shows a positive association with the duration of the vacancy, which is in the opposite direction of what models with wage posting would predict. They point out, however, that a key empirical challenge is in controlling for worker-level heterogeneity in the starting wage, which is likely a confounding factor of their analysis. Looking at the observed relationship in our data (shown in Figure 8), the relationship between the starting wage and vacancy duration remains inconclusive. Then again, this picture still mixes up many different factors, such as firm and worker heterogeneities and calendar time effects.

A key advantage of our data is that we observe the employment and earnings histories of those workers who are matched to a given vacancy for many years before and after the match. This allows us to control for fixed worker level-characteristics by decomposing the starting wage into worker- and firm effects using the framework of Abowd et al. (1999) (AKM). More precisely, we build a yearly panel of daily wages (always looking at the job held on June 30) of all workers and firms observed in the ASSD and estimate the model

$$\log w_{it} = \theta_i + \psi_{\mathbf{J}(i,t)} + x'_{it}\beta + \varepsilon_{ijt}, \tag{1}$$

where w_{it} denotes the wage of worker i in year t, θ_i identifies the worker effect, $\psi_{\mathbf{J}(i,t)}$ identifies the firm effect (where $\mathbf{J}(i, t)$ denotes the firm where i is employed in year t). We also control for observable time-varying worker characteristics x_{it} (specifically, we control for a fourth-order polynomial in experience and firm tenure as well as yearly dummies) and ε_{it} denotes the residual. Since the model is computationally very demanding, we will only use the years 2000 to 2014 for our baseline results.[16]

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[16]The basic assumption of the AKM framework is additive separability between firm and worker effects. How well does this describe the data? To assess this, we computed the average residual ε_{it} according to the decile of the firm and worker effect, as proposed by Card, Heining, and Kline (2013). Generally, deviations from additive separability appear to be mild (the absolute value always stays below 0.015) and concentrated among establishments paying high wages. See Figure 17 in the Appendix for details.
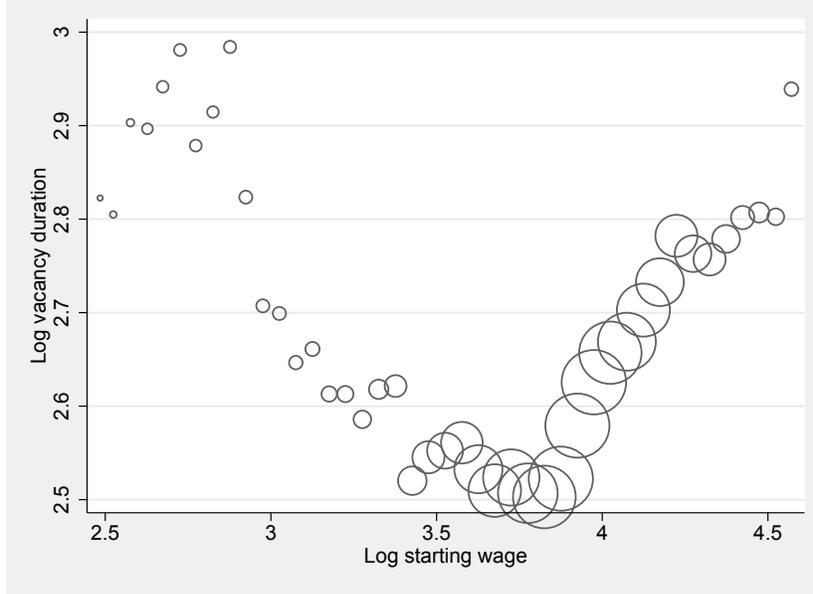
Figure 8: Log daily starting wage and vacancy duration

We then relate the components of the wage to vacancy duration by estimating

$$\log d_{ijk} = \beta_0 + \hat{\theta}_i \beta_\theta + \hat{\psi}_j \beta_\psi + \hat{\varepsilon}_{ijk} \beta_\varepsilon + z'_{ijk} \gamma + \eta_{ijk}, \tag{2}$$

where d_{ijk} denotes the vacancy duration of vacancy k posted by firm j and eventually matched to worker i. $\hat{\theta}_i$, $\hat{\psi}_j$ and $\hat{\varepsilon}_{ijk}$ denote the estimated values from equation (1)[17] and z_{ijk} is a vector of characteristics of the firm worker pair, including all variables contained in x_{it}.

While we show the results of a naive regression of log vacancy duration on the starting wage in column 1 of Table 2, column 2 shows the results of applying the decomposition by estimating specification (2).[18] We obtain a clearly negative relationship to the firm effect, while the person and experience effect enters positively. This means that high-wage firms fill their vacancies more quickly, while firms are willing to incur longer vacancy duration if hiring a high-wage worker or a worker with more experience. The wage residual enters positively: If firms pay high wages given the observables, they also fill their vacancies less quickly. While this appears to conflict with the basic intuition of the directed search model, it could also be that we do not

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[17]Since the AKM regression is in yearly periodicity, we calculate $\hat{\varepsilon}_{ijk}$ by regressing the log starting wage connected to vacancy k on $\hat{\theta}_i$, $\hat{\psi}_j$, and x_{it}, where we replace the yearly dummies by quarterly dummies to adequately control for seasonality and aggregate shocks.

[18]The standard errors reported in the regression tables do not yet control for the estimation uncertainty in the AKM decomposition, as this is computationally very expensive. We will do so in future versions of the paper.

	(1)	(2)	(3)	(4)
Log starting wage	0.0864***			
	(0.0114)			
AKM person effect		0.431***	0.172***	0.182***
		(0.0175)	(0.0171)	(0.0152)
AKM worker experience effect		0.291***	0.175***	0.135***
		(0.0141)	(0.0177)	(0.0152)
AKM establishment effect		-0.233***	-0.266***	-0.280***
		(0.0339)	(0.0359)	(0.0303)
AKM residual		0.0525***	-0.0600***	-0.0496***
		(0.0112)	(0.0104)	(0.00911)
Quarter FE	Yes	Yes	Yes	Yes
Further Controls	No	No	Yes	Yes
Region/Industry FE	No	No	No	Yes
Observations	278434	278434	271060	271060
Adjusted R^2	0.010	0.016	0.042	0.066

Standard errors clustered at firm level in parentheses

Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Regression results

yet control adequately for match specific heterogeneity. If we add more controls in column 3, all previous findings remain unchanged (even though somewhat smaller in size), while the sign of the residual changes. This also remains the case once we control for region (2-digit zip codes) and industry (2-digit NACE) fixed effects in column 4.

