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Vacancy Durations and Entry Wages: Evidence from Linked Vacancy-Employer-Employee Data

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Vacancy Durations and Entry Wages: Evidence from Linked Vacancy-Employer-Employee Data *

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Abstract

This paper explores the relationship between the duration of a vacancy and the starting wage of a new job, using unusually informative data comprising detailed information on vacancies, the establishments posting the vacancies, and the workers eventually filling the vacancies. We find that vacancy durations are negatively correlated with the starting wage and that this negative association is particularly strong with the establishment component of the starting wage. We also confirm previous findings that growing establishments fill their vacancies faster. To understand the relationship between establishment growth, vacancy filling and entry wages, we calibrate a model with directed search and ex-ante heterogeneous workers and firms. We find a strong tension between matching the sharp increase in vacancy filling for growing firms and the response of vacancy filling to firm-level wages. We discuss the implications of this finding as well as potential resolutions.

Keywords: Vacancy Posting, Vacancy Duration, Recruiting, Search, Wages.
JEL codes: E24, J31, J63.

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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), however, shows that the number of vacancies as measured in JOLTS survey data is an imperfect predictor of hiring outcomes across U.S. establishments. Their evidence suggests that firms rely heavily on additional instruments to recruit workers, which has important implications for aggregate labor market dynamics (Kaas and Kircher, 2015; Gavazza, Mongey and Violante, 2018). Despite this important contribution, many aspects of vacancy posting and filling are still poorly understood, mainly due to the lack of detailed microdata.

The aim of this paper is to explore the empirical relation between the duration of a vacancy and the entry wage of a filled position. Despite the central role of the vacancy filling rate in search and matching models of the labor market, our empirical knowledge about the determinants of vacancy durations and their relation to entry wages (and other labor market outcomes) is very limited. This gap in knowledge is striking given the large body of empirical evidence on unemployment durations and workers' re-employment wages and, more generally, on the role of worker search behavior in the formation of new employment relationships. To understand the matching process in the labor market, it seems important to understand both the role of worker *and* employer behavior. In this paper, we aim to fill this gap by shedding light on the role of employer behavior for the creation of – and wages paid in – new job matches.

To study the relationship between vacancy durations and entry wages, we use a linked dataset comprising information on (i) characteristics and durations of posted vacancies, (ii) employment of and wages paid by the establishment posting the vacancy, and (iii) the earnings history of the worker eventually filling the vacancy. The rich information contained in this dataset allows us to study in detail the vacancy filling patterns and their relation to wages in newly filled jobs.

The main finding emerging from our empirical analysis is that high-wage establishments fill their vacancies more quickly. This relationship, however, is masked in the raw data, as vacancies with long durations tend to be filled with high-wage workers, resulting in a positive correlation between vacancy durations and wages. Thus, our analysis reveals the importance of using matched data to distinguish the effect of establishments and matches from worker-level heterogeneity in the analysis of the determinants of vacancy duration. We perform a broad set of empirical checks and find our main result to be very robust.

The evidence allows us to evaluate existing theories of the matching process. The canonical search and matching model with random search and wage bargaining cannot account for the empirical observations that high-wage firms face shorter vacancy durations, as it predicts that firms that face tighter labor markets pay higher wages but also experience longer vacancy durations. Instead, our evidence points to theories where firms face a trade-off between paying higher wages and facing longer vacancy spells. Most notably, theories of directed search where firms post a wage and workers direct their search towards the more desirable sub-markets are better suited to explain the evidence (Moen, 1997). As recently shown by Kaas and Kircher (2015), these theories have important implications for the evolution of aggregate matching efficiency and fluctuations of starting wages over the business cycle. We reassess these issues in the light of our evidence.

The vacancy data come from the Austrian public labor market administration ("Arbeitsmarktservice", AMS), which contains the universe of vacancies posted through the AMS platform. The AMS is by far the most important platform of vacancy posting by Austrian establishments and covers almost 60% (!) of all vacancies posted by Austrian establishments.[1] The AMS vacancy dataset contains an (anonymized) employer-identifier which allows us to link the posting establishment to the Austrian Social Security Database (ASSD). The link at the *establishment* level allows us to study AMS vacancy posting by Austrian establishments in a very similar way as Davis, Faberman, and Haltiwanger (DFH 2013) did for all US vacancies using JOLTS data. For vacancies that were filled through direct mediation of the AMS, the information on vacancy durations and -characteristics can be linked to the earnings history of the worker eventually filling the vacancy. We exploit the link at the *worker* level to study the association between vacancy durations and entry wages.[2]

We argue that our analysis is interesting not only for the Austrian labor market, but also for a better understanding of vacancy posting and filling behavior of firms more generally.

[1] Statistics Austria runs a large quarterly vacancy survey ("Offene Stellen Erhebung") providing evidence on vacancy posting by Austrian establishment on all platforms. The survey asks, for each single vacancy reported by the sampled establishment, whether the vacancy was posted on the AMS platform. On average, 57% of vacancies were posted at the AMS. During the period 2009 to 2017 the AMS coverage rate was 57% and fluctuated between 53% (2009) and 61% (2013) without showing a trend.

[2] The Austrian vacancy database has so far not been extensively used for academic research. Among the few studies exploiting these data is the study of Lalive, Landais and Zweimüller (2015) on market externalities of UI (and who use the AMS vacancy data to determine which workers are competing for the same vacancies); and work in progress by Card, Colella and Lalive (2018) on gender discrimination in vacancy posting and -filling. See also Riese and Bruckbauer (1987) for an early descriptive study using individual vacancy data from the Austrian public employment service. Mueller, Osterwalder and Zweimüller (2018) describe the potential of the AMS vacancy database for labor market research and provide a detailed description of the AMS vacancy database and its link to the ASSD. The ASSD has been extensively used in previous studies (see e.g. Lalive, van Ours and Zweimüller (2006); Card, Chetty and Weber (2007); Card, Lee, Pei and Weber (2015); Alvarez, Borovickova and Shimer (2016); Borovickova and Shimer (2018)). For a detailed description of the ASSD, see Zweimüller et al. (2009).

First, the possibility to link information on vacancy durations and -characteristics to information on the wage of the worker filling the vacancy provides the opportunity to shed new light on a central prediction of search models where firms post a wage. In these models, employers face a trade-off between paying a high wage and filling a vacancy quickly versus paying a low wage but having to search longer until the vacancy is filled. This includes theories of directed search (Moen, 1997) as well as random search (Burdett and Mortensen, 1998) with the central assumption that firms post a wage or commit to a wage offer before meeting the worker. Directed search theory predicts that firms posting higher wages attract more applicants, whereas theories based on random search predict that firms offering higher wages face a higher probability of the offer being accepted. While search models with wage posting have become important theoretical frameworks in labor and macroeconomics, evidence on predictions of these theories in general – and the trade-off between vacancy durations and entry wages in particular – is very scarce. Faberman and Menzio (2018) is the only paper we are aware of that has studied this trade-off. They find a positive correlation in data from the Earnings and Opportunities Pilot Project (EOPP) in the U.S. in the early 1980s.[3] Our research builds on theirs and assesses the extent to which the positive correlation is confounded by the presence of worker heterogeneity. Our analysis is particularly well suited to address this issue because we observe the entire labor market history of the workers matched to a vacancy and thus can use wage and employment histories as additional controls. Moreover, for a subset of workers in our data, we observe multiple unemployment spells and thus we can assess the within-person correlation of starting wages and vacancy durations faced by the establishments hiring the worker. A *second* reason why our results are of more general interest is that the patterns of vacancy posting and hiring by Austrian establishments are similar to those in other countries, even in countries with quite different labor market institutions. In fact, comparing vacancy patterns in the Austrian data to US evidence by DFH (2013) shows a surprising degree of similarity. For instance, hiring and separations rates of Austrian establishments are of a similar order of magnitude as those of the US. Similar to DFH (2013) we find: (i) growing establishments do not only generate more hires per vacancies but also fill their vacancies more quickly, (ii) vacancy rates and vacancy yields (= hires per vacancy) vary strongly with the establishments' industry, size and employment turnover, (iii) more than 30% of workers are employed in establishments that do not hire any worker in a given month, (iv) a large fraction of establishments posting no vacancy at the end of the previous month hire workers in the subsequent month and (v) the majority of vacancies are posted by establishments that post more than one vacancy in the same month.

[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.

A *third* reason why our analysis is of more general interest relates to the information content and quality of our data. The Austrian vacancy data provide information, on a daily basis, on the vacancy posting date, the desired start date of the job (= date when the job become available), and the vacancy filling date. This allows us not only to estimate the vacancy filling rate quite precisely. We also show that about 25% of all vacancies are filled *before* the desired start date. Moreover, AMS staff frequently checks with the posting establishment on inactive vacancies and documents in the data when a vacancy lapses. Hence the AMS job posting site is not plagued with inactive ("phantom") vacancies that have been found important in privately operated job posting sites (Albrecht, Decreuse and Vroma, 2017). The richness of the AMS data also leads to alternative vacancy concepts (including the JOLTS concept), which we will discuss in detail below.

The evidence that emerges from our empirical analysis is that, with sufficient controls for worker heterogeneity, the correlation between vacancy durations and starting wages turns from positive to negative. This is particularly evident when we control for worker fixed effects in regression analysis, comparing the outcomes of the matching process for the same individual across different unemployment spells. We go one step further by decomposing wages into fixed worker- and establishment-characteristics using the technique proposed by Abowd, Kramarz and Margolis (1999) (AKM). This allows us to look at the association between the vacancy duration to the establishment- , worker- and residual-components of the starting wage. Our results show two underlying opposing forces: On the one hand, it takes longer to fill a vacancy for establishments targeting workers in the high-wage segment of the labor market. On the other hand, we find that vacancies with higher starting wages are filled more quickly. We show that this negative association is particularly strong with the establishment component of the starting wage. Viewed through the lens of search theory, the latter result implies that establishment wage effects are more tightly correlated with the value of a job accruing to the worker than the residual component of the starting wage.

To understand better the relationship between vacancy filling and posted wages, we calibrate a model with directed search, posted wages and ex-ante heterogeneous workers and firms. The model of Kaas and Kircher (2015) is a natural starting point, as it characterizes directed search in the context of firm heterogeneity and was calibrated explicitly to match the facts documented in DFH (2013). In their model, posted wages act as a recruitment device. Firms that want to grow fast post higher wages to reduce the time to fill a vacancy. We enrich the model of Kaas and Kircher by allowing for ex-ante worker heterogeneity. This allows us to match the empirical finding that it takes longer for firms to hire high-wage workers. Qualitatively, our model also matches the empirical finding of a negative relationship between firm-level wages and vacancy duration. Quantitatively, however, the model predicts an elasticity that is at least an order of magnitude larger than in the data. It is possible to calibrate the model differently to do better in this dimension, but only at the cost of not matching the evidence in DFH on the relationship between vacancy filling and firm growth. The implication of this finding is quite clear: the measured elasticity between establishment-level wages and vacancy durations is an order of magnitude too small to account for substantial variations of matching efficiency across establishments, and thus the evidence points to theories that allow for measures of recruiting effort that do not rely on the starting wage, as in Gavazza, Mongey and Violante (2018). We also discuss potential extensions of the model of Kaas and Kircher (2015) that may resolve the tension between matching the patterns in DFH and our paper.

Our paper proceeds as follows: Section 2 discusses the related empirical literature and Section 3 discusses the institutional background. Section 4 introduces the data, discusses the vacancy duration concepts, and discusses the procedure linking vacancy data to employer-employee data. Section 5 replicates previous evidence on vacancy posting, hiring, and employment growth in our linked data set. Section 6 analyses the relationship between vacancy duration and entry wages. Section 7 sets up the model and confronts its predictions with the data. Section 8 concludes.

2 Related Empirical Literature

Our contribution relates to a number of studies of vacancy behavior. With data from the Job Openings and Labor Turnover Survey (JOLTS) for the US, DFH (2013) show that faster growing establishments 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 in the JOLTS data. Since the JOLTS has only been available since December 2000, many earlier studies focused on the Help Wanted Index (Abraham (1983); Abraham (1987); Blanchard and 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 and Ridder (1991); van Ours and Ridder (1992); Holzer (1994); Gorter, Nijkamp and

Rietveld (1996); Burdett and Cunningham (1998); Dickerson (2003); Davis, Röttger, Warning and Weber (2014); Faberman and Menzio (2018)) or online job board data (e.g. Barron, Berger and Black (1999); Banfi and Villena-Roldan (2016); Marinescu and Wolthoff (2016); Marinescu (2017); Modestino, Shoag and Ballance (2017); Hershbein and Kahn (2018); see also Kuhn (2014) for a general discussion of internet job search). 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 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, Bradley, Stott and Upward (2008) who covers the labor market for teenagers for one region of the UK. Third, 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 under-sampled (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. Finally, a few recent studies provide interesting findings on the relationship between number of applications and the posted wage (in particular, see Marinescu and Wolthoff (2016) and Banfi and Villena-Roldan (2016)). This is interesting because, in models of directed search, a higher number of applications is the channel through which firms are able to fill vacancies more quickly. Unlike our dataset, the above empirical analyses do not directly observe the duration of a vacancy, which is the key variable entering the firm's posting and recruiting decisions. The fact that our data contain precise information on the duration of a vacancy allows for a much more straightforward mapping from empirics to theory, particularly in regards to the quantitative predictions of models of directed search.

3 Institutional Background

In this section, we discuss the institutional background relevant for our analysis of vacancy durations and entry wages. Since we are looking at vacancies posted at the Austrian public employment service (“*Arbeitsmarktservice*”, AMS) we start with a brief discussion of the role of the AMS as a player on the Austrian labor market. We then discuss institutions and relevant features of the wage setting process in Austria.

3.1 The AMS on the Austrian Labor Market

The AMS is by far the most important job-matching platform in Austria, comprising almost 60% of all vacancies posted by Austrian firms. The mission of the AMS is bringing together job seekers and employers and reducing search frictions on the labor market to a minimum. Targeted workers include both employed or unemployed workers looking for a job as well firms with open vacancies of all kinds. AMS services are free of charge, both for workers and for firms.

The AMS is organized in one federal, nine state and 104 local (labor market district) offices. Social partners (employer federations and worker organizations) are involved at all levels and instrumental in monitoring the organization’s corporate governance. Social partners are also involved in designing labor market policies, including measures to improve the efficiency of the matching process (such as “eAMS,” the implementation and improvement of online services).

Besides its central role as a mediator between workers and employers on the Austrian labor market, the AMS administers income support programs (UI benefits, unemployment assistance, and related transfers) and is in charge of providing and organizing active labor market policies.[4] In 2017, the AMS employed 6,284 (5,606 full-time equivalent) workers. AMS staff managed income support payments of about 6.2 billion Euros and active labor market policy subsidies (for 364,000 job seekers) of about 1.3 billion Euros. Together with the budget of the AMS organization (0.9 billion Euros), total expenditures administered through the AMS amounted to 8.2 billion Euros or 2.2% of Austrian GDP (see AMS (2018)).

3.2 The Wage Setting Process in Austria

Wage setting in Austria is subject to collective bargaining agreements that cover about 95% of Austrian workers. These agreements are the outcome of negotiations between

[4] An additional task of the AMS is the economy-wide management of the admission process of immigrants to the Austrian labor market.

unions and employer associations at the industry level. Importantly for our purpose, these collective bargaining agreements only set wage floors. Ultimately, wages are determined by supplementary establishment bargaining as well as bilaterally between workers and firms.[5] As a consequence most wages are substantially above the wage floor. For instance, Leoni and Pollan (2013) study "overpayments" (the ratio of effective wages over collectively bargained wages). They find that, in the years when the regional extended benefit program was in place in the late 1980s and early 1990s, effective wages of blue collar workers were, on average, between 20 to 25% above the collectively bargained minimum wages. Unfortunately, the ASSD does not contain information that would allow a mapping of a wage observation to the corresponding collective bargaining agreement. There are more than 400 such agreements per year and wage floor vary across bargaining units. Some of our (low-) wage observations will therefore be bound by these agreements, which is likely to bias our results towards zero.[6]

4 Data and Conceptual Issues

Here we start with describing the AMS vacancy database, focusing in particular on the information on the timing and characteristics of AMS vacancies. The rich information on vacancy timing raises conceptual issues relating to the measurement of the vacancy duration of a vacancy, which we discuss in the following subsection. Finally, we describe how we link AMS vacancies to establishment- and worker information from the social security register (ASSD). This link will eventually allow us to analyze the association between vacancy durations and entry wages.

4.1 The AMS Vacancy Database

The AMS vacancy register database, explained in detail in Mueller, Osterwalder and Zweimüller (2018), contains information on all vacancies posted through the AMS and covers the years 1987-2014. The data quality has been initially low but substantially improving over time. In what follows, our analysis focuses on the period 1997-2014, as for these years all the variables of interest for our analysis are available, including industry codes and worker-level identifiers that allow matching to the ASSD.

[5] Moreover, Austrian collective bargaining agreements often feature clauses that require actually paid wages to rise in lockstep with the wage growth of the wage floors, although some some clauses specify lower wage growth. In the context of the present analysis this is less relevant because we concentrate on entry wages in newly formed job matches which are not constrained by these latter agreements, which only apply to ongoing employment relationships.

[6] Indeed, our robustness analysis in the Appendix reveals that the results become slightly stronger when we trim the sample at the 5th and 95th percentile (see Tables A8 and A13).

A particular advantage of the AMS vacancy register is the detailed (daily) information on vacancy timing. More precisely, the data contain: (i) the date when the vacancy is posted, (ii) the desired start date of the job, and (iii) 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 skill requirements, as well as characteristics of the firm posting the vacancy such as the region, industry and firm size. 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 identifier 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 14% of all vacancies never result in a hire. Of the remaining vacancies, around 27% are hired through the AMS system while 73% are filled through a different channel (see Table A1 in the Appendix). In correspondence with the AMS, we verified that the AMS frequently follows up – at least once every two weeks – with the firm posting the vacancy regarding the status of the vacancy. Taken together, this suggests that the AMS job posting site is plagued much less with issues related to inactive vacancies than in privately operated job posting sites (see Albrecht, Decreuse and Vroman (2017) for a theoretical analysis of this issue). Another strength of the AMS vacancy data is that it separately records outcomes for vacancies for multiple workers, see Table A1 and Figure A1 in the Appendix. Vacancies with at least one other identical vacancy account for one third of all vacancies in the AMS vacancy data base.

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 ("*Offene-Stellen-Erhebung*" OStE, akin to the JOLTS) and conducted by Statistik Austria since 2009. Figure 1 shows that the AMS- and OStE vacancy stocks co-move very closely, with a correlation coefficient of 0.89. While the similarity of the two time-series is reassuring, calculating an AMS coverage rate (= AMS-stock / OStE-stock) is problematic because the underlying vacancy concepts are different.[7] Fortunately, the OStE survey provides direct information whether or not a given

[7]The vacancy concept underlying the OStE survey is more vague than the vacancy concept underlying AMS stock. The AMS stock displayed in Figure 1 includes all posted vacancies, including those that are not

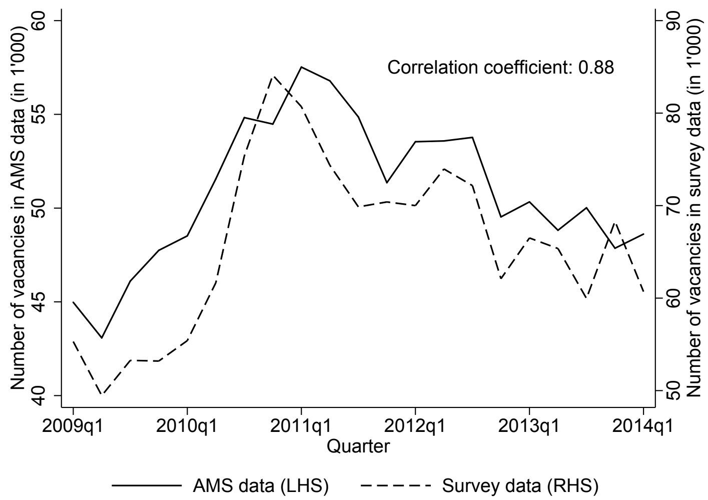


Figure 1: AMS Vacancy Data vs. Representative Vacancy Survey Data

vacancy is posted through the AMS platform. The fraction of vacancies posted at the AMS – as observed in the OStE survey – is (by construction) based on the same vacancy concept and thus gives us a reasonably accurate coverage rate. During the period 2009 to 2017, the share of vacancies posted at the AMS fluctuated 57% and 61% (2013) without showing any trend. Edelhofer and Knittler (2013) show that AMS vacancies are by and large (though not perfectly) representative for all vacancies posted by Austrian firms. In particular, AMS vacancies are more concentrated on occupations in the middle of the skill spectrum and have somewhat lower education requirements than vacancies not posted via the AMS.

4.2 Measuring the Duration of AMS Vacancies

A first issue to be clarified is the definition of a vacancy and how we measure a vacancy's duration. Our starting point is the BLS's definition of an open position, which is applied in the collection of the JOLTS data and specifies that a job is open only if it meets all three of the following conditions: (1) A specific position exists and there is work available for that position, (2) the job could start within 30 days, and (3) there is active recruiting for workers from outside the establishment location that has the opening. These conditions were set in analogy to how the BLS and the ILO define and measure unemployment.

The analogy of the BLS's definition to AMS's vacancy data is not straightforward. The AMS vacancy data contains a measure of vacancy duration, measured in days, defined as the difference between the date the vacancy is filled and the desired start date of the job (=

immediately available. In contrast, the OStE stock includes vacancies that are "available within a certain period". This implies that the latter stock is based on a more narrow definition than the former, thus overestimating the AMS coverage rate.

the date when the job becomes available). In what follows, we refer to this concept as the *AMS duration*. This is similar to the concepts of a vacancy in JOLTS, except that the job must be immediately available rather than within the next 30 days. To gain a more comprehensive view of vacancy filling, we define two alternative vacancy durations: the *JOLTS duration*, which measures the duration since posting, but at most 30 days in advance of the date of availability; and the *Posting duration,* which measures the (unrestricted) duration since posting. To be more precise, let's define the date when the vacancy is posted in the AMS as t_{posted}, the date when the job becomes available as $t_{available}$ and the date when the vacancy is filled as t_{filled}. Then, the three vacancy concepts translate into the following duration measures:

1. *AMS duration*: $d^{AMS} \equiv \max\left\{t_{filled} - t_{available}, 0\right\}$
2. *JOLTS duration*: $d^{JOLTS} \equiv \max\left\{t_{filled} - max\{t_{posted}, t_{available} - 30\}, 0\right\}$
3. *Posting duration*: $d^{Posting} \equiv t_{filled} - t_{posted}$

The AMS data contain d^{AMS} for the entire sample period, measured in days. However, the exact (daily) date of t_{posted}, $t_{available}$, and t_{filled} is available not before 2007. Before 2007, we know t_{posted}, $t_{available}$, and t_{filled} only at monthly precision. To have a comparable measure for the full length of the sample period, we approximate these dates for the earlier period by the 15th of each month and compute the JOLTS and posting vacancy duration measures accordingly.[8]

Note that it is not a priori clear, which vacancy concept should be applied for our analysis. Ideally, vacancy duration (just like unemployment duration) should measure the duration of the recruiting (search) spell. Thus, if a firm posts a vacancy but does not actively try to fill it or cannot fill it because it is posted too far in advance of the date of availability, it should not be counted as part of the vacancy stock. However, it is difficult to draw the line in practice since recruiting effort is not directly observable. Our analysis below uses all three vacancy duration measures. We want to stress that a key advantage of our data is that we can accurately calculate the daily vacancy filling rate without imposing any assumptions. This is different from previous studies (such as DFH) relying on repeated observations of the vacancy stock, which cannot observe the vacancy filling rate directly but have to impose assumptions to infer this rate from stock samples and total hires.

[8]We checked whether this approximation may lead to biased estimates of vacancy durations. It turns out that there is little difference between the exact and proxied *JOLTS-* and the *Posting duration* measures for the period 2007-2014, where the relevant dates are observed at daily precision (see Appendix Figure A3). See also Elsby, Michaels and Ratner (2015) for a more detailed discussion of the concept of a vacancy in the JOLTS.

Table 1: Summary Statistics for Different Measures of Vacancy Duration

	Vacancy Duration Concept		
A. All filled vacancies	AMS	JOLTS	Posting
Mean days	30.8	41.3	48.2
Median days	15.0	30.0	33.0
Percent with duration = 0 days	24.2	7.6	5.8
Percent with duration = 1-7 days	13.0	9.1	8.7
Percent with duration = 8-30 days	30.8	37.0	31.0
Percent with duration = 31-90 days	24.4	37.0	41.3
Percent with duration > 90 days	7.5	9.3	13.3
B. Filled vacancies, intermediated through the AMS only	AMS	JOLTS	Posting
Mean days	19.0	27.8	33.9
Median days	7	19	20
Percent with duration = 0 days	33.5	13.4	12.6
Percent with duration = 1-7 days	19.6	16.4	16.2
Percent with duration = 8-30 days	29.3	41.2	34.1
Percent with duration = 31-90 days	13.9	24.5	29.5
Percent with duration > 90 days	3.7	4.4	7.6

Notes: Authors' tabulations with the AMS universe for the years 1997-2014. Lapsed vacancies are excluded for this tabulation.

Table 1 shows summary statistics for the three different vacancy duration concepts among the set of vacancies that are eventually filled (i.e., do not lapse).[9] Panel A of the table looks at all filled vacancies, while Panel B looks at vacancies filled through mediation of the AMS. For the universe of AMS vacancies, it turns out the average *AMS duration* is 30.8 days, the average *JOLTS duration* is 41.3 days, and the average *Posting duration* is 48.2 days. Panel B looks at the same indicators when only vacancies eventually filled through mediation of the AMS are considered. It turns out that, irrespective of the particular vacancy measure, vacancies filled with AMS mediation last substantially shorter.

An important reason for the shorter duration of vacancies filled through mediation of the AMS is delayed reporting. Vacancies filled through the AMS system are tracked in real time and the recorded filling date typically corresponds to the true filling date. Information on vacancies filled outside the AMS system is collected by AMS staff who frequently checks up with the posting establishment. Since AMS staff only checks whether the vacancy is still

[9]The statistics look very similar when we restrict the sample to the years 2007 and later, where the JOLTS and Posting duration is measured in exact days.

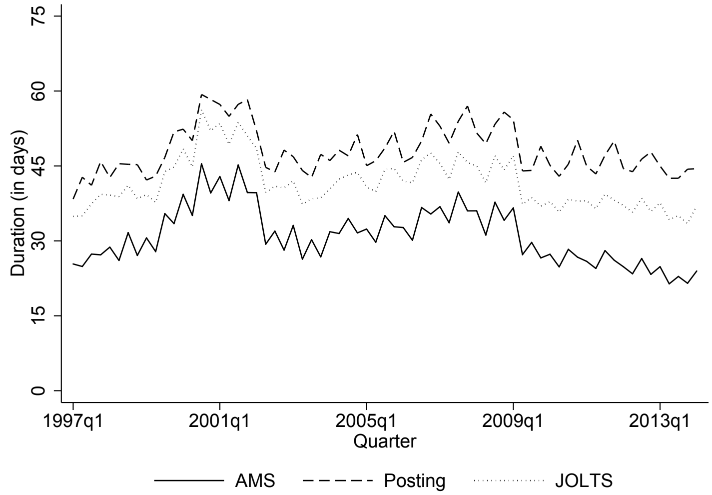


Figure 2: Comparison of Different Measures of Vacancy Duration

active or not (rather than the filling or lapsing date), the recorded filling date is typically later than the true filling date, leading to systematically longer vacancy durations for vacancies filled outside the system.[10] Another potential reason why durations are shorter for vacancies mediated through the AMS is that firms post vacancies at the AMS and only turn to other recruiting channels if the search through the AMS was not successful, though it seems just as plausible that the opposite holds true.

The three vacancy concepts show a very strong correlation over time, both at seasonal and business-cycle frequency. This is shown in Figure 2. The correlation coefficient of the quarterly average of the AMS vacancy duration and the Posting duration is 0.81 and the correlation coefficient of the AMS vacancy duration and the JOLTS duration is 0.97.[11]

The vacancy timing information in the AMS data allows us to explore how vacancy filling varies with the duration of a vacancy. To shed light on this question, Figure 3 draws the vacancy filling hazard against "time to job availability", which is defined as $\tilde{d} = t_{filled} - t_{available}$. Notice that $\tilde{d}$ coincides with *AMS duration* for positive values of $\tilde{d}$, but counts a duration as negative when it is filled prior to the date of availability (when

[10]Comparing Panels A and B of Table 1 shows that the difference is larger for *JOLTS* and *Posting durations* than for *AMS duration*. This is consistent with AMS staff following up immediately available vacancies more frequently than vacancies that are not yet available, leading to larger reporting delay for not immediately available vacancies. Delayed reporting can also explain why the discrepancy is smaller for *JOLTS duration* than for *Posting duration,* as the latter measure is based on a broader vacancy stock (with a larger fraction of not immediately available vacancies).

[11]In the Appendix Figures A4 and A5, we also show that he vacancy filling rate observed in our data exhibits realistic business-cycle patterns, with an elasticity with respect to the labor market tightness of between -0.37 and -0.47, which is consistent with estimates of the matching function. Vacancy lapses do not appear to have any systematic correlation with labor market tightness or the unemployment rate, as is evident from Figure A6 in the Appendix.

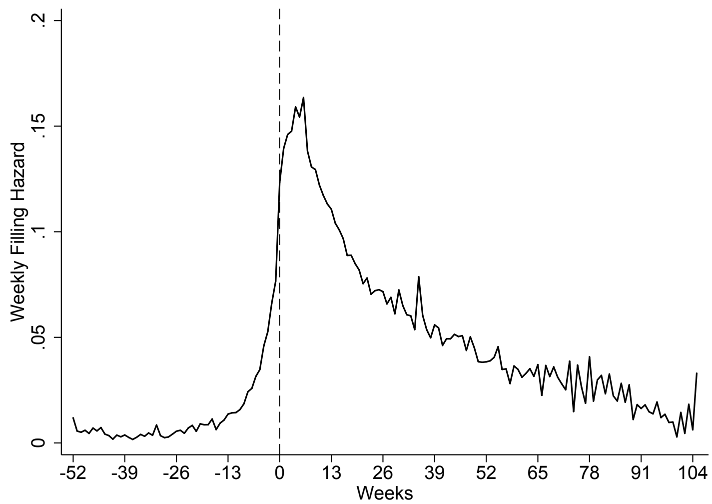


Figure 3: Vacancy-Filling Hazard, Relative to the Date of Availability of the Job

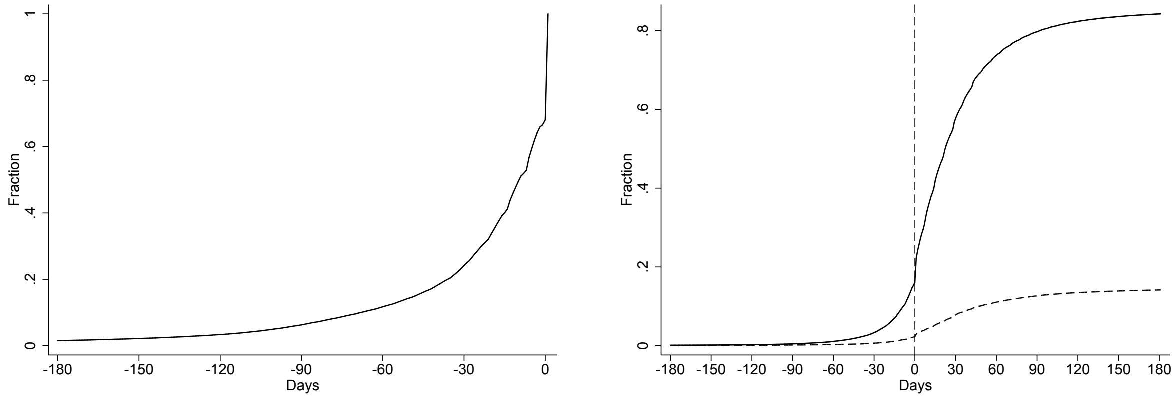
AMS duration is zero). $\tilde{d}$ is zero for vacancies posted and filled at the desired start date.[12] Figure 3 shows how the weekly filling rate varies with $\tilde{d}$. The graph reveals that the filling rate gradually increases before, peaks at, and gradually falls after the desired start date.[13] Clearly, these dynamic patterns reflect both duration dependence and heterogeneity and it is not possible to disentangle these two factors.[14]

Figure 4 plots the cumulative fraction of posted vacancies (Panel a) and the cumulative fraction of filled and lapsed vacancies (Panel b) against $\tilde{d}$. Panel (a) reveals that two thirds of AMS vacancies are posted before the desired start date, and roughly one quarter are posted earlier than one month before that date. Panel (b) shows that a non-negligible fraction of AMS vacancies are filled (while very few lapse) before the desired start date. The vast majority (85 percent) of AMS vacancies gets eventually filled. In sum, Figures 3 and 4 show

[12]When calculating the filling rate as in Figure 3, 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 $\lambda(\tau) = \lim_{h \to 0}[\Pr(\tau \leq \tilde{d} \leq \tau + h)/h]/[\Pr(t_{posted} - t_{available} \leq \tau \leq \tilde{d})]$, where we only count vacancies after they were posted, i.e. $\tau \geq t_{posted} - t_{available}$, at any given time τ.

[13]Appendix Figure A2 shows similar patterns for the vacancy lapse hazard.

[14]True negative duration dependence in vacancy filling rates may arise in the presence of stock-flow matching (Coles and Smith, 1998), in the presence of phantom vacancies (Albrecht, Decreuse and Vroman, 2017) or due to non-sequential search where employers select a pool of applicants and then make a job offer (Davis and Samaniego de la Parra, 2017). 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 duration exhibit low filling rates. For examples of models with heterogeneous filling rates, see Davis (2001), where vacancies for high-productivity jobs exhibit higher filling rates, or Kaas and Kircher (2015), where fast-growing firms post higher wages to attract more applicants. 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.



(a) Cumulative fraction posted

(b) Cumulative fraction filled (solid) and lapsed (dashed)

Figure 4: Cumulative Fraction Posted, Filled and Lapsed, Relative to the Date of Availability of the Job

that early posting and filling are quantitatively relevant. This is interesting per se and points to a margin of employment adjustment that has so far not been recognized.