In Table 6 in the Appendix, we compare our preferred specification (column 4 in Tabe 2) in column 1 to different variations of the model: We show that the findings are robust to controlling for the firm size and the lagged yearly firm growth rate, or wage growth on and the duration of the job following the match. Since many firms and some workers show up repeatedly in our data, we can also estimate specifications controlling for worker and firm fixed effects. The results are also robust to this variation[19].
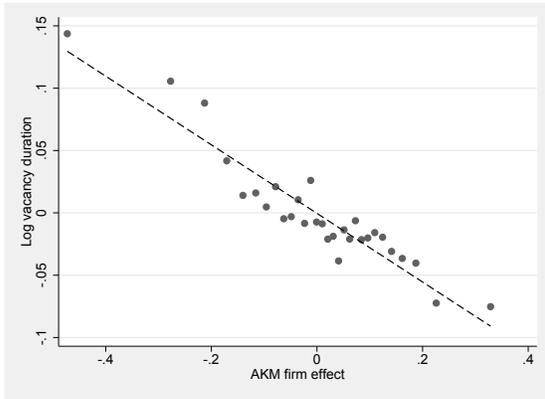
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[19]The experience effect turns negative once we control for a worker fixed effect. However, this is hard to interpret since we hold the worker and the age of the worker constant.
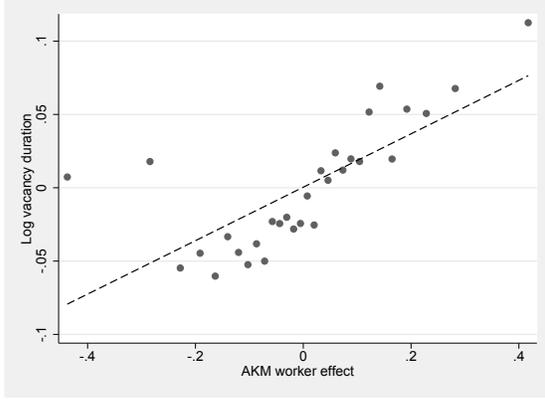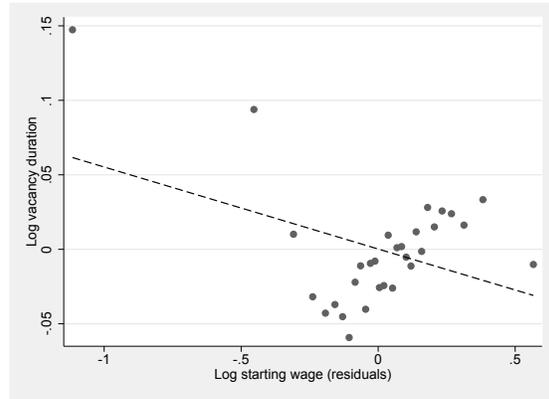
(a) AKM worker wage effect and vacancy duration
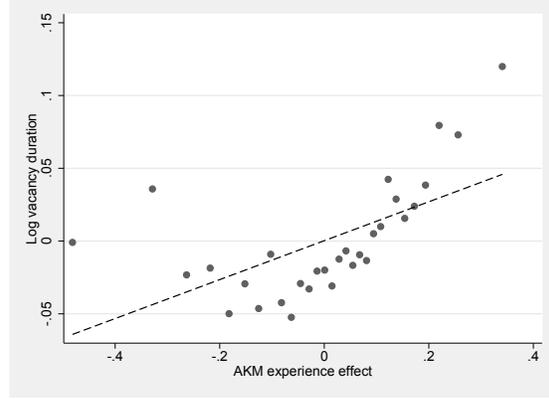
(b) AKM experience wage effect and vacancy duration

(c) AKM firm wage effect and vacancy duration

(d) AKM wage residual and vacancy duration

Figure 9: Estimated wage components and vacancy duration

To demonstrate how the worker, the experience, the firm effect as well as the residual affect vacancy duration, we show added-variable plots in Figure 9, where we give a graphical representation of the regression coefficients in column 4 by regressing the variables on the horizontal and vertical axis on all other control variables and then plot the residuals.[20] The plots indicate a very strong association of the worker, experience, and firm effect with vacancy duration. Panel (d), on the other hand, indicates that the coefficient on the wage residual is probably driven by outliers and hence hard to interpret.

A potential concern is that our results may be driven by the too restrictive assumptions of the AKM decomposition. In particular, the estimates could be biased due to endogenous mobility, as discussed by Postel-Vinay and Robin (2002). They argue that the estimated person effects might be driven by the sequential sampling

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[20]We allocate observations to bins according to 100 percentiles of the variable on the horizontal axis, which ensures that each point in the plot is based on roughly the same number of observations.
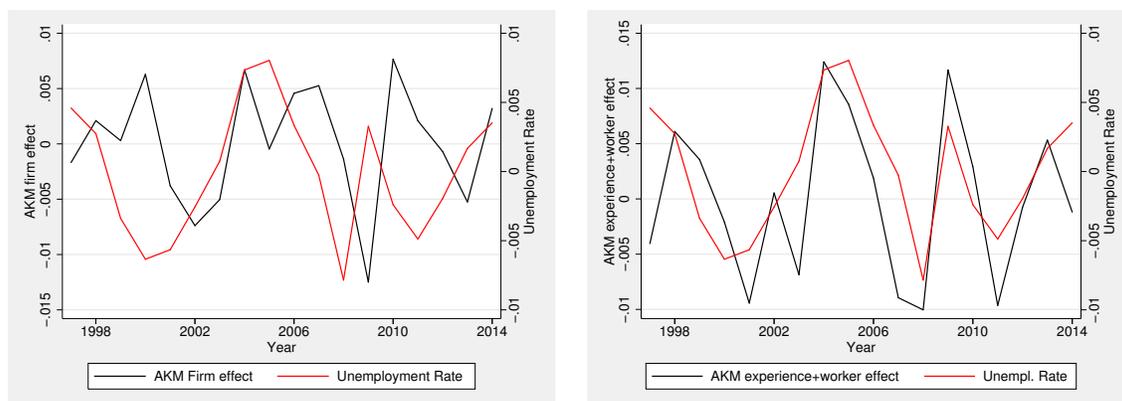
(a) Establishment effects   (b) Worker effects