4.3 Linking AMS vacancies to the ASSD

In the empirical analysis below, we will primarily focus on the empirical association of vacancy durations and entry wages. This is based on a dataset linking AMS vacancies to information on workers and establishments from the Austrian social security database (ASSD). The ASSD, explained in detail in Zweimüller, Winter-Ebmer, Lalive, Kuhn, Wuellrich, Ruf and Büchi (2009), is a linked employer-employee dataset and covers the universe of all private sector workers (about 80% of the total workforce) from 1972 onwards. The ASSD collects all information necessary to verify old-age pension claims. For this purpose, it records the complete earnings- and employment history for each worker. Moreover, the ASSD provides information on unemployment insurance spells, and spells on other social insurance programs (sickness, disability, etc.) and also includes a limited set of worker and establishment characteristics.

To construct our linked vacancy-employer-employee dataset, we exploit AMS information on the identity of (i) the establishment posting the vacancy and (ii) the worker eventually filling the vacancy. We proceed in two steps. *First*, we use the information on establishment identifiers both in the ASSD and AMS vacancy data, and the mapping translating them. However, the mapping is not unambiguous. Below we confine the analysis to the set of unique matches, covering around 54 per cent of all identifiers recorded in the vacancy data. In a *second* step, we exploit information in the AMS vacancy data on the identity (= the anonymized social security number) of the worker filling the vacancy. This information is available for hires mediated through the AMS, which happens to be the case for about 25% of all AMS vacancies. These AMS vacancies can be linked to ASSD information on earnings and employment of the worker filling the vacancy.[15]

The above procedure yields two linked vacancy-employer-employee datasets: (i) the "firm sample", based on an establishment identifier in the AMS vacancy data that can be unambiguously linked to the ASSD; and (ii) the "worker sample", based on an unambiguous person identifier in both datasets. By construction, the latter sample is a subset of the former (as many vacancies are eventually not filled through AMS mediation, in which case no person identifier is recorded). The firm sample links AMS vacancy information to ASSD information on the establishments' employment dynamics (employment, hirings, separations, etc.). Inter alia, we can observe all hires after an establishment has posted a vacancy on the AMS platform. The worker sample links AMS vacancy information to the ASSD earnings- and employment history of the worker filling a vacancy. This latter information allows us to study the association between vacancy durations and entry wages.

To check the quality of the linking procedure, we compare vacancy characteristics in the linked firm- and worker samples to the AMS universe to vacancy characteristics in the AMS universe. This is a check whether the linkable vacancies are a representative subset of the AMS universe. In Table 2, we report summary statistics, comparing the universe of vacancies to our matched subsamples.[16] In moving from the AMS universe to the firm sample, we exclude non-linkable vacancies leaving us with 54.2% of the vacancies in the AMS universe. In addition, we exclude vacancies for part-time jobs from our matched subsamples to limit any issues regarding the hours margin in our wage analysis, since the ASSD only measures daily but not hourly wages. In moving from the firm sample to the worker sample, we only include vacancies resulting in a hire through mediation of the AMS system where a worker identifier was available leaving us with 20.1% of the vacancies in the firm sample.[17] While the worker sample – the sample used to explore vacancy durations and entry wages – is substantially smaller than the AMS universe, the descriptive statistics suggest that it is not that different in terms of vacancy characteristics. Overall, the evidence in 2 suggests that the linking procedure works well and is unlikely to be contaminated by the fact that a large number of AMS vacancies cannot be linked due to missing establishment- or

[15]The main reason for the non-uniqueness of the matching is that the vacancy register and the ASSD use a different firm/establishment logic, which is a not an uncommon problem with data sources stemming from different data providers.

[16]In line with published statistics of Statistik Austria, we exlcude vacancies for apprenticeships, vacancies from firms in agriculture and fishing, and extraterritorial organizations from the data. The data with these sample restrictions closely replicates the official time series on AMS vacancies published by Statistik Austria.

[17]We also exclude observations where the observed starting wage was zero (69 cases).

Table 2: Vacancy Characteristics: AMS Universe vs. Matched Subsamples

	AMS Universe	Firm Sample	Worker Sample
Vacancy Characteristics			
At least apprenticeship (%)	50.3	54.2	48.4
Permanent contract (%)	78.4	72.9	79.4
Hired through system (%)	23.3	23.3	100.0
Fixed working time (%)	21.2	23.9	28.2
Full time (%)	75.2	100.0	100.0
Small firm (%)	44.6	41.8	41.7
Vienna (%)	17.0	12.0	8.7
Major Industries			
Manufacturing (%)	10.3	12.1	16.8
Construction (%)	7.0	10.0	12.5
Wholesale and Retail (%)	14.8	10.8	13.8
Accommodation and Food (%)	23.3	31.2	23.1
Real Estate, Professional, and Admin (%)	26.1	26.0	21.8
Vacancies	5,354,139	2,183,199	439,341
Establishments	269,157	93,400	61,232

Notes: Authors' tabulations of the vacancy register data for the years 1997-2014. A small firm is defined in the vacancy register data as a firm with 1-10 employees.

person identifiers.[18] In particular, the worker sample looks quite similar to the full sample of vacancies in terms required formal education, skills, contract type and size of the posting firm.

A second check assessing the representativeness of our linked vacancy-employer-employee dataset compares the establishments posting linkable vacancies to the universe of establishments in the ASSD, which covers all private sector establishments. In Appendix Figure 5, we plot the distribution of firm-wage effect estimated following Abowd, Kramarz and Margolis (1999). Panels (a) and (b) compare the distribution in the ASSD establishment universe to the corresponding distributions but considering only establishments in the firm and the worker subsample, respectively. While we discuss this concept in more detail below, it is an estimate of the average wage paid in a firm, controlling for observed and unobserved

[18]The regression samples in Section 6 are usually somewhat smaller than this number because most regressions use the natural logarithm of vacancy duration as the dependent variable, which is not defined for the sizeable fraction of the sample with a vacancy duration of zero. See further below in this section for a discussion of this issue. In addition, some control variables are not available for all observations in the worker sample.

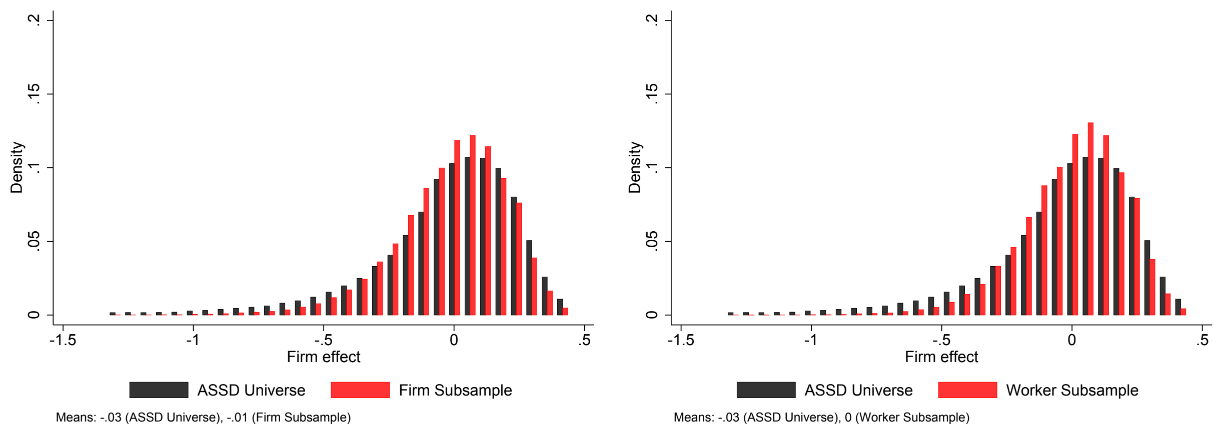


Figure 5: Distribution of Firm Wage Effects, ASSD Universe vs. Matched Firm and Worker Samples (Weighted by Average Employment)

worker characteristics. Clearly, the distributions look very similar, with less mass at both ends of the distributions compared to the ASSD Universe. In Table A2 in the Appendix, we also checked whether the firm and worker samples are similar to the ASSD universe in terms of industry composition, employer size and worker turnover. It turns out that the firm and worker samples are somewhat more concentrated in manufacturing, construction, retail trade and tourism. Subsamples are also more likely medium sized, while very small and very large establishments are underrepresented. The subsamples compare very well to the universe in terms of the distribution across employment turnover categories.

In sum, while many vacancies cannot be linked, the characteristics of linkable vacancies look very similar to characteristics of the *AMS vacancy universe*. This suggests that the linking procedure works and is unlikely invalidated by missing establishment or person identifiers. However, with respect to industry and firm size the composition of establishments in the linked samples is somewhat different from the one in the *ASSD establishment universe*. This is likely due to either differences in the likelihood to post vacancies or selectivity in establishments' propensity to post vacancies on the AMS platform. While this calls for a cautious interpretation of our results, our main takeaway is that the linked vacancy-employer-employee data is a highly informative data source for studying vacancy durations and entry wages. We also probe the robustness of our main findings in Section 6 below and find that they are not sensitive to controlling for establishment size nor to splitting the sample by establishment size.

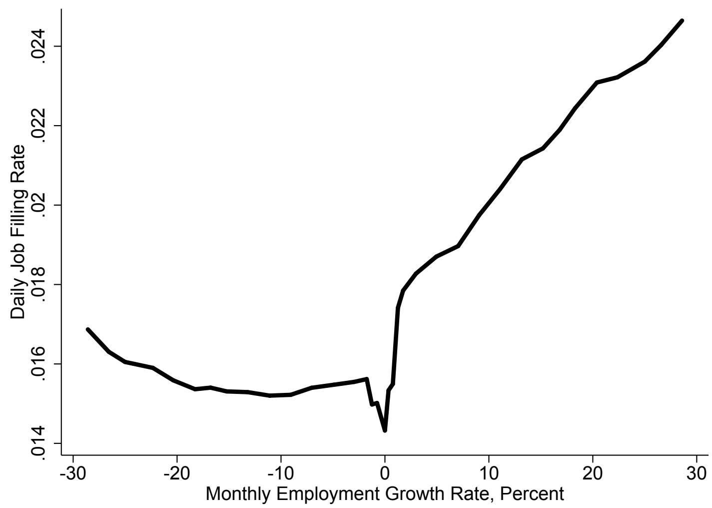


Figure 6: Establishment Growth and Vacancy Filling

5 Vacancy Filling and Firm Growth

One of the major contributions of DFH is the finding that, at the firm level, the stock of vacancies is an insufficient statistic for hiring. Based on JOLTS data they find that 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, gross hires and separations. As argued above, the JOLTS is subject to aggregation bias, leading to under-sampling of vacancies with short durations. Moreover, JOLTS does not collect direct information on the duration of a given vacancy. While DFH compute a daily job filling rate based on gross hires, separations and vacancy postings and correct for biases due to time aggregation, it makes sense to reconsider their findings, as our data sample from the flow and provide a direct measure of job filling. Moreover, it is also interesting to analyze whether the same patterns emerge in a different labor market setting, such as in Austria.

We calculate the monthly employment 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 207 growth rate bins, allowing for mass points at -2 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. As DFH, we smooth the results using a centered five-bin moving average.

The result of this exercise can be seen in Figure 6.[19] We find that same hockey-stick type pattern as for DFH's model implied vacancy filling rate: a strong positive relationship between vacancy filling and employment growth for growing firms and a constant filling rate for shrinking firms. Quantitatively, the patterns are not as strong as in DFH who find that the daily job filling rate increases fivefold from 0.05 for shrinking firms to around 0.25 for firms growing 30%, whereas in our data the vacancy filling rate nearly doubles from 0.014 to somewhat above 0.024. This conclusion is confirmed when we compute the elasticity of job filling rates to gross hires, as shown in Appendix Figure A10. We find a robust positive relationship, which indicates that firms that hire more workers not only post more vacancies but also fill a given vacancy faster. The elasticity of the daily filling rate to the hires rate is substantially smaller in our data, with a value of 0.18 compared to the elasticity of 0.82 in DFH. It is not clear whether the discrepancy in the magnitude is due to differences in the measurement of the job filling rate or differences in the labor market setting between the U.S. and Austria. Unfortunately, we cannot compute DFH's model implied filling rate and distinguish between these two hypotheses, because DFH's method requires the entire stock of vacancies for a given firm whereas in the AMS data we only observe a subset of vacancies posted on the AMS website and thus we cannot distinguish the two potential sources of the discrepancy in the magnitude of the elasticity.[20] In any event, we believe a direct measure of vacancy filling as in the AMS data is preferable. Note that the fact that we only observe AMS vacancies, shouldn't bias the elasticity, as long as the filling and hiring patterns are the same for AMS vacancies as for other job openings. Although we cannot check empirically, there is no apriori reason to believe that the relationship between vacancy filling and hiring is different for AMS vacancies and vacancies posted elsewhere.

In summary, the evidence here confirms the view that vacancy postings are not a sufficient statistic for hiring at the firm level and that firms that grow quickly use other recruiting channels to attract workers.[21] Appendix Table A4 also shows patterns of hiring and vacancy posting in the Austrian data similar to those presented by DFH for the US. While AMS vacancy rates tend to be smaller and AMS vacancy yields larger when compared to those from JOLTS in DFH, this is not surprising as JOLTS measures all vacancies at surveyed establishments whereas the AMS vacancy database only covers vacancies posted at the AMS. This is also the reason why in our analysis below we focus on outcomes at the vacancy level such as vacancy duration rather than outcomes at the establishment level such as vacancy yields.

[19] Appendix Figure A8 shows the same pattern for the sample of immediately available vacancies.

[20] In the Appendix, we also show the vacancy yield has the same hockey-stick patterns as in DFH, see Appendix Figure A7. Again, because we don't observe all vacancies at given firm, we prefer to focus here directly on the object of interest, which is the rate of vacancy filling.

[21] Appendix Figure A9 provides evidence that there is no relationship between vacancy lapses and firm growth.

Table 3: Additional Statistics on Hires and Vacancies

	AMS		DFH (2013)
	All Vacancies	Immediately Available	
Employment at establishments with no hires in t	38.1	38.1	34.8
Employment at establishments with no vacancies at end of t-1	75.3	80.3	45.1
Hires in t at establishments with no vacancies at end of t-1	65.8	73.3	41.6
Vacancies at end of t at establishments with no vacancies at end of t-1	18.2	21.6	17.9

Notes: Immediately available and all vacancies between 1997–2014 for the firm subsample. Hiring in period t means hired between period $t-1$ and period t. Firmsize is calculated as the sum of all individuals with qualification 10 or 14 within the same firm identifier. If we record a vacancy but no firmsize or hiring, we change the relevant value from missing to zero.

Finally, in Table 3 we look at further vacancy and hiring indicators. We find that establishments with no hires at the monthly frequency account for 38% of employment, which compares to 35% in DFH. We also find that 75% of employment is in establishments with no AMS vacancy posted during the previous month; and 66% of employment in establishments that hire in the current month but did not post an AMS vacancy in the previous month. The corresponding numbers in DFH are 45% and 42%, respectively. Note that higher numbers are to be expected in the Austrian data, as AMS vacancies make up only 60 percent of all posted vacancies. Finally, we find a high degree of persistence in the establishment-level incidence of AMS vacancies: only 18% of vacancies are posted in establishments with no vacancy in the previous month, the same magnitude as in DFH.

In the Appendix Table A3, we present further evidence showing that hiring and separations rates are of a similar order of magnitude in the ASSD as in JOLTS. The fact that labor turnover among Austrian firms is at least as high as in the US has been pointed out in Stiglbauer et al. 2003. Similar to DFH, we find that vacancy rates and vacancy yields vary substantially across industries (see Table A4 in the Appendix). While we find remarkably similar vacancy patterns, AMS vacancy patterns differ from JOLTS with respect to employer size: DFH report that vacancy rates increase (and vacancy yields decrease) with employer size, the opposite is true in the Austrian data. The most likely reason is that larger firms are more likely to post their vacancies on platforms other than the AMS.

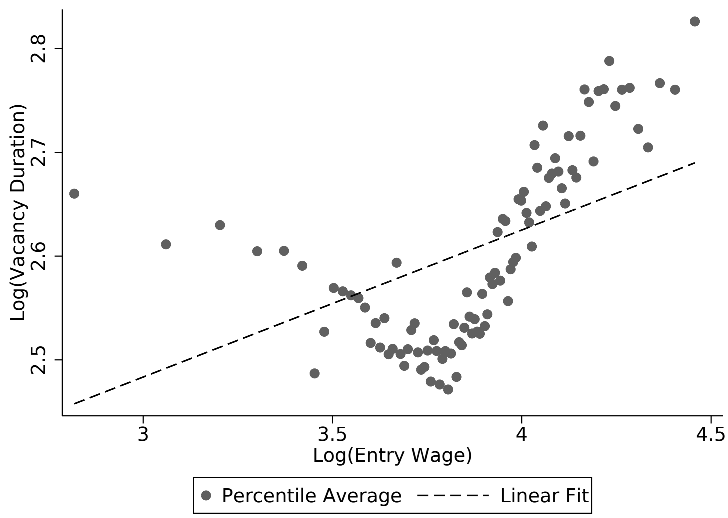


Figure 7: Log Daily Entry Wage and Log Vacancy Duration

Notes: Each data point corresponds to the average within a given wage percentile of the sample. The sample is trimmed for wage values below the first and above the 99th percentile.

6 Vacancy Durations and Entry Wages

A central assumption in many search-theoretic models of the labor market is that firms post wages or commit to a wage offer, and that the promised wage affects the likelihood of filling a job opening. This is true both in models of directed search such as Moen (1997), where a higher posted wage increases the number of workers applying to the job, or in models of random search such as Burdett and Mortensen (1998), where a higher posted wage increases the likelihood for a given worker to accept the job offer.

Evidence on the relationship between vacancy filling and entry wages is scarce, with the exception of Faberman and Menzio (2018) who use data from the Earnings and Opportunities Pilot Project (EOPP) in the U.S. for the years 1980 and 1982. In stark contrast with the above canonical search models, they document a positive relationship between vacancy durations and entry wages, even after controlling for firm- and worker characteristics. Faberman and Menzio interpret their evidence cautiously, arguing that is not necessarily in contradiction with search theory because their controls may be insufficient to account for all the relevant heterogeneity that bears on the relationship between starting wages and vacancy duration.

With the matched vacancy-employer-employee data we can go one step further. Since we can link the posted vacancy to the earnings history of the worker filling the vacancy, we can look in more detail on the relationship between the vacancy durations and entry wages of eventually filled vacancies.

We start our empirical analysis in Figure 7 by plotting the raw averages of log vacancy durations for each percentile bin of the distribution of entry wages. As evident from the figure, the relationship between entry wages and vacancy duration appears to be non-linear. There is a negative slope in the lowest percentiles of the entry-wage distribution, but a strongly positive relationship at medium and high percentiles of the entry wage distribution. While the linear regression line clearly does not provide a good fit to the data, it is drawn for comparison purposes with the paper of Faberman and Menzio (2018) whose sample of around 1,500 job openings was too small to assess non-linearities in the relationship between entry wages and vacancy duration.

Table 4 further analyzes the relationship between vacancy durations and entry wages. Column 1 documents an overall positive relationship between vacancy durations and entry wages when controlling for time fixed effects. In Column 2 we include indicators for early posting (dummies for 0-7 days, 8-30 days, 31-60 days, and more than 60 days). The inclusion of early-posting dummies addresses the concern that firms trying to fill their vacancies quickly may be posting early. The results show that this concern is not of first-order relevance. Posting ahead of time of the date of job availability does not seem to confound the duration/entry-wage relationship. In Column 3 we include further control variables for the required education level of the job, and the gender, age, age squared and the year of labor market entry of the person matched to the job. The conditional correlation becomes much smaller in magnitude and is no longer significant, suggesting that observed characteristics are important correlates for vacancy durations.

Column 4 is our preferred specification. In this column, we additionally control for region-, industry- and 6-digit-occupation-fixed effects. The conditional correlation suggests an elasticity of vacancy durations with respect to the entry wage of -0.035. Note that the negative sign is in line with the qualitative prediction of wage-posting models. The fact that the sign on the wage changes when including a fine grid of industry and occupation dummies (i.e. when moving from Column 1 to Column 4 in Table 4) suggests that heterogeneity at the worker- and match level is an important confounder of the relationship between vacancy durations and entry wages. These results also echo the results in Marinescu and Wolthoff (2016), who find that the relationship between applications and posted wages has the expected (positive) sign only when including job title fixed effects in the regression.[22] Overall, however, the relation remains economically small, with a 1% increase in the entry wage being associated with a 0.03% decrease in the duration of a vacancy.

In Column 5, we show that the relation is robust to the inclusion of further worker- and firm covariates, which are available only for a subsample of firms in our sample. It turns out

[22]To be precise, in their results the sign only changes when they include job title fixed effects but not when they just include 6-digit SOC codes.

that vacancies with longer durations are associated with longer subsequent job durations though not with higher wage growth on the filled job. Moreover, including these variables in the regression does not alter significantly the coefficient of the entry wage. This alleviates concerns that the coefficient of the entry wage is biased due to a possible negative correlation with wage growth on the job. This latter robustness check is important, because theories of posted wages ultimately apply to wages over the entire duration of the job and not just the entry wage. We also find that younger firms are filling vacancies more quickly, but there is no clear relation between firm size and vacancy durations. The final Column 6 shows results for a subsample of workers with at least two unemployment spells. This allows to include individual fixed effects in the regression model to control for any time-invariant observed and unobserved worker heterogeneity. The regression coefficient on the entry wage is remarkably similar to the one in Column 4. Based on the evidence of Table 1 we conclude that there exists a robust, negative, and significant association between vacancy durations and entry wages, but the economic significance of the relationship is small.

As discussed in section 4.2 above, the richness to the vacancy leads to alternative definitions of a vacancy. The measurement concept underlying the results of Table 4 is *AMS duration.* Results in Appendix Tables A5 and A6 show that the relationship between vacancy durations and entry wages relationship is robust and very similar results emerge when we measure the dependent variable as *JOLTS duration* or *Posting duration*.[23]

As demonstrated by the results in Table 4, worker- and job-specific heterogeneity as captured by occupation dummies and individual worker fixed-effects are an important confounder of the relationship between vacancy durations and entry wages. Since our vacancy-employer-employee data let us observe the earnings histories of those workers who are matched to a given vacancy for many years before and after the match, we can go one step further. We decompose the starting wage into worker- and firm effects using the framework of Abowd, Kramarz and Margolis (1999) (AKM) and then relate each component of the wage to vacancy durations. More precisely, we build a yearly panel of daily wages (always looking at the job held on June 30) of the universe of workers and firms observed in the Austrian matched employer-employee data (ASSD) and estimate the model

$$\log w_{it} = \theta_i + \psi_{\mathbf{J}(i,t)} + x_{it}'\rho + d + \varepsilon_{ijt}, \tag{1}$$

[23]In addition, Table A7 in the Appendix shows that the results are not affected when we use weights that adjust for selection of our baseline sample relative to the full sample of vacancies posted at the AMS based on educational requirements of the job, industry and region for each year in the sample period (see the table notes for futher details). Furthermore, Table A8 shows that the results are robust to (1) trimming the sample below the 1st and above 99th percentile of the distribution of starting wages, (2) trimming the sample below the 5th and above 95th percentile of the distribution of starting wages, (3) restricting the sample to men or (4) to ages 25-54.

Table 4: Linear Regressions with Log Vacancy Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.157	0.157	0.017	-0.034	-0.029	-0.041
	(0.012)***	(0.012)***	(0.012)	(0.008)***	(0.010)***	(0.019)**
On-job wage growth					-0.023	
					(0.033)	
Log job duration					0.023	
					(0.002)***	
Lagged firm growth					-0.054	
					(0.007)***	
Firm age					-0.002	
					(0.000)***	
Log firm size					0.009	
					(0.005)*	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	290822	290822	281097	281097	176158	126854
R^2	0.011	0.012	0.043	0.112	0.120	0.568

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level, except for column 5 where clustered standard errors did not converge due to the presence of many dummy variables. Early posting fixed effects are dummies for posting the vacancy 0-7 days, 8-30 days, 31-60 days, and more than 60 days prior to the desired start date. Controls include gender, age, age squared, and dummies for the minimum educational requirement of the job as well as year of labor market entry.

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), year dummies d_t and ε_{ijt} denotes the residual. Since the model is computationally very demanding, we use the years 1985 to 2014 of the ASSD data to estimate (1).[24] We then relate the components of the entry

[24]The basic assumption of the AKM framework is additive separability between firm and worker effects. To assess how well this describes the data, we computed the average residual ε_{ijt} 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 A11 in the Appendix for details.

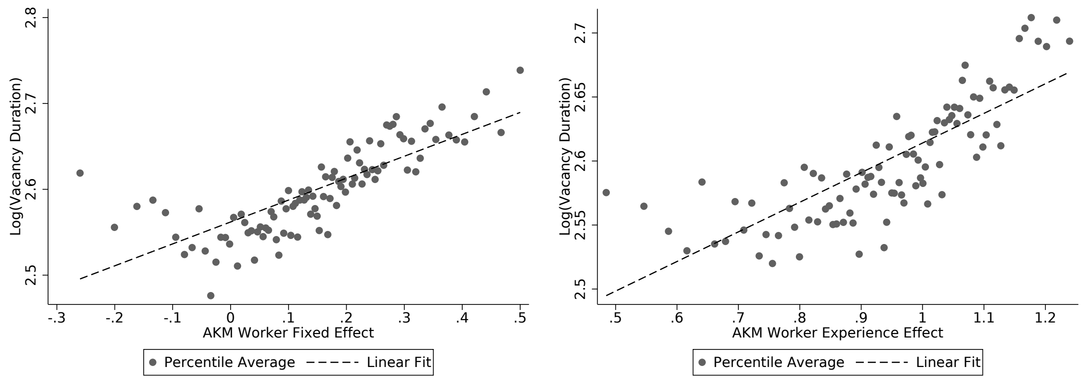


Figure 8: AKM Worker Effects and Log Vacancy Duration

Notes: The figures show partial correlations of AKM worker effects and log vacancy duration, i.e. controlling for the AKM establishment effects, the AKM residuals and the AKM person experience effect (left) resp. the AKM person experience effect (right). Each data point corresponds to the average within a given percentile of the AKM worker effect in the sample. The sample is trimmed for wage values below the first and above the 99th percentile.

wage to vacancy duration by estimating

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

where d_{ijk} denotes the vacancy duration of vacancy k posted by firm j and eventually matched to worker i. $\hat{\psi}_j$, $\hat{\theta}_i$, $x'_{it}\hat{\rho}$ and $\hat{\varepsilon}_{ijk}$ denote the estimated coefficients from equation (1) and z_{ijk} is a vector of additional characteristics of the firm-worker pair. Note that $x'_{it}\hat{\rho}$ is a pure worker experience effect as tenure is zero by definition for entry wages.

Figures 8-10 present partial correlation graphs of vacancy durations and the various wage components. The points in the graph correspond to the percentile bins of the distribution of wage components, which are drawn against the average (log) vacancy durations associated with the respective bin. Figure 8 draws the vacancy durations, respectively, against the AKM person (pre-experience) effect (left panel), and the AKM experience effect (right panel). Both graphs reveal a clear positive relationship suggesting that both dimension of worker heterogeneity are strongly associated with longer vacancy durations which, in terms of magnitude, seem equally relevant. Figure 9 plots vacancy durations against the AKM establishment effect and reveals a clear negative relationship. Taken together, Figures 8 and 9 reveal a clear picture: Vacancies posted by high-wage firms last shorter, vacancies filled by high-wage workers last longer. In Figure 10, we plot the percentile bins of the residual wage distribution against vacancy durations. The conditional correlation is less clear. This is reassuring as we would have expected that there are many unobserved wage determinants (not attributable to permanent worker- or establishment-differences) corre-

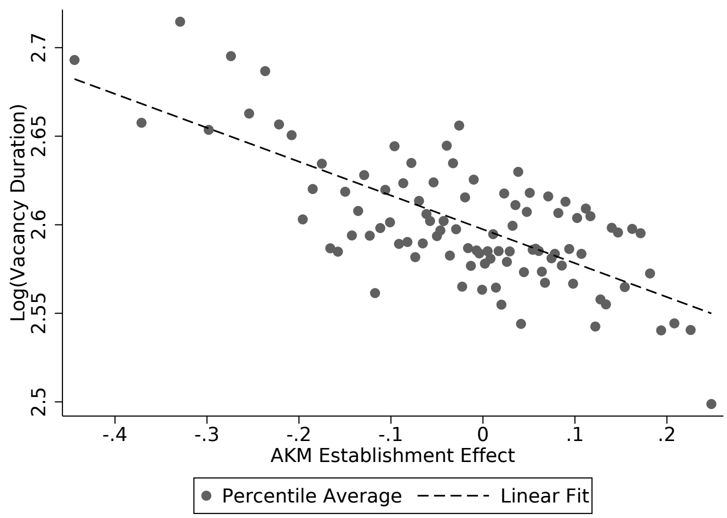


Figure 9: AKM Establishment Effect and Log Vacancy Duration

Notes: The figure shows partial correlations of AKM establishment effects and log vacancy duration, i.e. controlling for AKM worker effects and the AKM residual. Each data point corresponds to the average within a given percentile of the AKM establishment effects in the sample. The sample is trimmed for wage values below the first and above the 99th percentile.

lating with vacancy durations in both directions, thus yielding a less clear-cut association. In addition, the AKM person and AKM establishment effects are measured with error and thus these person- and firm-level measurement errors also go into the residual.

We proceed by presenting regression results that include the components of the AKM decomposition (2) instead of the log entry wage as regressors (Table 5). The interesting benchmark for comparison is the naive regression of log vacancy duration on the starting wage in Column 1 of Table 4. Column 2 shows the results corresponding to the figures 8-10. In particular, the regression reveals the most notable result visible from Figure 9: high-wage firms manage to fill their vacancies more quickly.[25] The elasticity of the vacancy duration with respect to the firm (log-)wage component is -0.172 and highly statistically significant. Size and significance of this effect turn out very robust and do not change when we add control variables (Column 3), region-, industry- and occupation-fixed effects (Column 4), when we look at the subsample where controls for the subsequently formed match and other firm-level controls can be observed (Column 5), and when we confine the sample by workers who are repeatedly observed filling a vacancy so that individual fixed effects can

[25]Note that the coefficients on the AKM effects in Column 2 do not have to add up to the coefficient on the entry wage in column 1. E.g., consider the case where the variance of one of the components is tiny but its effect on vacancy duration is large, then the regression coefficient on the log entry wage in column 1 will do little to reflect the effect of the component with the small variance, whereas the regression in column 2 will because it breaks out all components of the entry wage.

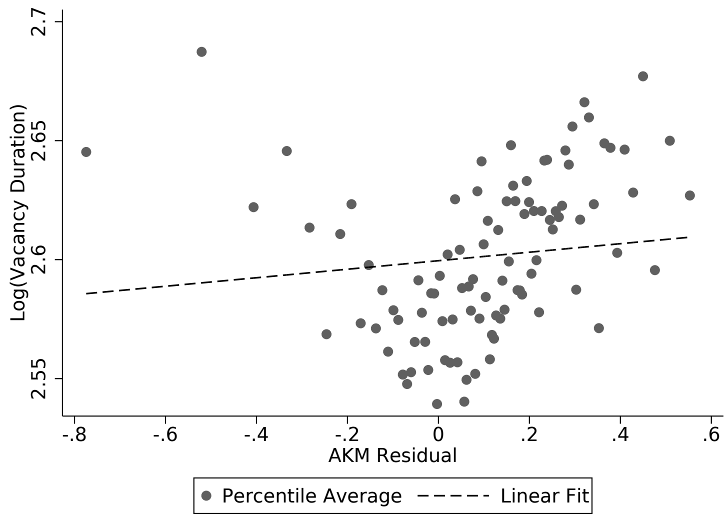


Figure 10: AKM Residual and Log Vacancy Duration

Notes: The figure shows partial correlations of AKM residuals and log vacancy duration, i.e. controlling for AKM worker and establishment effects. Each data point corresponds to the average within a given percentile of the AKM residual in the sample. The sample is trimmed for wage values below the first and above the 99th percentile.

be included instead of the worker's AKM wage component (Column 6).[26] Qualitatively, this result appears consistent with a model in which some firms post higher wages to attract more workers and fill vacancies more quickly. In the next section, we confirm this conjecture evaluating a dynamic model of wage posting and directed search. We also confront the model's quantitative predictions with the results in Table 5. As discussed in detail in the next section, the estimated effect in our data is at least one order of magnitude smaller than the prediction of our wage-posting model.

Table 5 also reports the estimates of the remaining wage components on vacancy durations. Both the AKM worker and the AKM experience components are positively associated with vacancy durations. This suggests that, in the raw data, worker heterogeneity is the dominant force behind the overall positive relationship of vacancy durations and entry wages. If we interpret these AKM worker effects as proxy for innate and accumulated human capital, these patterns may be either the result of longer decision lags in the hiring process of high-skilled workers or due to more competition among firms the high-skill segments of the labor market (i.e., a tighter labor market). The fact that unemployment durations tend to be shorter for higher-skilled workers lends support for the latter view, though it does not preclude the presence of both mechanisms. Introducing controls in Column 2

[26]We do not control for region-, industry- and occupation-fixed effects in this specification due to possible multicollinearity introduced by the presence of a large set of dummy variables.

Table 5: Linear Regressions with Log Vacancy Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.157					
	(0.012)***					
AKM establishment effect		-0.172	-0.194	-0.209	-0.236	-0.280
		(0.036)***	(0.038)***	(0.025)***	(0.021)***	(0.042)***
AKM worker fixed effect		0.512	0.248	0.063	0.047	
		(0.018)***	(0.018)***	(0.015)***	(0.018)***	
AKM worker exp. effect		0.392	0.274	0.046	0.018	0.100
		(0.015)***	(0.018)***	(0.015)***	(0.018)	(0.089)
AKM residual		0.113	0.008	-0.030	-0.014	-0.014
		(0.012)***	(0.011)	(0.008)***	(0.010)	(0.019)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Further Controls	No	No	No	No	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	290822	278606	271198	271198	171426	123824
R^2	0.011	0.018	0.046	0.113	0.121	0.571

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. Early posting fixed effects are dummies for posting the vacancy 0-7 days, 8-30 days, 31-60 days, and more than 60 days prior to the desired start date. Controls include gender, age, age squared, and dummies for the minimum educational requirement of the job as well as year of labor market entry. Additional controls include on-job wage growth, log(job duration), lagged firm employment growth, firm age and log(firm size).

reduces the size of both the estimated coefficients by up to 50%, but a robust, significantly positive association remains. The size of the coefficients further decline when we introduce 6-digit occupation dummies (Column 4), suggesting that occupation dummies and AKM worker effects are substitutes.[27] All regressions in Columns 2-6 include the AKM residual that captures unobserved earnings-determinants not attributable to permanent worker- or firm-differences. The correlation of these factors with vacancy durations is positive in Columns 2 and 3, but turns negative once 6-digit occupation effects are included, which mirrors the results in Table 4. The main takeaway of Table 5 is quite clear: vacancies that are eventually filled by high-wage workers last longer; vacancies that are posted by high-wage firms last shorter.