Figure 10: Establishment and worker wage effects over the business cycle

of alternative (high) wages, which leads to persistent differences between otherwise identical individuals. One way to address this concern is by looking only at workers who change jobs with an intermediate spell of unemployment. Intermediate unemployment spells break the link of sequential sampling, as a wage offered to a currently unemployed worker will only depend on worker ability and firm productivity and not on the employment history. To probe the robustness of our results, we re-estimate the worker and firm effects restricting our panel to job changes interrupted by registered unemployment spells (but excluding recalls). The restriction implies that, for every firm and worker, we lose a large number of observations leading to less precise estimates.[21] Nevertheless, estimating our preferred specification on this sample in column 6 of Table 6 reveals that the conclusions are unchanged.

Another interesting question is how prevalent high-wage workers and high-wage firms are over the business cycle. To shed light on this question, we look at the AKM effects of the average firm posting vacancies as well as the average worker matched to a vacancy at different points in time. In Figure 10, we plot these numbers against the log unemployment rate (yearly averages, HP-filtered using smoothing parameter 100). While the time series are still quite short and we aim to provide results covering more years in a future version of the paper, there are some preliminary conclusions one can draw: While there does not seem to be a clear relationship between the firm effect and the business cycle (the correlation coefficient is close to zero), the average hired worker seems to commove very closely with the unemployment rate, implying that firms are relatively more likely to hire high-wage workers during recessions.

Summing up, we find stark relationships between wages and vacancy durations in the data. Holding all other factors equal, firms take longer to hire high-wage workers,

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[21]In addition, we cannot identify either the firm or worker effect for some vacancies (we lose 12% of all observations).
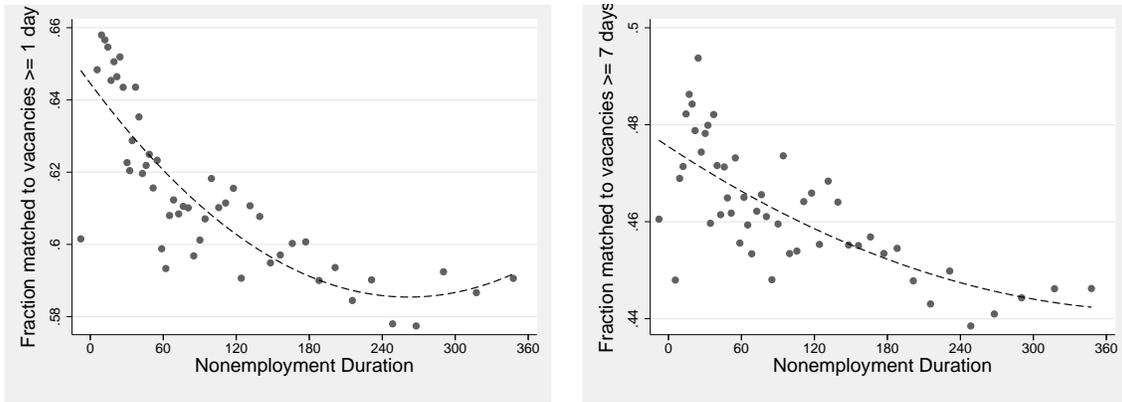
(a) Fraction matched to vacancies ≥ 1 day

(b) Fraction matched to vacancies ≥ 7 days

Figure 11: Fraction matched to higher-duration vacancies, by unemployment duration

while high-wage firms fill their vacancies more quickly. Moreover, during recessions the distribution of vacancies shifts toward high-wage workers and high-wage firms.

6 Does the Stock Match with the Flow?

Another interesting question is how the vacancy duration and the nonemployment duration of the matched worker relate. Models involving random search do not predict any specific relationship, while alternative models such as stock-flow matching (see, e.g., Coles & Petrongolo, 2008 and Coles & Smith, 1998) posit that the stock of the unemployed is matched to the flow of vacancies, and vice versa, suggesting a negative relationship between the duration of a vacancy and the non-employment spell of the matched worker.

In Figure 11, we plot nonemployment duration against the probability to be matched to a vacancy with $d \geq 1$ or 7 days. There is a marked negative relationship, meaning that workers with long nonemployment durations are more likely matched to vacancies with short durations. Random search assumes that workers search randomly among the current stock of vacancies every period, implying a zero correlation between nonemployment and vacancy duration. In Table 3, we show that these correlations are robust to a number of variations of the setting: It still holds if we add controls (among them time effects) and region as well as industry fixed effects. Columns 3 and 4 imply that the results even hold within firms and within worker. In Table 7 in the Appendix, we show that the results also hold for the probability that the vacancy duration exceeds 30 days, even though they become weaker.

To check whether the observed pattern of matches is compatible with random search, we propose a nonparametric test that is immune to concerns about heterogeneity and the business cycle. Denote by U_t and V_t the number of unemployed and

	(1)	(2)	(3)	(4)
Log nonemployment duration	-0.0347***	-0.0302***	-0.0221***	-0.0428***
	(0.00116)	(0.00107)	(0.00121)	(0.00289)
Controls	No	Yes	Yes	Yes
Region/Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	No
Worker FE	No	No	No	Yes
Observations	185164	172484	163605	80689
Adjusted R^2	0.008	0.077	0.163	0.088

(a) Dependent variable $\mathbb{1}\{d \geq 1\}$

	(1)	(2)	(3)	(4)
Log nonemployment duration	-0.0207***	-0.0167***	-0.0103***	-0.0237***
	(0.00131)	(0.00116)	(0.00134)	(0.00297)
Controls	No	Yes	Yes	Yes
Region/Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	No
Worker FE	No	No	No	Yes
Observations	185164	172484	163605	80689
Adjusted R^2	0.003	0.059	0.140	0.072