The results in Table 5 are based on the *AMS duration* concept. In Table 6, we repeat the analysis above for the two alternative definitions of vacancy duration. Column 1 repeats the results from our preferred specification (Column 4 in Table 5). In Columns 2 and 3, we use as a dependent variable the duration of a vacancy according as measured by the *JOLTS duration* and *Posting duration* concepts, respectively. Using these alternative vacancy duration measures does not change the results of Table 5. While the estimated correlations are somewhat smaller, the overall picture remains: shorter durations of vacancies posted by high-wage firms; longer durations of vacancies filled by high-wage workers.[28] The fact that the elasticities are somewhat smaller is mainly due to the fact that the average duration for these alternative measure is somewhat longer. Furthermore, the Table 6 shows results for alternative specifications, where in Column 4 we use *AMS duration* as a dependent variable and in Column 5 we use a dummy variable for whether *AMS duration* was positive (times 100). Both of these specifications confirm a strongly negative relationship between vacancy durations and the AKM establishment effect. The results on the AKM worker effect are not as robust, though this specification controls for a lot of worker-level controls. In separate results not shown here, the AKM worker effect was strongly positively associated with vacancy duration when not using the controls shown in the table here.

In the Appendix Table A13, we provide further evidence on the relationship between vacancy durations and entry wages. A potential concern is that assumptions underlying the AKM decomposition are too restrictive. For instance, they could be biased due to endogenous mobility. Postel-Vinay and Robin (2002) argue that the estimated person effects might be driven by the sequential sampling of alternative (high) wages leading to persistent differences between otherwise identical individuals. We address this concern by looking

[27]Column 4 also adds industry and region fixed effects, but in results available on request we confirmed that the drop in the coefficients is mainly due to the inclusion of the occupation dummies.

[28]In the Appendix, we provide the full set of results using the the time-since-posting measure (Table A10) and the JOLTS vacancy concept (Table A9) .

Table 6: Results for Alternative Specifications and Vacancy Concepts

	(1) Baseline	(2) JOLTS	(3) Posting	(4) Linear	(5) Extensive
AKM establishment effect	-0.209	-0.112	-0.118	-4.376	-4.444
	(0.025)***	(0.019)***	(0.019)***	(0.837)***	(0.758)***
AKM worker fixed effect	0.063	0.062	0.059	0.146	-2.629
	(0.015)***	(0.011)***	(0.011)***	(0.384)	(0.466)***
AKM worker exp. effect	0.046	0.038	0.031	-0.214	-1.896
	(0.015)***	(0.011)***	(0.011)***	(0.408)	(0.478)***
AKM residual	-0.030	-0.016	-0.015	-0.866	-1.031
	(0.008)***	(0.007)**	(0.006)**	(0.233)***	(0.257)***
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE (6 digits)	Yes	Yes	Yes	Yes	Yes
Observations	271198	326842	330781	406351	406351
R^2	0.113	0.210	0.333	0.101	0.126

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. The results in Column (1) are the same as the results in Column 4 of Table 5, whereas the other columns report results with different dependent variables: Column (2) uses the log of JOLTS duration; Column (3) uses the log of duration since posting as dependent variable; Column (4) uses vacancy duration, measured in days, in linear form as dependent variable instead of log vacancy duration; Column (5) uses a dummy for whether the vacancy duration was positive times 100 as dependent variable. See footnote of Table 5 for further details regarding the control variables.

only at job changes associated 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 and firm type and not on the employment history. Nevertheless, estimating our preferred specification on this sample in Column 4 of Table 5 reveals that the conclusions are unchanged.[29]

An alternative robustness check in Table A13 is based on the subsample of observations where we can rely on at least 10 observations per worker and 10 observations per firm in the earnings regression retrieving AKM worker and AKM establishment effects. This yields slightly stronger association on AKM worker fixed- and experience-effects, but almost no change in the association of vacancy durations and AKM establishment effects. Excluding outliers (trimming at 1/99 or 5/95 percentiles of the entry wage distribution) yields very

[29]Re-estimating the worker and firm effects restricting our panel to job changes interrupted by registered unemployment spells implies that, for every firm and worker, we lose a large number of observations leading to less precise estimates. In addition, we cannot identify either the firm or worker effect for some vacancies.

similar results, except that the effect of the AKM residual is somewhat stronger (more negative). Furthermore, we restrict the sample to men or to prime-age workers (aged 25-54). The idea is to check whether the results in a sample with strongly attached workers look different from the results in the baseline sample. These robustness checks yield estimates of the association between vacancy durations and AKM wage components that are in line with the above patterns, both qualitatively and quantitatively. Finally, we reports results where we split the sample by establishment size. We find that the coefficient on the AKM establishment coefficient is very similar for both small and large establishments. This is reassuring given that large establishments are somewhat under-represented in our sample, and it suggests that our main results would not change if we had more large establishments in our sample.[30] Overall, our robustness checks confirm that the estimates presented in Table 5 are stable.

We conclude that our vacancy-employer-employee data reveal a clear-cut and robust relationship between vacancy durations and entry wages: vacancies posted by high-wage firms last shorter; vacancies filled by high-wage workers last longer; and there is a small negative relationship with the AKM wage residual conditional on occupation effects. These results points to the importance of both firm- and worker-heterogeneity to explain observed vacancy durations. In the next section we set up a theoretical framework that, in our view, is a natural starting point to rationalize the above findings.

7 Theoretical Framework

In this section, we evaluate our evidence through the lens of directed search theory. The model of Kaas and Kircher (2015) is a natural starting point, as it characterizes directed search in the context of firm heterogeneity in productivity and was calibrated explicitly to match the facts documented in DFH (2013). In the Kaas and Kircher model, posted wages act as a recruitment device: firms that want to grow fast post higher wages to reduce the time it takes to fill a vacancy. As demonstrated in Kaas and Kircher (2015), the model has important implications for the evolution aggregate matching efficiency over the business cycle.[31]

[30] Furthermore, results do not change much in weighted regression (Table A11), with weights that adjust for selection of our baseline sample relative to the full sample of vacancies posted at the AMS based on educational requirements of the job, industry, region for each year in the sample period (see the table notes for futher details).

[31] In principle, one could also consider a version of the model of Burdett and Mortensen (1998), but we are not aware of any version of this model that was set up and calibrated towards the facts in DFH. In addition, the Burdett and Mortensen model generates a negative relationship of vacancy durations and wages only due to the presence of on-the-job search, where employed workers on different rungs of the job ladder have

The goal of the exercise here is to re-calibrate the model to match the features of the Austrian labor market, including the DFH-type evidence documented in section 5. We then use the model to evaluate whether the model can match three key observations of the previous section: (1) the positive association of vacancy durations with raw (unconditional) starting wages, (2) the positive association of vacancy durations with AKM worker effects, and most importantly, (3) the negative association of vacancy durations with AKM establishment effects.

7.1 Kaas and Kircher (2015) with Ex-Ante Worker Heterogeneity

We extend the model of Kaas and Kircher to the case of ex-ante worker heterogeneity.[32] We follow Kaas and Kircher as closely as possible and concentrate here on the features that are specific to the model with ex-ante worker heterogeneity.

In the model, there is a continuum of firms, which produce $F(y, x, L_1, L_2, ..., L_N, y, x)$ units of output with $L_1 \geq 0$, $L_2 \geq 0$, ..., $L_N \geq 0$ labor inputs. x is fixed firm-level productivity and y is a firm-level productivity shock. New firms pay a setup cost K, draw a fixed firm type x with probability $\pi(x)$ and die at exogenous rate $\delta_0(x)$, which potentially differs across firm types.[33] Firms are hit with a firm-level productivity shock y with probability π_y and which is drawn uniformly at random from the interval $[1 - \bar{y}, 1 + \bar{y}]$. Firms search for new employees by posting V_i vacancies for workers of type i, paying a fixed wage w_i, and paying recruitment costs $C(V_1, V_2, ..., V_N, L_1, L_2, ..., L_N, y, x)$. The posted wage determines the number of workers applying to the opening, λ_i, and thus determines the vacancy filling rate m_i. There are N different types of workers and there is a continuum of workers for each worker type. Workers direct their search to a particular firm-vacancy sub-market j and quit their job at exogenous rate s_0, which we assume to be the same across worker types. The quit rate is the lower bound on the total separation rate $s_i \in [s_0, 1]$ for a given worker type, as firms hit by negative productivity shocks may decide to layoff some or all of their workers of a given type. In equilibrium, workers are indifferent between the different sub-markets. Workers supply a unit of labor when employed, and receive b_i when unemployed. There is no on-the-job search.

As Kaas and Kircher, we solve in our numerical simulations the social planner version of the problem with flat-wage contracts.[34] In equilibrium, wages vary both across worker and

different acceptance probabilities of outside offers, whereas in our data we only observe the matching process of unemployed workers.

[32]The model of Kaas and Kircher also features aggregate shocks, which we abstract from here.

[33]Kaas and Kircher assume this mainly to match the establishment dynamics in the data.

[34]See their paper and our model appendix for further details.

firm types. Even though there is no bargaining, wages vary across worker types because workers don't search in submarkets that deliver less than the value of unemployment and thus, the unemployment benefit b_i is a critical determinant of the posted wage. Posted wages also depend on fixed and transitory firm productivity, x and y, and the size of its labor force for each type of worker, $L_1, L_2, ..., L_N$. Newly-born firms tend to post more vacancies and at higher wages because they want to grow quickly toward their optimal size. The relationship between firm productivity and posted wages is less clear and depends on assumptions about the shape of the vacancy posting cost function. All else equal, firms that face a higher cost of posting a vacancy, post a higher wage in order to fill their vacancies more quickly.

7.2 Calibration

We start by parameterizing the model of Kaas and Kircher (i.e., without worker heterogeneity). We follow them as closely as possible, allowing for 5 different firm types x and 5 different shocks y on the interval $[1 - 0.312, 1 + 0.312]$, but re-calibrate certain parameters to match certain features of the Austrian labor market and vacancy data (see Table B1 in the Appendix for all the parameter values): First, we set the vacancy cost scale parameter c to 0.11 to match a weekly vacancy filling rate of 0.10. Second, we set the parameters k and r of the matching function $m(\lambda) = (1 + k\lambda^{-r})^{-\frac{1}{r}}$ to target a weekly job finding rate of 0.033 and an elasticity of job finding to labor market tightness of 0.72. Finally, we set the entry cost K to 2.4. As discussed in the Appendix of Kaas and Kircher, this is a pure normalization since all firms' value functions are linearly homogeneous in the vector (x, b, c, K).

In the model extension with ex-ante heterogeneous workers, we assume the following functional forms for the production function and vacancy posting costs[35]:

$$F(\boldsymbol{L}, y, x) = yx \sum_{i=1}^{N} \left(a_i(x) L_i^{\alpha} \right), \tag{3}$$

$$C(\boldsymbol{V}, \boldsymbol{L}, y, x) = \sum_{i=1}^{N} \left(\frac{c_i}{1+\gamma} \left(\frac{V_i}{L_i} \right)^{\gamma} V_i \right), \tag{4}$$

which are the same as in Kaas and Kircher (2015), except that we sum over N types of workers and $a_i(x)$ denotes worker-type-specific productivity, which potentially interacts with firm type x. Note that our assumption of additivity of worker types in production and vacancy costs implies that there are no complementarities in production or vacancy posting

[35]See also Eeckhout and Kircher (2018) who provide an extension of the model of Kaas and Kircher (2015) with more general production functions, but linear vacancy posting costs.

Table 7: Calibration of Key Parameters in Model with Ex-Ante Heterogeneous Workers

	Parameters	Kaas & Kircher	Model Extension w/ Worker Heterogeneity	
			(1)	(2)
Worker Productivities:	$a_1(x_1)/a_2(x_1)$	1/1	0.7/1.3	0.9/1.1
	$a_1(x_2)/a_2(x_2)$	1/1	0.7/1.3	0.8/1.2
	$a_1(x_3)/a_2(x_3)$	1/1	0.7/1.3	0.7/1.3
	$a_1(x_4)/a_2(x_4)$	1/1	0.7/1.3	0.6/1.4
	$a_1(x_5)/a_2(x_5)$	1/1	0.7/1.3	0.5/1.5
Vacancy Posting Costs:	c_1	0.11	0.07	0.10
	c_2	0.11	0.08	0.08

between worker types, as the marginal product and the marginal vacancy posting cost for each worker type i is independent of the number of other types of workers employed at the same firm. In the model without worker heterogeneity, the firm productivity levels for each type of firm are directly taken from Kaas and Kircher, but then scaled down by a factor of 0.815 in the case of the model with multiple worker types to target that the average firm size in the economy remains unchanged.

In what follows, we present three calibrations: (i) the baseline model of Kaas and Kircher without ex-ante worker heterogeneity, but calibrated to Austrian data, (ii) a model with worker heterogeneity, where relative worker productivities are independent of firm productivities, and (iii) a model with worker heterogeneity with complementarities between worker skills and firm productivities (generating positive assortative matching as high-skilled workers are relatively more productive at high-productivity firms). Table 7 presents the assumed parameter values on worker productivities and vacancy posting costs in the three calibrations. The two calibrations with ex-ante worker heterogeneity assume (for simplicity) two types of workers and set relative worker productivities to match the dispersion of AKM worker fixed effects in the data with a standard deviation of 0.3. As shown in Table 8 below, the correlation of worker and firm types in calibration (iii) (assortative matching) is 0.51, which is in the range of estimates provided by Borovickova and Shimer (2018) using Austrian data. All our calibrations with ex-ante worker heterogeneity assume that type-2 workers are preferred by all firms and thus we refer to them as the high-skilled type. There is nothing, however, that restricts us to do so; in principle, we could allow for type-2 workers to be less productive than type-1 worker at low productivity firms, which would generate even stronger positive assortative matching.

Note that we assume that $b_i = bE(a_i(x))$, where $b = 0.1$, i.e. the unemployment benefit is proportional to average worker productivity across firms. We calibrate the model such that the replacement rate (b over average wage) is 0.7, as in Kaas and Kircher. In the versions with heterogeneous workers, we calibrate vacancy posting costs c to match a job-filling rate of 0.11 for the worker of type 1 and 0.094 for the worker of type 2, to generate the positive association of AKM-worker fixed effects and vacancy duration. This calibration strategy generates vacancy posting costs that are nearly identical across worker types. In fact, if we were to impose identical costs, the results would be very similar.[36] The key point here is that vacancy posting costs are less than proportional to worker-ability and thus, for workers of type 1, firms post fewer vacancies but at a higher filling rate (by increasing posted wages).

7.3 Results

We start by reporting a few results of the model without ex-ante worker heterogeneity, calibrated to Austrian data. Panel A in Table 8 shows selected model results in the model where the vacancy cost elasticity , γ, varies between 1 and 0.1.[37] As can be seen in the Table, the elasticity of vacancy duration to the starting wage is negative and very large. In other words, the posted wage appears to be a very strong instrument to affect vacancy duration by affecting the length of the queue in a given labor market. The elasticity declines substantially with the parameter γ but remains below -1. At the same time the model with a low value of γ , is inconsistent with the DFH-type of evidence, which shows that the job filling rate is strongly positively correlated with employment growth and hiring at the firm level. This is also illustrated in Figure 11, which shows that a calibration with $\gamma = 0.5$ yields a good fit to the relationship of the firm growth and the weekly vacancy filling rate.

Panels B and C of Table 8 show the results for the model with ex-ante heterogeneous workers. The table includes the AKM regression coefficients, which were estimated on data simulated from the model with 20,000 firms and 400,000 workers over a period of 10 years.[38] The results show that now the relationship between the entry wage and vacancy duration is positive, with a similar coefficient as in the data. Just like in our empirical results, however, this masks the differential effects of the AKM worker and AKM firm effects on vacancy duration: The coefficient on the AKM worker effect is positive and similar to the one in the data. This is not surprising, given that we calibrated the vacancy cost scale parameter c to generate a job filling rate of 0.11 for the low-skilled worker and 0.094 for the high-skilled

[36]See Engbom and Moser (2018) for a similar finding in the context of an extension of the model of Burdett and Mortensen (1998) to ex-ante worker heterogeneity.

[37]The Appendix Table B2 contains the results for various alternative calibrations, including the original calibration in the paper of Kaas and Kircher (2015).

[38]To be precise, we estimated the model for 520 weeks and then used the data from the last week of each year to estimate the AKM worker and firm fixed effects. In analogy to the empirical results, in a second step, we then estimated the linear regressions of log vacancy duration on the starting wage and the AKM effects.