Standard errors clustered at firm level in parentheses

Controls: Quartely FEs, requ. ed. FEs, gender, age, age squared, experience, experience squared, year of labor market entry

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Dependent variable $\mathbb{1}\{d \geq 7\}$

Table 3: Regression results

vacancies in period t, respectively. Under the null hypothesis of random matching, the number of matches in period t is given by

$$M_t = M(\tilde{U}_t, \tilde{V}_t),$$

where $\tilde{U}_t \equiv \sum_{i=1}^{U_t} s_{it}$ and $\tilde{V}_t \equiv \sum_{j=1}^{V_t} a_{jt}$ denote the "effective" number of unemployed and vacancies, respectively. s_{it} and a_{jt} summarize heterogeneity affecting the job-finding rate of workers of type i and the vacancy-filling rate for vacancies of type j, respectively (search effort, skill, matching efficiency, early posting, and so on). Appealing to the law of large numbers, we will ignore the distinction between expected and actual matches, which should be innocuous given the sample size of our data.

The number of matches between workers of type i and vacancies of type j in period t is then given by

$$M_t^{ij} = \frac{s_{it}}{\tilde{U}_t} \frac{a_{jt}}{\tilde{V}_t} M_t.$$

Hence, given the random matching assumption, if a given worker i meets any vacancy, the probability that she meets vacancy j should be proportional to a_{jt}, which should hold irrespective of s_{it}. Put differently, we should not observe a differential probability of being matched to vacancy j as opposed to any other vacancies for different workers. In formal terms, this intuition can be expressed as

$$\log \frac{M_t^{ij}/M_t^{ik}}{M_t^{lj}/M_t^{lk}} = 0,$$

meaning that, under the assumption of random matching, worker i has the same odds of being matched to firm j vs. firm k as worker l.

To derive a test, we can define cutoffs $\bar{d}_u$ and $\bar{d}_v$ for nonemployment and vacancy duration d_i and d_j, respectively. Since under random matching s_{it} and a_{jt} are independent (conditional on t),

$$\mathbb{E}\left[M_t^{ij}|d_i \leq \bar{d}_u, d_j \leq \bar{d}_v\right] = \frac{\mathbb{E}\left[s_{it}|d_i \leq \bar{d}_u\right]}{\tilde{U}_t} \frac{\mathbb{E}\left[a_{jt}|d_j \leq \bar{d}_v\right]}{\tilde{V}_t} M_t,$$

and likewise for all other inequalities. Similar to the previous argument,

$$\log \frac{\mathbb{E}\left[M_t^{ij}|d_i \leq \bar{d}_u, d_j \leq \bar{d}_v\right]/\mathbb{E}\left[M_t^{ij}|d_i \leq \bar{d}_u, d_j > \bar{d}_v\right]}{\mathbb{E}\left[M_t^{ij}|d_i > \bar{d}_u, d_j \leq \bar{d}_v\right]/\mathbb{E}\left[M_t^{ij}|d_i > \bar{d}_u, d_j > \bar{d}_v\right]} = 0.$$

A short-term unemployed worker should have the same relative odds of being matched to a vacancy with short vs. long duration compared to a long-term unemployed worker.
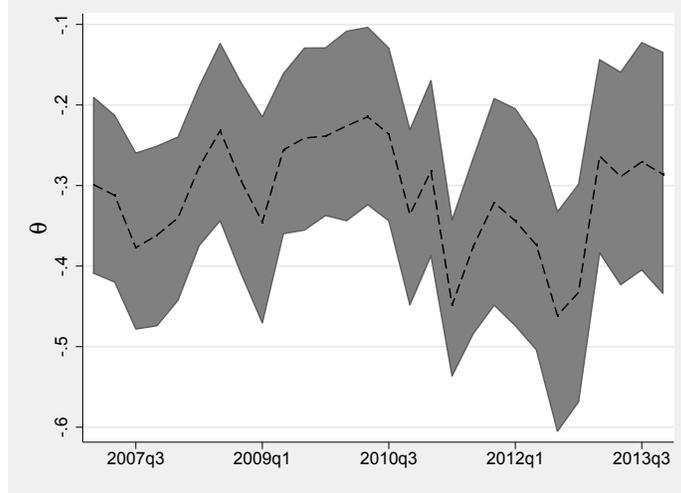
Figure 12: Test statistic and bootstrapped confidence bands over time

In order to implement the test, we assume discrete time and daily periodicity (t denotes the day). Under the null hypothesis of random matching,

$$\theta_t \equiv \log \frac{\hat{M}_t^{00}/\hat{M}_t^{01}}{\hat{M}_t^{10}/\hat{M}_t^{11}} \xrightarrow{P} 0,$$

where $\hat{M}_t^{00}$ denotes the observed number of matches between a worker with $d_i \leq \bar{d}_u$ and a firm with $d_j \leq \bar{d}_v$, and likewise for $\hat{M}_t^{01}$, $\hat{M}_t^{10}$, and $\hat{M}_t^{11}$. Given random matching, single observations within t are i.i.d. and hence we can calculate confidence bands for θ_t by bootstrapping. To gain power and limit computational time, we calculate the quarterly average, given by

$$\theta_q = \frac{1}{N_q} \sum_{t \in q} \theta_t,$$

where q denotes the quarter and N_q the number of observations within quarter q. θ_q is bootstrapped by resampling within days to account for potential calendar or business cycle effects.

In Figure 12, we plot θ_q along with the bootstrapped confidence bands (500 replications for every quarter) if $\bar{d}_u$ and $\bar{d}_v$ are fixed at the 25th percentile or nonemployment and vacancy duration within every quarter, respectively. This corresonds to 43 days for nonemployment duration and 0 days for vacancy duration if the cutoff is fixed at the 25th percentile. We can reject random matching for virtually all periods if the cutoff is fixed at the 25th percentile. Moreover, the test statistic is always negative, meaning that workers with short nonemployment durations are relatively more likely to be matched to vacancies with long durations compared to workers with long

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nonemployment duration, which is consistent with models of stock-flow matching.[22]

7   Conclusion

In this paper, we study how vacancy durations are related to re-employment wages, and other characteristics of the worker and the firm that form a new employment relationship. We employ a new data set which matches information on individual vacancies posted by firms to individual employment and earnings histories of workers. We establish two main facts. *First*, there is a strong positive relationship between the duration of a vacancy and the worker wage-effect and robust negative association between the duration of the vacancy and the firm wage-effect. The latter finding is consistent with theories of directed search, where more job seekers apply to more productive firms. *Second*, we provide evidence that the longer a worker remains unemployed the more likely she is to be matched to a newly available vacancy rather than an existing vacancy. This finding directly supports the main prediction of theories of stock-flow matching and indicates negative duration dependence in the set of job opportunities available to unemployed workers.