Table 8: Simulation Results of Model of Kaas and Kircher and Model Extension with Ex-Ante Worker Heterogeneity

Panel A.		Kaas and Kircher		
	Data	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 0.1$
Elast. of Vacancy Duration to Starting Wage	0.16	-21.8	-17.9	-3.9
Elast. of Hiring Rate to Job Filling Rate	0.18	0.27	0.14	0.03

Panel B.		Model Extension w/ Worker Heterogeneity w/o PAM		
	Data	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 0.1$
Correlation of Worker and Firm Types	—	0.00	0.01	0.01
Elast. of Vacancy Duration to				
... Starting Wage	0.16	0.22	0.25	0.26
... AKM Firm Fixed Effect	-0.19	-9.9	-7.4	-1.9
... AKM Worker Fixed Effect	0.25	0.23	0.26	0.26
... AKM Residual	0.01	-25.3	-24.7	-8.8
Elast. of Hiring Rate to Job Filling Rate	0.18	0.25	0.14	0.03

Panel C.		Model Extension w/ Worker Heterogeneity w/ PAM		
	Data	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 0.1$
Correlation of Worker and Firm Types	—	0.51	0.51	0.48
Elast. of Vacancy Duration to				
... Starting Wage	0.16	0.21	0.29	0.30
... AKM Firm Fixed Effect	-0.19	-13.5	-7.0	-0.8
... AKM Worker Fixed Effect	0.25	0.09	0.22	0.29
... AKM Residual	0.01	-23.6	-25.0	-3.8
Elast. of Hiring Rate to Job Filling Rate	0.18	0.26	0.15	0.04

Notes: Panel A shows the results of the model without worker heterogeneity, i.e. the model of Kaas and Kircher calibrated to the Austrian data. Panel B shows results for the the calibration (1) and Panel C shows results for the the calibration (2) of the model with worker heterogeneity in Table 7. The model calibration in Panel C features substantial Positive Assortative Matching (PAM), as can be seen in the correlation of worker and firm types in the table. The statistics from the data refer to the coefficients reported in column 1 and 3 of Table 5. The statistics from the model are based on simulated data with 20,000 firms and 400,000 workers over a period of 10 years.

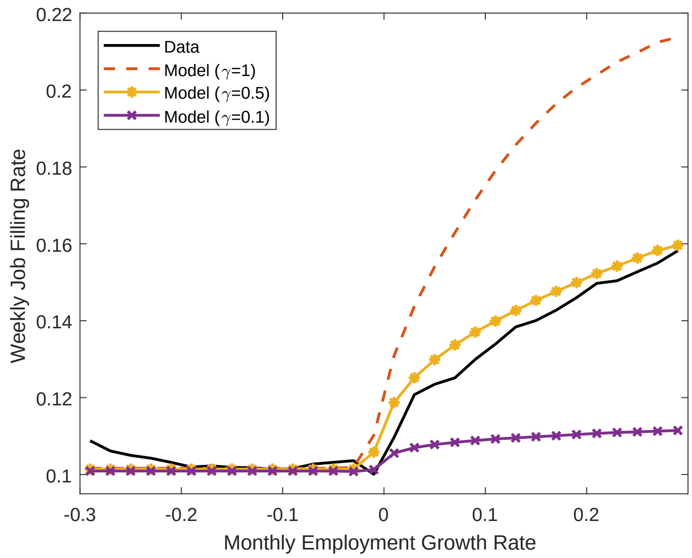


Figure 11: Weekly Job Filling Rates by Employment Growth in Data and Model

worker. Qualitatively, the model matches the sign of the coefficient on the AKM firm effect. However, just like in the baseline model, the magnitude of the coefficient is more than an order of magnitude higher than in the data. Similarly, the coefficient on the AKM residual of the starting wage is very negative in the model but close to 0 in the data. The model version with a lower value for the vacancy cost elasticity parameter γ lowers the elasticity of vacancy duration to the AKM firm effect and the AKM residual, but at $\gamma = 0.1$ the model no longer matches the elasticity of the hiring rate to the job filling rate and the relationship of the job filling rate to the growth rate of the firm (see Figure B1 in the Appendix). The similarity of the results in the model without and with complementarities between high-skilled workers and high-x firms, suggests that our regressions results are not affected by the issues related to AKM that impede the identification of assortative matching.

7.4 Discussion and Further Extensions

Overall, the results so far appear to suggest that firms are not using posted wages as an active recruiting device, at least not in a manner that is quantitatively large enough to explain the sharp increase in vacancy filling rate for growing firms. Rather, the results in DFH (2013) and our replication of their results appear to be driven by other channels of recruiting effort, as in the model of Gavazza, Mongey and Violante (2018). This conclusion, however, rests on important assumptions.

First, our model simulations are based on a version of the model of Kaas and Kircher with flat-wage contracts. Allowing for wage-tenure contracts may break the link between

Table 9: Simulation Results of Model of Kaas and Kircher with Ex-Ante Worker Heterogeneity and Non-Wage Amenities

Elasticity of Vacancy		Model w/o PAM			Model w/ PAM		
Duration to:	Data	$\sigma_\psi = 0$	$\sigma_\psi = 0.1$	$\sigma_\psi = 0.2$	$\sigma_\psi = 0$	$\sigma_\psi = 0.1$	$\sigma_\psi = 0.2$
Starting Wage	0.16	0.25	0.22	0.17	0.29	0.25	0.18
AKM Firm Effect	-0.19	-7.4	-0.55	-0.09	-7.0	-0.61	-0.11
AKM Worker Effect	0.25	0.26	0.24	0.22	0.22	0.27	0.24
AKM Residual	0.01	-24.7	-0.07	0.00	-25.0	-0.06	0.00

Notes: All model simulations are based on model with $\gamma = 0.5$. The correlation of worker and firm types and the elasticity of the hiring rate to the job filling rate are the same as in Panel B (for model without PAM) and Panel C (for model with PAM) of Table 8. The statistics from the data refer to the coefficients reported in column 1 and 3 of Table 5. The statistics from the model are based on simulated data with 20,000 firms and 400,000 workers over a period of 10 years.

starting wages and the value of a job if wage growth is inversely related to the starting wage. It is important to note here, however, that our regressions results in the empirical section are not affected when we control for wage growth on the job and the duration of the job, suggesting that the restriction to flat-wage contracts in our model is reasonable, at least in the present empirical application.

Second, there could be a potential endogeneity issue, in the sense that firms may post higher wages for vacancies they expect to take longer to fill. This type of heterogeneity in vacancy filling rates would lead the coefficient on the AKM firm effect and the AKM residual to be biased towards zero or even a positive number. Yet, if this were the case, firms should respond also on other margins. In particular, firms expecting long vacancy durations should post further in advance of their desired start date. Our empirical results, however, are not strongly affected once we control for the duration between dates of posting and desired job start (which we observed in the data for each single vacancy). In other words, even when we line up vacancies that were posted equally early (= equally long before the desired job start date), the relationship between vacancy posting and starting wages remains similar.

Finally, measurement error in wages or the presence of non-wage amenities could bias the coefficients on the firm effect and the residual toward zero. This is particularly relevant as our model predicts a rather small dispersion in wages for a given worker type. While measurement error is likely to be small in administrative data, non-wage amenities have a potentially similar effect on the estimated relationship between entry wages and vacancy duration. Moreover, recent work by Hall and Mueller (2018) and Sorkin (2018) suggests that non-wage amenities exhibit a large dispersion across both jobs and firms and are crucial to understand features of the data such as the job acceptance behavior of unemployed workers or worker flows across firms. Introducing match-specific heterogeneity into the model leaves the model structure unchanged, but the wage now satisfies $log(w) = log(\hat{w}) + \psi$, where w is the per-period value of the job, $\hat{w}$ is the observed wage and $\psi \sim \mathcal{N}(0, \sigma_\psi^2)$ is a non-wage amenity, which can be interpreted as fixed attributes of the job or the firm (or the job seeker's valuation thereof) that the employer cannot influence when posting the vacancy. We assume that both w and ψ are constant over the duration of the job. Our model gives the total value of the job w and together with the draw of the non-wage amenity ψ, we get a value for the observed wage $\hat{w}$. Hall and Mueller estimate the standard deviation of non-wage values of jobs to be 0.35, but we adopt here a somewhat more conservative approach and consider values of 0.1 and 0.2. Table 9 shows the results of the simulations of the model with non-wage amenities. It turns out that the bias in the estimated elasticity of both the AKM firm effect and the AKM residual is large, even for the case with $\sigma_\psi = 0.1$. The reason is that the dispersion of wages for a given worker type in the model is quite small and thus even a small degree of dispersion in non-wage amenities attenuates the estimated relationship strongly.[39] Interestingly, the elasticity of vacancy duration with respect to the AKM residual is close to zero, whereas the elasticity of vacancy duration to the AKM firm effect remains negative and close to the one in the data. The reason is that the AKM firm effects average out *some* of the match-specific noise introduced by the non-wage amenities. In summary, these results provide a potential resolution of matching both our DFH-type evidence as well as our evidence on vacancy durations and entry wages in the context of a model of directed search. The results also point to the challenges in recovering a negative relationship between vacancy durations and entry wages in the data and provide additional support for our approach of relating vacancy duration not only to the entry wage but also to its firm-level component.

8 Conclusion

In this paper, we study how vacancy durations are related to entry wages of workers filling a position. We exploit data from a new linked data set combining information on (durations and characteristics of) individual vacancies and matched employer-employee data. The resulting vacancy-employer-employee dataset allows us to link vacancy information to the employment dynamics (growth, hirings, separations) of the posting firm as well as to the wages of the workers eventually filling a vacancy. Exploiting the link of the vacancy to the worker allows us to study the association between vacancy durations and entry wages. We find that starting wages and vacancy durations are positively correlated in raw data, but

[39] The reason is that unemployed workers are very willing to trade off a higher wage with a longer unemployment spell and thus, firms only need to post a slightly higher wage to shorten their vacancy spell.

the correlation turns negative when controlling sufficiently for worker-level heterogeneity. Moreover, we find that the negative association is particularly strong with the establishment component of the starting wage. The link of the vacancy to the firm allows us to replicate in the Austrian data the results of Davis, Faberman and Haltiwanger (2013) that growing firms fill their vacancies faster.

To understand the relationship between firm growth, vacancy filling and posted wages, we extend the model of Kaas and Kircher (2015) to allow for ex-ante heterogeneous workers. While the model qualitatively captures our empirical findings, there is a strong tension between matching the sharp increase in vacancy filling for growing firms and the response of vacancy filling to firm-level wages. The implication of this finding is clear: the measured elasticity between establishment-level wages and vacancy durations is an order of magnitude too small to account for substantial variations of matching efficiency across establishments, and thus the evidence points to other mechanisms as the main drivers of aggregate recruiting intensity over the business cycle, as e.g. in the model of Gavazza, Mongey and Violante (2018). We remain cautious, however, in our assessment and believe that the wage posting mechanism may still play a role in explaining some of the variation in recruiting intensity, as a moderate degree of dispersion in non-monetary job amenities considerably alleviates the aforementioned tension in the model of Kaas and Kircher.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–334.

Abraham, Katharine G, "Structural-Frictional vs. Deficient Demand Unemployment: Some New Evidence," *American Economic Review*, 1983, *73* (4), 708–24.

Abraham, Katharine G., "Help-Wanted Advertising, Job Vacancies, and Unemployment," *Brookings Papers on Economic Activity*, 1987, *18* (1), 207–248.

Albrecht, James, Bruno Decreuse, and Susan Vroman, "Directed Search and Phantom Vacancies," *Mimeo*, 2017.

Alvarez, Fernando, Katarina Borovickova, and Robert Shimer, "The Proportional Hazard Model: Estimation and Testing using Price Change and Labor Market Data," *NBER Working Paper No. 22188*, 2016.

AMS, "Geschäftsbericht 2017, Trendwende am Arbeitsmarkt.," 2018.

Andrews, M. J., S. Bradley, D. Stott, and R. Upward, "Successful Employer Search? An Empirical Analysis of Vacancy Duration Using Micro Data," *Economica*, 2008, *75* (299), 455–480.

Banfi, Stefano and Benjamin Villena-Roldan, "Do High-Wage Jobs Attract more Applicants? Directed Search Evidence from the Online Labor Market," Documentos de Trabajo 327, Centro de Economia Aplicada, Universidad de Chile 2016.

Barnichon, Regis, "Building a composite Help-Wanted Index," *Economics Letters*, 2010, *109* (3), 175–178.

Barron, John M, Mark C Berger, and Dan A Black, "Employer Search, Training, and Vacancy Duration," *Economic Inquiry*, 1999, *35* (1), 167–192.

Berman, Eli, "Help Wanted, Job Needed: Estimates of a Matching Function from Employment Service Data," *Journal of Labor Economics*, 1997, *15* (1), S251–92.

Blanchard, Oliver Jean and Peter Diamond, "The Beveridge Curve," *Brookings Papers on Economic Activity*, 1989, *20* (1), 1–76.

Borovickova, Katarina and Robert Shimer, "High Wage Workers Work for High Wage Firms," *Mimeo*, 2018.

Burdett, Kenneth and Dale T. Mortensen, "Wage Differentials, Employer Size,and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.

——— and Elizabeth J Cunningham, "Toward a Theory of Vacancies," *Journal of Labor Economics*, 1998, *16* (3), 445–78.

Card, David, David S. Lee, Zhuan Pei, and Andrea Weber, "Inference on Causal Effects in a Generalized Regression Kink Design," *Econometrica*, 2015, *83* (6), 2453–2483.

———, Fabrizio Colella, and Rafael Lalive, "Does Stated Gender Preference Affect Recruiting?," *Mimeo, University of Lausanne*, 2018.

———, Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

———, Raj Chetty, and Andrea Weber, "Cash-On-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market," *Quarterly Journal of Economics*, 2007, *122* (4), 1511–1560.

Coles, Melvyn G and Eric Smith, "Cross-Section Estimation of the Matching Function: Evidence from England and Wales," *Economica*, 1996, *63* (252), 589–97.

——— and ———, "Marketplaces and Matching," *International Economic Review*, 1998, *39* (1), 239–54.

Davis, Steven J., "The Quality Distribution of Jobs and the Structure of Wages in Search Equilibrium," *NBER Working Paper No. 8434*, 2001.

——— and Brenda Samaniego de la Parra, "Application Flows," *Mimeo*, 2017.

———, Christof Röttger, Anja Warning, and Enzo Weber, "Job Recruitment and Vacancy Durations in Germany," *Regensburger Diskussionsbeiträge zur Wirtschaftswissenschaft No. 481*, 2014.

———, R. Jason Faberman, and John C. Haltiwanger, "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics*, 2013, *128* (2), 581–622.

Dickerson, Andy, "The Distribution and Determinants of Job Vacancies: Evidence From the 2001 Employers Skill Survey," *Royal Economic Society Annual Conference 2003 Paper No. 63*, 2003.

Eeckhout, Jan and Philipp Kircher, "Assortative Matching With Large Firms," *Econometrica*, 2018, *86*, 85–132.

Elsby, Michael W. L., Ryan Michaels, and David Ratner, "The Beveridge Curve: A Survey," *Journal of Economic Literature*, 2015, *53* (3), 571–630.

Engbom, Niklas and Christian Moser, "Earnings Inequality and the Minimum Wage: Evidence from Brazil," *Opportunity and Inclusive Growth Institute Working Paper No. 7*, 2018.

Faberman, R. Jason and Guido Menzio, "Evidence on the Relationship between Recruiting and the Starting Wage," *Labour Economics*, 2018, *50*, 67–79.

Gavazza, Alessandro, Simon Mongey, and Gianluca Violante, "Aggregate Recruiting Intensity," *American Economic Review*, 2018, *108* (8), 2088–2127.

Gorter, Cees, Peter Nijkamp, and Piet Rietveld, "Employers' Recruitment Behaviour and Vacancy Duration: An Empirical Analysis for the Dutch Labour Market," *Applied Economics*, 1996, *28* (11), 1463–1474.

Hall, Robert E. and Andreas I. Mueller, "Wage Dispersion and Search Behavior: The Importance of Non-Wage Job Values," *Journal of Political Economy*, 2018, *126* (4), 1594–1637.

Hershbein, Brad and Lisa B. Kahn, "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings," *American Economic Review*, 2018, *108* (7), 1737–72.

Holzer, Harry J, "Job Vacancy Rates in the Firm: An Empirical Analysis," *Economica*, 1994, *61* (241), 17–36.

Holzer, Harry J., Lawrence F. Katz, and Alan B. Krueger, "Job Queues and Wages," *Quarterly Journal of Economics*, 1991, *106* (3), 739–768.

Kaas, Leo and Philipp Kircher, "Efficient Firm Dynamics in a Frictional Labor Market," *American Economic Review*, 2015, *105* (10), 3030–60.

Kuhn, Peter, "The Internet as a Labor Market Matchmaker," *IZA World of Labor*, May 2014, p. 18.

Lalive, Rafael, Jan van Ours, and Josef Zweimüller, "How Changes in Financial Incentives Affect the Duration of Unemployment," *Review of Economic Studies*, 2006, *73* (4), 1009–1038.

Marinescu, Ioana Elean and Ronald Wolthoff, "Opening the Black Box of the Matching Function: the Power of Words," *Mimeo*, 2016.

Marinescu, Ioana Elena, "The General Equilibrium Impacts of Unemployment Insurance: Evidence from a Large Online Job Board," *Journal of Public Economics*, 2017, *150*, 14–29.

Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance, "Upskilling: Do Employers Demand Greater Skill When Workers are Plentiful?," *Mimeo*, 2017.

Moen, Espen R., "Competitive Search Equilibrium," *Journal of Political Economy*, 1997, *105* (2), 385–411.

Mueller, Andreas I., Damian Osterwalder, and Josef Zweimüller, "The Austrian AMS Vacancy Database," *Mimeo*, 2018.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Riese, Martin and Stefan Bruckbauer, "Die Laufzeit der offenen Stellen in Österreich 1984 - 1986," *in: Bundesministerium für Arbeit und Soziales (Hrsg.), Die Dynamik des Arbeitsmarktes. Forschungsberichte aus Sozial- und Arbeitsmarktpolitik Nr. 19*, 1987, pp. 9–62.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95* (1), 25–49.