Our analysis also reveals that vacancies are often filled before the desired start date: early posting and early filling are important employment adjustment margins for firms. Morover, vacancy characteristics vary over the business cycle: during recessions, the typical vacancy requires higher skills and fewer routine tasks.

In future work, we plan to extend the empirical analysis on the relationship between vacancy duration and the starting wages in new jobs. In particular, firms may not only try to attract workers by posting higher wages but also by committing to higher wage growth or lower layoff risk. We can empirically assess the importance of these features for workers' application behavior, by relating these firm-level outcomes to vacancy duration. Moreover, we plan on carrying out a deeper analysis of the vacancy filling rate over the business cycle and of how it relates to the components of the starting wage. This has potentially important implications for the Beveridge curve: As documented in the paper, firms post more vacancies targeted at high-ability workers in recessions and take longer to fill these vacancies, which may shift the Beveridge curve outward. Furthermore, we plan on calibrating a version of the model of Burdett and Mortensen (1998) to see whether and for what parameter values we can match the moments documented in our data. Finally, our results on the relationship between

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[22]The pattern is less clear if we fix the cutoff at the 50th percentile (see Appendix Figure 20, with the statistic becoming positive in the initial period. Interestingly, this is reminiscent of the assumptions in the stock-flow model where only the distinction between the stock and the flow of both sides of the market plays a role.

unemployment duration and vacancy duration at the time of the match, which support the notion of stock-flow matching in the labor market, deserve further scrutiny. We plan on analysing how the relationship varies across local labor markets and time and, in particular, whether changes in the relative size of the flows and stocks of vacancies and unemployed affect the documented patterns in line with the predictions from the theory of stock-flow matching.

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A Further Empirical Results

	Matched differently	Matched	Lapsed
At least apprenticeship (%)	45.43	39.87	53.49
Manufacturing (%)	42.71	36.54	27.26
Permanent contract (%)	76.32	82.14	82.60
Hired through system (%)	0.00	100.00	0.00
Fixed working time (%)	22.18	26.04	22.34
Small firm (%)	45.44	44.29	45.18
Vienna (%)	18.12	10.76	16.58
Full time (%)	75.81	77.30	85.97
Start of observation period	1997.00	1997.00	1997.00
Observations	3.92e+06	1.40e+06	4.28e+06

Table 4: Summary statistics of AMS Vacancy Data according to outcome

Industry	Average Filling Rate ×100	Observations
Agriculture, forestry and fishing	13	71343
Mining and quarrying	11	1651
Manufacturing	10	225503
Electricity, gas, steam and air conditioning suppl	10	1995
Water supply, sewerage, waste management and remed	12	5141
Construction	9	155598
Wholesale and retail trade; repair of motor vehicl	10	361367
Accommodation and food service activities	10	78755
Transportation and storage	11	499314
Information and communication	8	18646
Financial and insurance activities	7	21257
Real estate activities	10	10809
Professional, scientific and technical activities	8	63009
Administrative and support service activities	10	669643
Public administration and defence; compulsory soci	14	33818
Education	12	23309
Human health and social work activities	10	75769
Arts, entertainment and recreation	11	24036
Other service activities	9	57479
Activities of households as employers; undifferent	11	2651
Activities of extraterritorial organisations and b	12	170
Total	10	2401263

Table 5: Vacancy-filling rate across industries

	(1)	(2)	(3)	(4)	(5)	(6)
AKM person effect	0.182***	0.196***	0.156***	0.144***		0.139***
	(0.0152)	(0.0173)	(0.0171)	(0.0167)		(0.0149)
AKM worker experience effect	0.135***	0.152***	0.0879***	0.0749***	-0.217***	0.113***
	(0.0152)	(0.0171)	(0.0171)	(0.0166)	(0.0837)	(0.0162)
AKM establishment effect	-0.280***	-0.276***	-0.293***		-0.339***	-0.225***
	(0.0303)	(0.0367)	(0.0328)		(0.0404)	(0.0273)
AKM residual	-0.0496***	-0.0237**	-0.0582***	-0.0134	-0.0674***	-0.0513***
	(0.00911)	(0.0103)	(0.0106)	(0.00932)	(0.0192)	(0.00927)
Log firm size		-0.00368				
		(0.00552)				
Lagged yearly firm growth		-0.0223**				
		(0.0111)				
Wage growth (on job)			0.0494*			
			(0.0297)			
Log job duration			0.0386***			
			(0.00244)			
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Further Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region/Industry FE	Yes	Yes	Yes	No	No	Yes
Firm FE	No	No	No	Yes	No	No
Worker FE	No	No	No	No	Yes	No
Only JUJ transitions	No	No	No	No	No	Yes
Observations	271060	216993	210405	258822	121471	260002
Adjusted R^2	0.066	0.067	0.069	0.157	0.102	0.065

Standard errors clustered at firm level in parentheses

Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Further regression results (dependent variable: log vacancy duration)

	(1)	(2)	(3)	(4)
Log nonemployment duration	-0.00559***	-0.00325***	-0.00351***	-0.00837***
	(0.000884)	(0.000822)	(0.000960)	(0.00209)
Controls	No	Yes	Yes	Yes
Region/Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	No
Worker FE	No	No	No	Yes
Observations	185164	172484	163605	80689
Adjusted R^2	0.000	0.037	0.114	0.077

Standard errors clustered at firm level in parentheses

Controls: Quartely FEs, requ. ed. FEs, gender, age, age squared, experience, experience squared, year of labor market entry

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression results: dependent variable $\mathbb{1}\{d \geq 30\}$
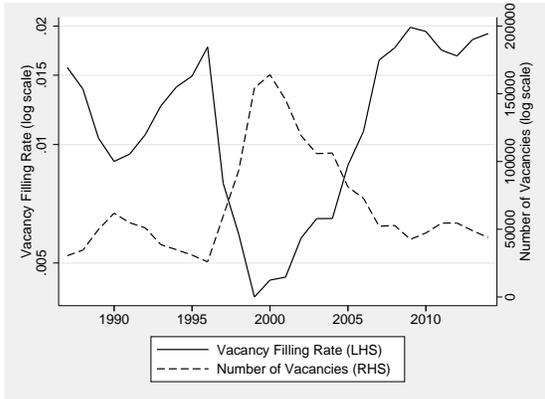
(a) Daily filling rate and number of vacancies
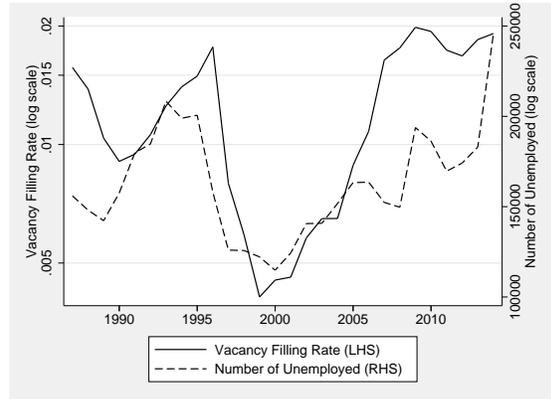
(b) Daily filling rate and number of unemployed
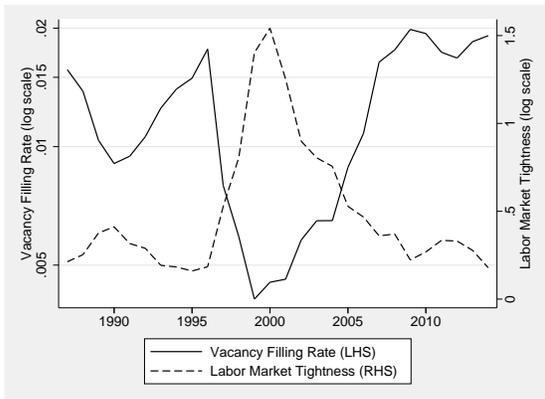
(c) Daily filling rate and labor market tightness
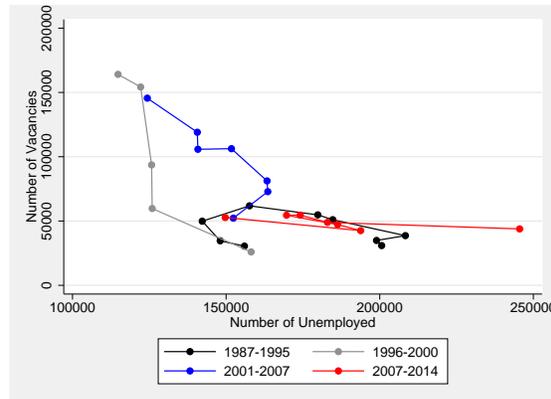
(d) Beveridge curve

Figure 13: Vacancy-filling rate and labor market aggregates
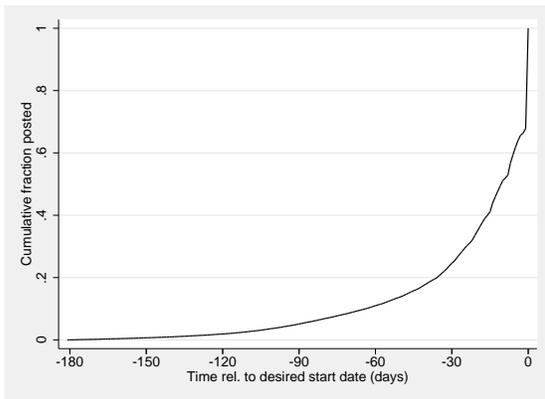
(a) Cumulative fraction posted
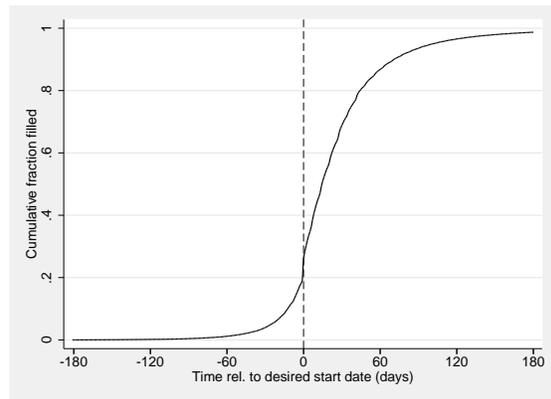
(b) Cumulative fraction filled