Sorkin, Isaac, "Ranking Firms Using Revealed Preference," *Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

Stiglbauer, Alfred, Florian Stahl, Rudolf Winter-Ebmer, and Josef Zweimüller, "Job Creation and Job Destruction in a Regulated Labor Market: The Case of Austria," *Empirica*, 2003, *30*, 127–148.

Sunde, Uwe, "Empirical Matching Functions: Searchers, Vacancies, and (Un-)biased Elasticities," *Economica*, 2007, *74* (295), 537–560.

van Ours, Jan and Geert Ridder, "Cyclical Variation in Vacancy Durations and Vacancy Flows : An Empirical Analysis," *European Economic Review*, 1991, *35* (5), 1143–1155.

____ and ____ , "Vacancies and the Recruitment of New Employees," *Journal of Labor Economics*, 1992, *10* (2), 138–55.

Yashiv, Eran, "The Determinants of Equilibrium Unemployment," *American Economic Review*, 2000, *90* (5), 1297–1322.

Zweimüller, Josef, Rudolf Winter-Ebmer, Rafael Lalive, Andreas Kuhn, Jean-Philippe Wuellrich, Oliver Ruf, and Simon Büchi, "Austrian Social Security Database," *NRN working paper No. 2009-03*, 2009.

Online Appendix

A Summary Statistics and Additional Figures and Tables

A.1 Descriptive Statistics and Figures

Table A1: Size and Structure of the AMS Vacancy Database, 1997-2014 (AMS Universe)

		Vacancies		Establishments
		N	%	N
A. Vacancies by Exit Status				
Total		5,354,139	100	269,157
Filled		4,625,795	86	256,503
	by AMS	1,249,553	27	164,139
	by Others	3,376,242	73	231,404
Lapsed Vacancies		728,344	14	111,705
B. Multiple Vacancies				
Total		5,389,723	100	269,027
Single Vacancies		1,432,928	27	247,585
Multiple Vacancies		3,956,795	73	140,396
	Identical	2,188,548	55	93,981
	Not Identical	1,768,247	45	110,050

Notes: Number of vacancies and number of distinct establishments for the universe of AMS vacancies. Panel A is based on vacancies with an outflow in our sample period 1997m9–2014m2 excluding right-censored spells, i.e. vacancies still in progress in 2014m2. Panel B is based on vacancies with an inflow in our sample period 1997m9–2014m2 excluding left-censored spells, i.e. vacancies that are already in progress in 1997m9. Hence, the difference between the total of outflows in Panel A and the total of inflows in Panel B is the number of censored spells.

One common issue with job board data is that firms post one vacancy but intend to hire multiple workers for that position. Survey data such as the JOLTS have an advantage in this respect, as they collect information on the number of open positions and do not rely on the number of postings. Luckily, the AMS asks firms about the number of open positions and records multiple and possibly identical vacancies as separate entries in the data. It makes this effort because it would like to know many unemployed workers can be matched to the firm. Figure A1 shows (employment-weighted) distribution of the number of vacancies by firm in a typical month, weighted by the employment share of each firm. About 50%

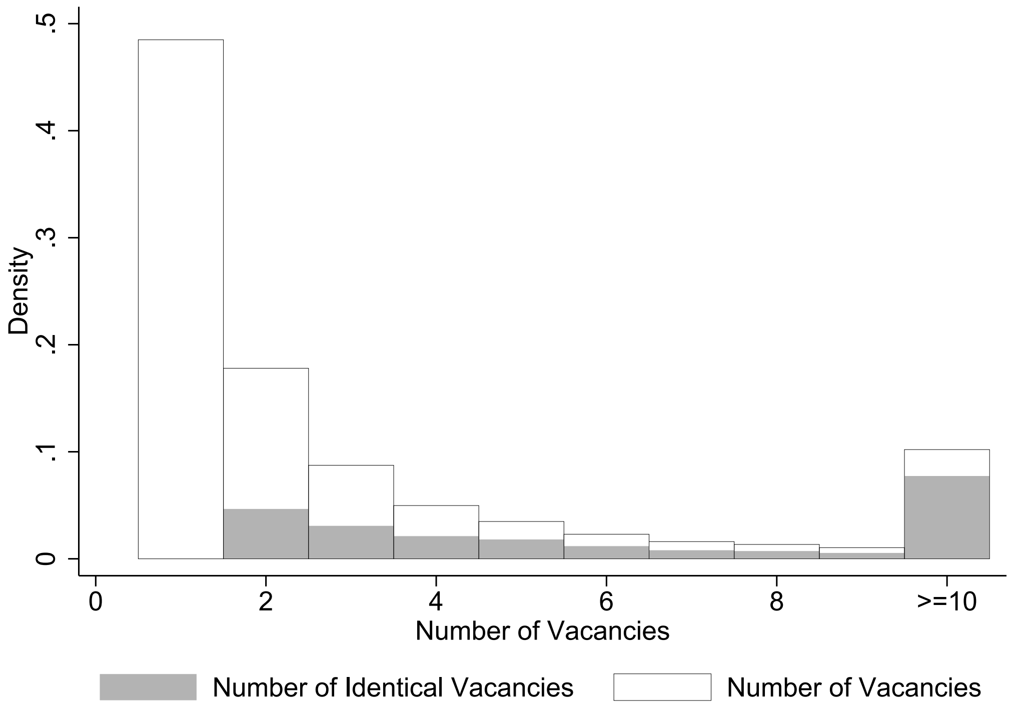
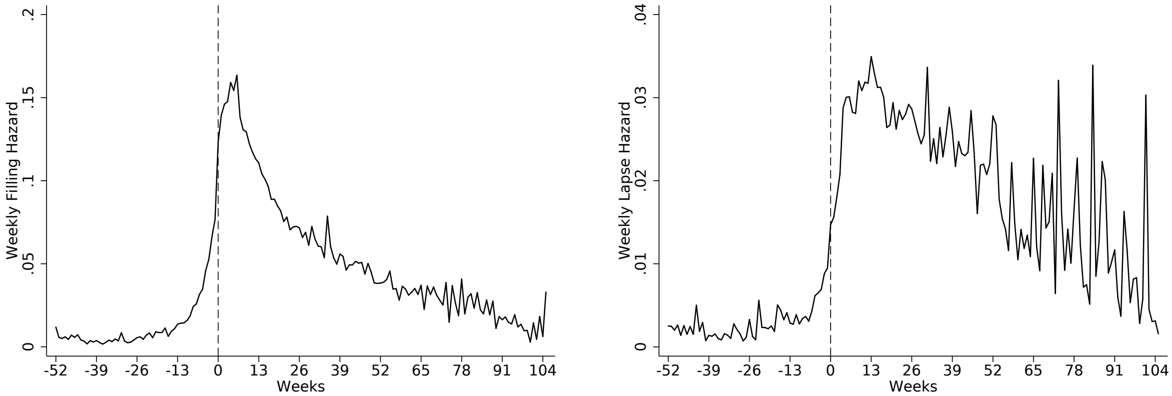


Figure A1: The Distribution of Number of Vacancies, by Firm and Month (Employment Weighted)

of employment is in establishments posting exactly one vacancy, 18% post two vacancies and the remainder of firms posts three or more vacancies.[40] We also find that many of the multiple vacancies are indeed identical: among firms that post at least two vacancies in a given month, 55% of vacancies have a twin-sister vacancy, meaning that all characteristics of the vacancy are identical (but not the vacancy outcomes such as vacancy duration). As can be seen in Figure A1, the share of identical vacancies is particularly high among firms that post 10 vacancies or more in a given month.

[40]We also find that 77% of firms in our firm sample do not have *any* vacancy open in a typical month.



(a) Filling Hazard (weekly)

(b) Lapse Hazard (weekly)

Figure A2: Vacancy Filling Hazard and Vacancy Lapse Hazard, Relative to the Date of Availability of the Job

(a) Posting duration

(b) JOLTS duration

Figure A3: Comparison of Duration Measures Based on Exact (Daily) or Proxied (Monthly) Posting Date

A.2 Vacancy Filling over the Business Cycle

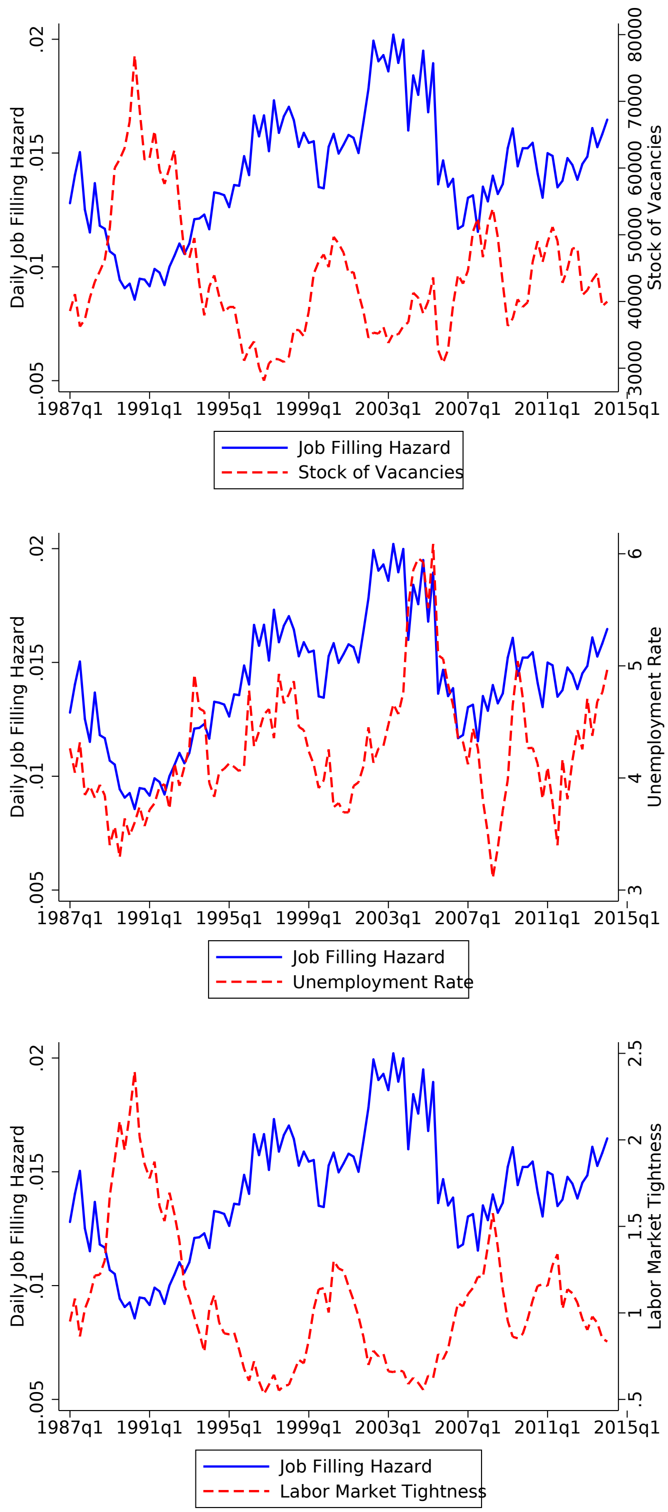


Figure A4: The Vacancy Filling Hazard, the Stock of Vacancies, the Unemployment Rate and Labor Market Tightness over Time

Notes: Labor Market Tightness is defined as the ratio of the stock of vacancies in the AMS data and the number of unemployed from labor force survey data (source: OECD). Labor Market Tightness is normalized to 1 at the beginning of the sample period. The elasticity of the job filling hazard to labor market tightness is -0.47.

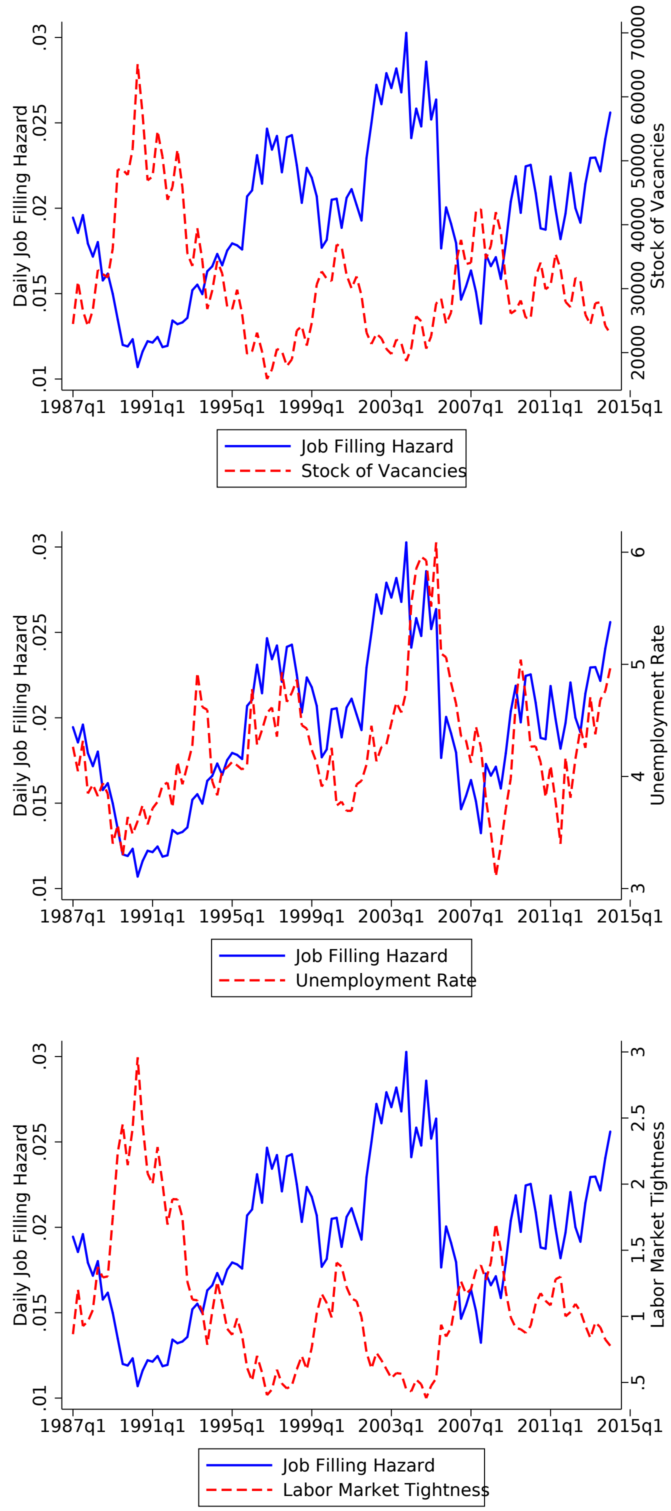


Figure A5: The Vacancy Filling Hazard, the Stock of Vacancies, the Unemployment Rate and Labor Market Tightness over Time (Immediately Available Vacancies Only)

Notes: Labor Market Tightness is defined as the ratio of the stock of vacancies in the AMS data and the number of unemployed from labor force survey data (Source: OECD). Labor Market Tightness is normalized to 1 at the beginning of the sample period. The elasticity of the job filling hazard to labor market tightness is -0.37.

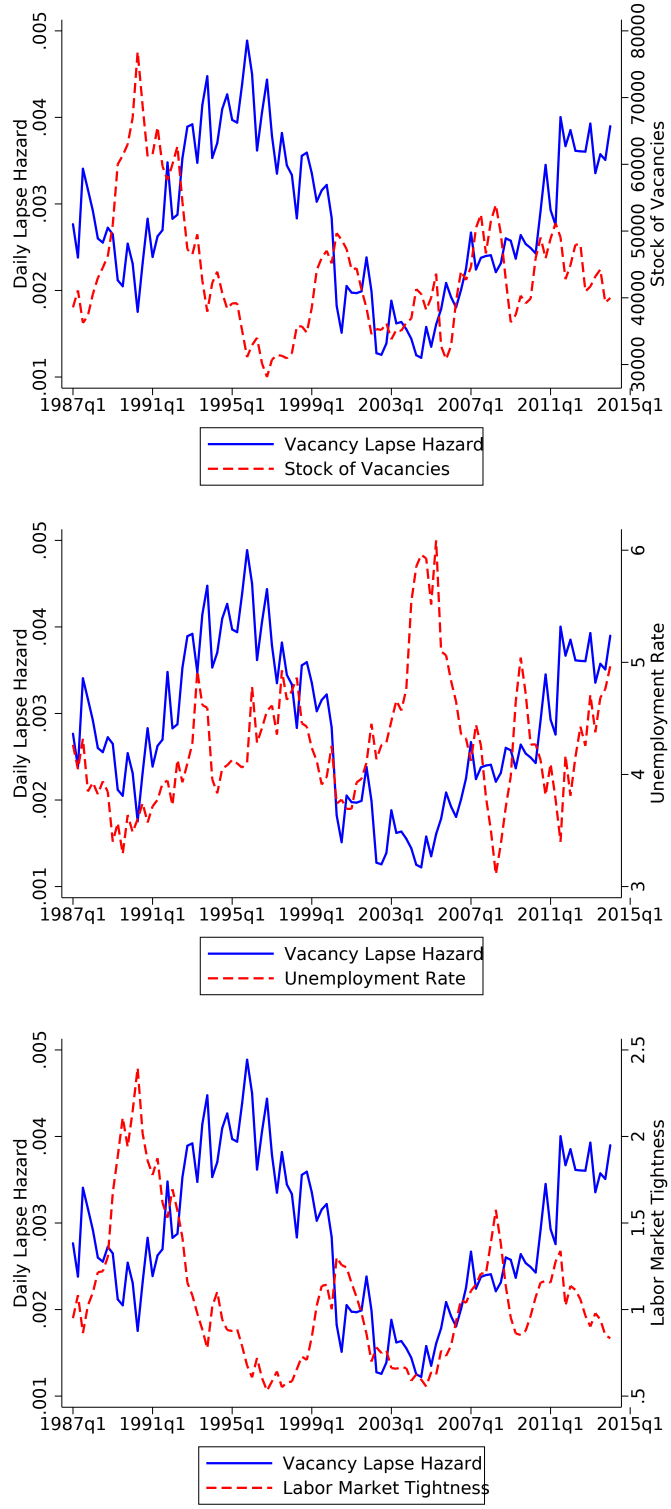


Figure A6: The Vacancy Lapse Hazard, the Stock of Vacancies, the Unemployment Rate and Labor Market Tightness over Time

Notes: Labor Market Tightness is defined as the ratio of the stock of vacancies in the AMS data and the number of unemployed from labor force survey data (Source: OECD). Labor Market Tightness is normalized to 1 at the beginning of the sample period. The elasticity of the lapse hazard to labor market tightness is 0.03.