Figure 14: Cumulative fraction posted and filled relative to desired start date, conditional on being posted not more than 180 early
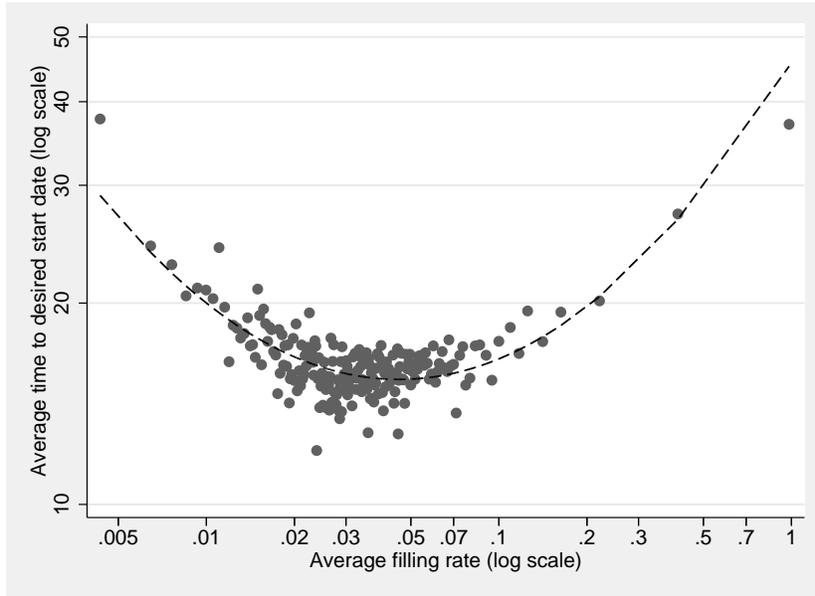
Figure 15: Early posting and average vacancy-filling rate on firm level
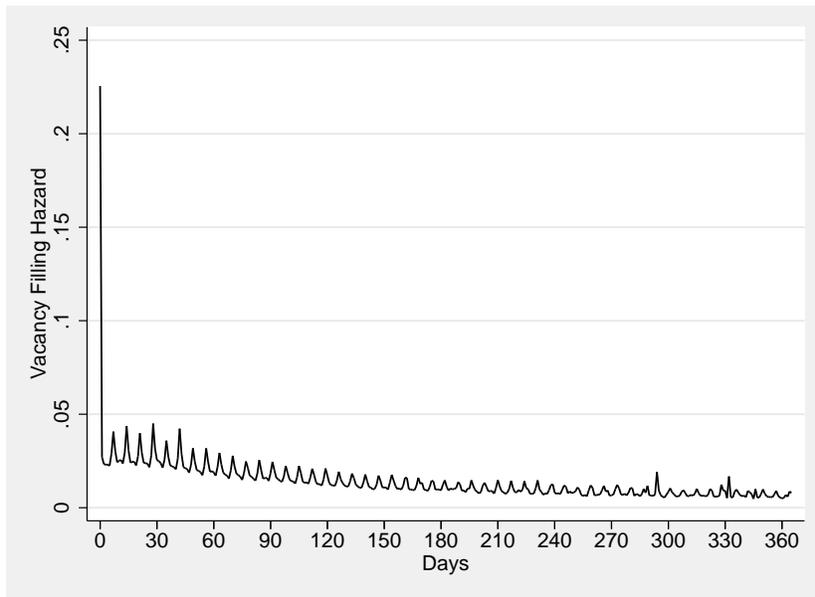
Figure 16: Daily vacancy-filling hazard
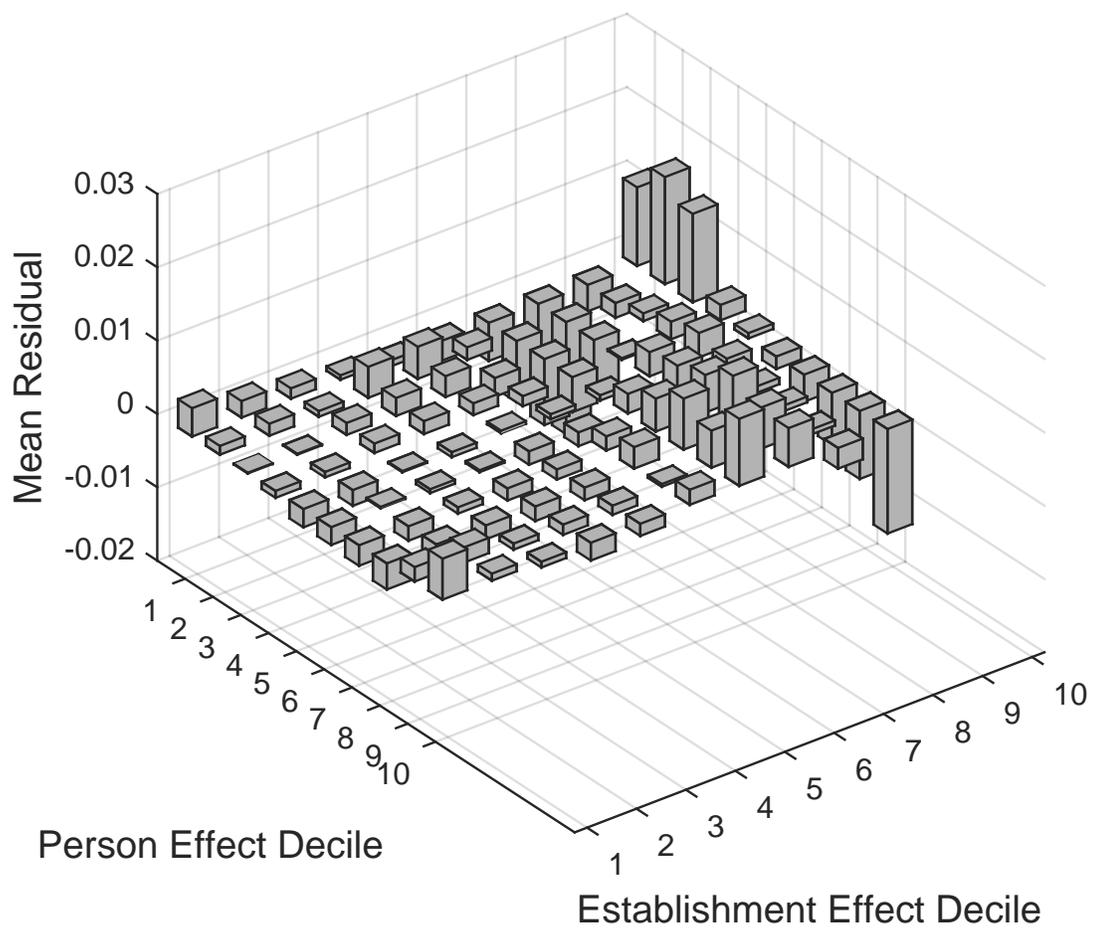
Figure 17: Mean residuals by person/establishment deciles
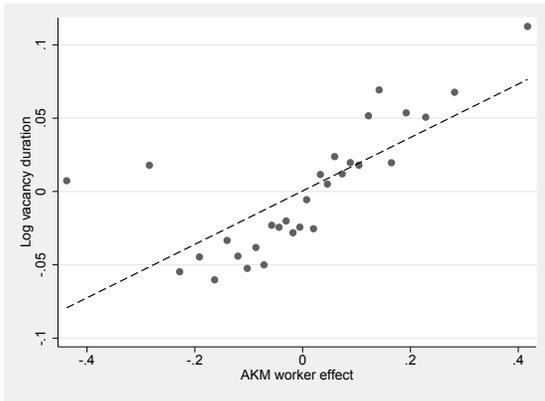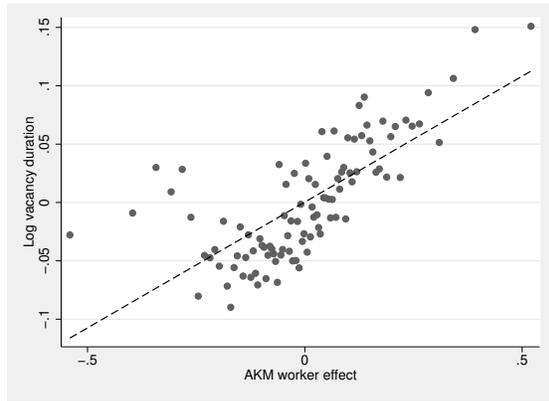
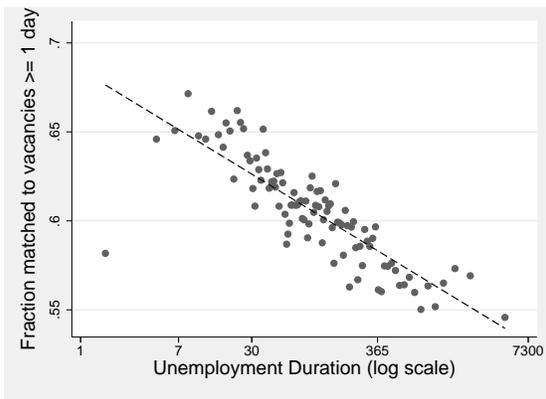(a) Baseline   (b) At least 5 observations
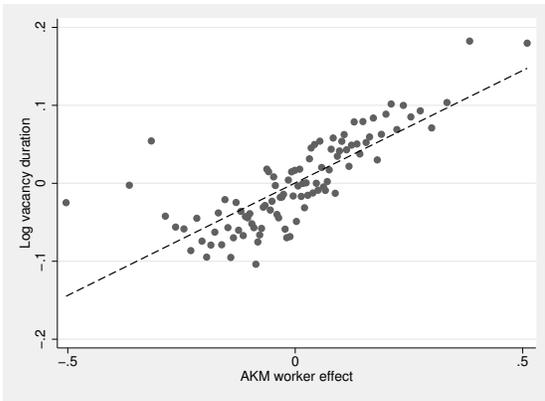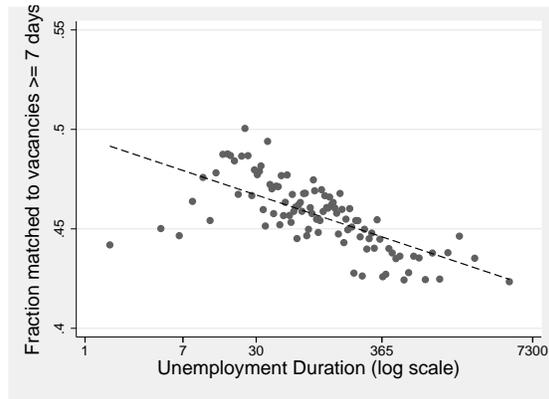
(c) At least 10 observations   (d) At least 15 observations
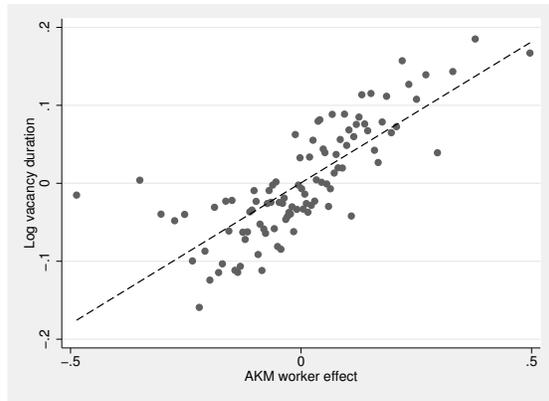
Figure 18: Partial correlations between AKM worker effects and log vacancy duration, according to number of observations per worker in AKM estimation

(a) Unemployment duration and fraction ≥ 1 day

(b) Unemployment duration and fraction ≥ 7 days

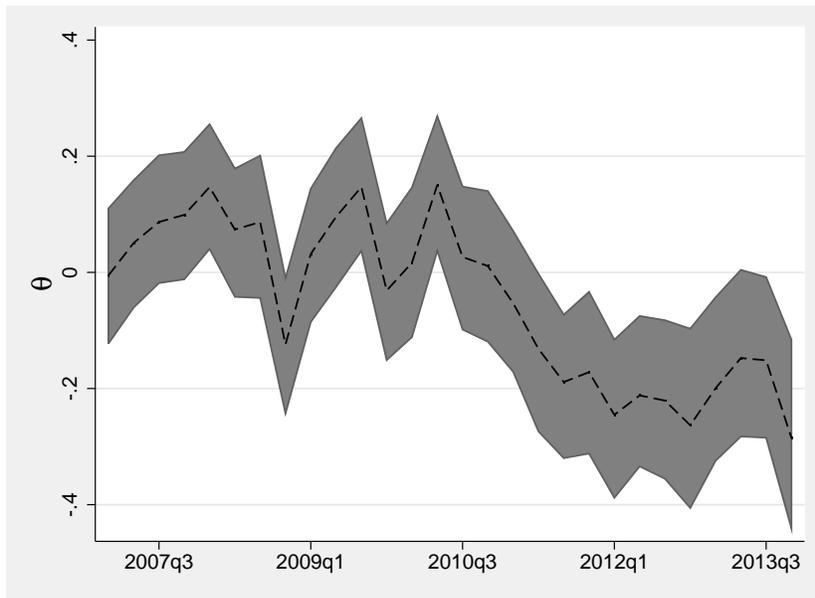Figure 19: Unemployment duration and vacancy duration (log scale)

Figure 20: Test statistic and bootstrapped confidence bands over time