A.3 Vacancy Filling and Firm Growth

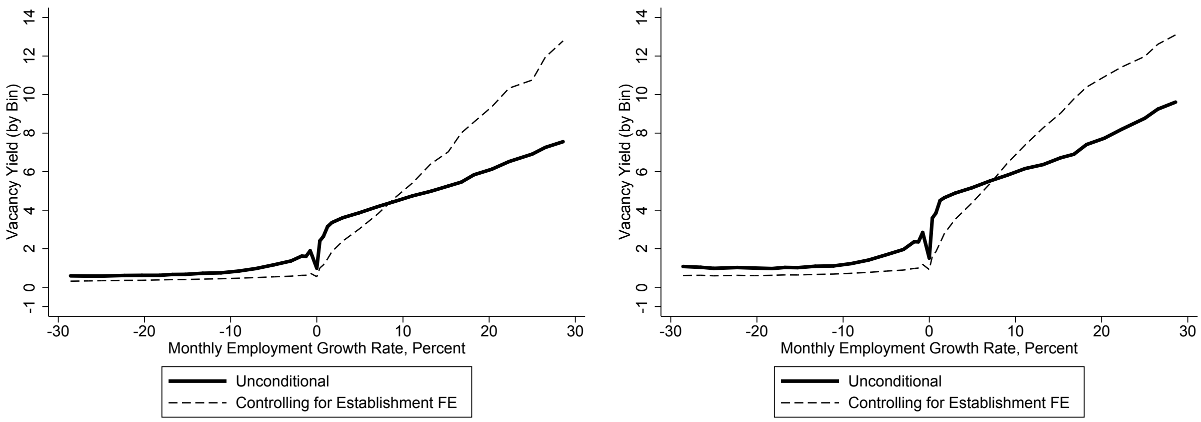


Figure A7: Establishment Growth and Vacancy Yields, for All Vacancies (Left) and Immediately Available Vacancies (Right)

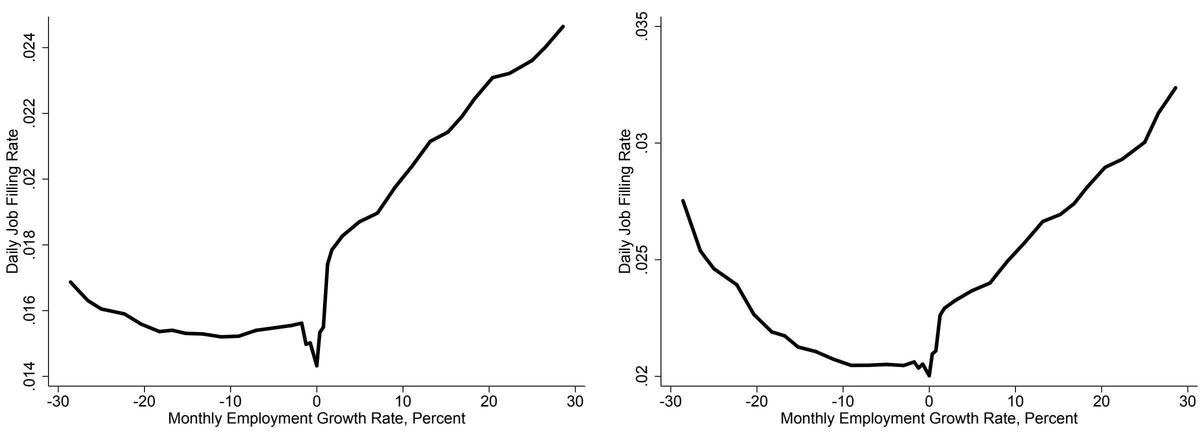


Figure A8: Establishment Growth and Vacancy Filling, for All Vacancies (Top) and Immediately Available Vacancies (Bottom)

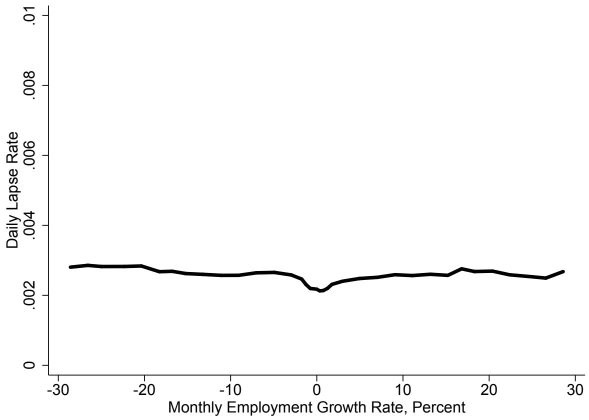


Figure A9: Establishment Growth and Vacancy Lapses, for All Vacancies (Left) and Immediately Available Vacancies (Right)

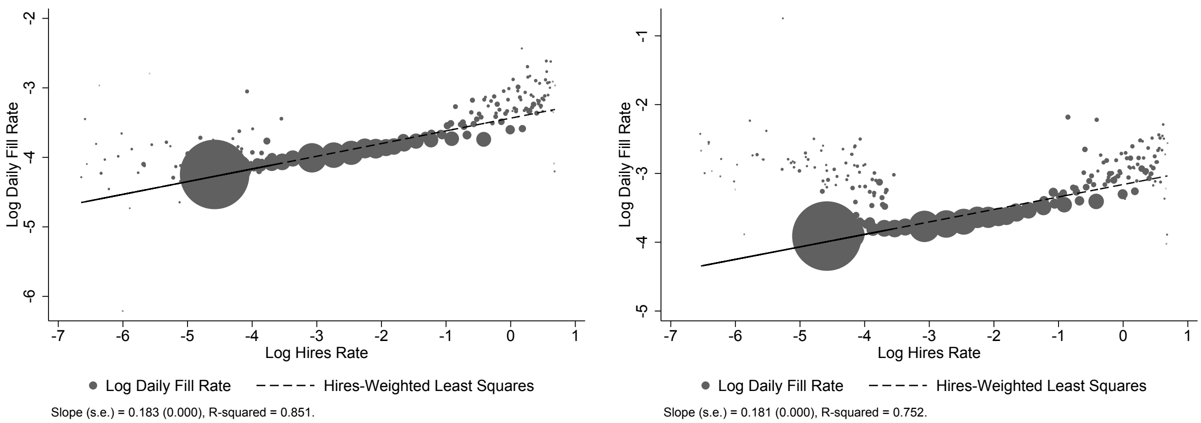


Figure A10: Job Filling Rates and Gross Hires Rates by Growth Rate Bin, for All Vacancies (Left) and Immediately Available Vacancies (Right)

Table A2: Employment Shares - ASSD Universe versus Matched Samples

	Employment Share		
	ASSD Universe	Firm Sample	Worker Sample
Austrian Sample	100.0	100.0	100.0
Major industry			
Manufacturing, mining, and quarrying	21.1	28.2	29.7
Construction	8.6	14.3	14.4
Wholesale and retail trade	18.6	21.1	21.3
Tourism, hotels, and restaurants	5.8	10.0	10.2
Transportation, information, and communication	7.2	6.3	6.2
Finance and insurance	4.3	2.9	2.6
Education, health, and social services	7.9	3.8	3.3
Other services	26.4	13.1	12.0
Establishment size classes			
0-9 employees	19.2	18.5	14.7
10-49 employees	22.7	33.8	33.1
50-249 employees	23.6	29.4	31.7
250-999 employees	17.9	15.5	17.1
1'000+ employees	16.6	2.9	3.3
Worker turnover category			
No Turnover	23.4	25.5	21.9
First Quintile	15.4	14.7	15.5
Second Quintile	15.3	14.8	15.5
Third Quintile	15.4	15.1	15.5
Fourth Quintile	15.7	15.0	16.5
Fifth Quintile	14.9	14.9	15.0
Establishment Wage Fixed Effects Quartiles			
First Quartile	5.7	8.4	9.0
Second Quartile	13.5	18.9	19.3
Third Quartile	32.4	27.9	27.3
Fourth Quartile	48.4	44.9	44.4

Notes: Employment shares based on ASSD employment for the three subsamples.

Table A3: Monthly Hires and Separation Rates - ASSD Universe versus Matched Samples

	Hires Rate			Separation Rate		
	ASSD	Firm	Worker	ASSD	Firm	Worker
Austrian Sample	4.4	4.6	4.7	3.8	4.0	4.1
Major industry						
Manufacturing, mining, and quarrying	2.6	2.6	2.6	2.4	2.4	2.4
Construction	6.0	5.6	5.6	5.8	5.5	5.6
Wholesale and retail trade	3.8	3.2	3.2	3.4	2.8	2.8
Tourism, hotels, and restaurants	10.1	10.7	10.9	8.1	9.0	9.3
Transportation, information, and communication	4.4	4.8	4.8	3.7	4.2	4.2
Finance and insurance	2.5	2.0	2.1	2.3	1.9	1.9
Education, health, and social services	4.1	4.4	4.4	3.5	3.8	3.9
Other services	4.8	6.4	6.7	4.0	5.7	6.1
Establishment size classes						
0-9 employees	6.1	6.3	6.8	5.5	6.6	7.5
10-49 employees	5.0	5.1	5.3	4.0	4.0	4.1
50-249 employees	3.9	4.0	4.1	3.3	3.3	3.4
250-999 employees	3.2	3.2	3.2	2.7	2.8	2.7
1'000+ employees	3.5	2.8	2.7	3.1	2.4	2.4
Worker turnover category						
No Turnover	0.0	0.0	0.0	0.0	0.0	0.0
First Quintile	0.7	0.8	0.8	0.9	0.9	0.9
Second Quintile	1.5	1.8	1.8	1.6	1.8	1.8
Third Quintile	2.6	3.1	3.0	2.5	3.0	2.9
Fourth Quintile	4.7	5.6	5.5	4.3	5.0	5.0
Fifth Quintile	19.3	19.4	19.1	15.6	16.2	16.1
Establishment Wage Fixed Effects Quartiles						
First Quartile	7.6	4.8	4.7	5.7	4.1	4.1
Second Quartile	5.2	4.6	4.7	4.6	4.1	4.2
Third Quartile	4.3	5.0	5.1	3.9	4.3	4.5
Fourth Quartile	3.6	4.4	4.5	3.1	3.8	3.9

Notes: Hires and separation rates based on ASSD data for the three subsamples.

Table A4: Vacancy Rates and Vacancy Yields by Industry, Size, Turnover, and Wage Fixed Effect

	Vacancy rate		Vacancy yield	
	All	Immediately Available	All	Immediately Available
Austrian Sample	1.7	1.1	2.8	4.1
DFH (2013)	2.5	.	1.3	.
Major industry				
Manufacturing, mining, and quarrying	0.9	0.7	2.8	3.9
Construction	1.5	1.1	3.5	4.8
Wholesale and retail trade	0.9	0.6	3.6	5.3
Tourism, hotels, and restaurants	4.8	2.3	2.5	4.6
Transportation, information, and communication	1.3	0.8	4.0	6.1
Finance and insurance	1.0	0.8	2.1	2.7
Education, health, and social services	1.0	0.6	4.3	7.9
Other services	3.7	2.9	2.0	2.5
Establishment size classes				
0-9 employees	3.3	1.9	1.9	3.2
10-49 employees	1.8	1.2	3.0	4.2
50-249 employees	1.3	1.0	3.6	4.8
250-999 employees	0.8	0.6	4.8	6.6
1'000+ employees	0.7	0.4	8.7	14.8
Worker turnover category				
No Turnover	1.6	1.0	0.0	0.0
First Quintile	0.5	0.3	2.1	3.1
Second Quintile	0.7	0.5	2.7	4.0
Third Quintile	1.0	0.7	3.3	4.7
Fourth Quintile	1.6	1.1	3.8	5.3
Fifth Quintile	5.2	3.5	4.2	6.1
Establishment Wage Fixed Effects Quartiles				
First Quartile	1.6	1.1	2.9	4.1
Second Quartile	1.5	1.0	3.0	4.5
Third Quartile	1.8	1.2	2.8	4.3
Fourth Quartile	1.8	1.2	2.8	4.1

Notes: Vacancy rate and vacancy yield based on stock vacancies for the years 1997–2014 for the firm subsample.

A.4 Vacancy Durations and Entry Wages

Table A5: Linear Regressions with Log JOLTS Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.113	0.117	0.025	-0.016	-0.013	-0.031
	(0.010)***	(0.008)***	(0.008)***	(0.006)**	(0.008)*	(0.013)**
On-job wage growth					-0.037	
					(0.027)	
Log job duration					0.023	
					(0.002)***	
Lagged firm growth					-0.023	
					(0.005)***	
Firm age					-0.000	
					(0.000)	
Log firm size					0.004	
					(0.004)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	354720	354720	338955	338955	213831	153640
R^2	0.022	0.141	0.166	0.211	0.216	0.573

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 4 for further details.

Table A6: Linear Regressions with Log Duration since Posting as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.110	0.116	0.023	-0.017	-0.013	-0.030
	(0.011)***	(0.008)***	(0.008)***	(0.006)**	(0.008)	(0.013)**
On-job wage growth					-0.039	
					(0.026)	
Log job duration					0.028	
					(0.002)***	
Lagged firm growth					-0.019	
					(0.005)***	
Firm age					-0.000	
					(0.000)	
Log firm size					0.001	
					(0.004)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	359321	359321	343051	343051	216606	155319
R^2	0.017	0.273	0.294	0.335	0.343	0.633

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 4 for further details.

Table A7: Weighted Regressions with Log Vacancy Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.151	0.151	0.013	-0.027	-0.018	-0.050
	(0.015)***	(0.015)***	(0.014)	(0.011)**	(0.014)	(0.020)**
On-job wage growth					-0.082	
					(0.050)*	
Log job duration					0.024	
					(0.003)***	
Lagged firm growth					-0.052	
					(0.009)***	
Firm age					-0.002	
					(0.001)***	
Log firm size					0.006	
					(0.006)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	290822	290822	281097	281097	176158	126854
R^2	0.014	0.015	0.046	0.131	0.141	0.604

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 4 for further details. Weights are constructed by running a probit regression for each year in the AMS universe of a dummy for being in the worker sample on dummies for educational requirement of job, region and industry and then taking the inverse of the predicted value of the probit regression. Values above 1000 are windsorized (affecting 0.01 percent of observations in the worker sample).

Table A8: Additional Robustness Checks

	(1)	(2)	(3)	(4)	(5)
Log entry wage	-0.034	-0.068	-0.065	-0.030	-0.028
	(0.008)***	(0.010)***	(0.013)***	(0.009)***	(0.008)***
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Occupation FE (6 digits)	Yes	Yes	Yes	Yes	Yes
Observations	281097	275484	253441	195100	184891
R^2	0.112	0.112	0.111	0.121	0.120

Notes: Column (1) reports the baseline results from Column 4 in Table 4; Column (2) reports results where the sample is trimmed below the 1st and above 99th percentile of the distribution of starting wages; Column (3) reports results where the sample is trimmed below the 5th and above 95th percentile of the distribution of starting wages; Column (4) reports results where the sample is restricted to men; Column (5) reports results where the sample is restricted to ages 25-54.

Table A9: Linear Regressions with Log JOLTS Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.113					
	(0.010)***					
AKM establishment effect		-0.117	-0.104	-0.112	-0.138	-0.200
		(0.025)***	(0.020)***	(0.019)***	(0.025)***	(0.028)***
AKM worker fixed effect		0.368	0.204	0.062	0.044	
		(0.015)***	(0.012)***	(0.011)***	(0.014)***	
AKM worker exp. effect		0.255	0.191	0.038	0.016	0.062
		(0.013)***	(0.013)***	(0.011)***	(0.014)	(0.060)
AKM residual		0.095	0.014	-0.016	-0.006	-0.011
		(0.010)***	(0.008)*	(0.007)**	(0.008)	(0.014)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Further Controls	No	No	No	No	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	354720	338831	326842	326842	207683	149904
R^2	0.022	0.026	0.166	0.210	0.216	0.574

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 5 for further details.

Table A10: Linear Regressions with Log Duration since Posting as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.110					
	(0.011)***					
AKM establishment effect		-0.137	-0.129	-0.118	-0.131	-0.202
		(0.030)***	(0.020)***	(0.019)***	(0.025)***	(0.028)***
AKM worker fixed effect		0.366	0.216	0.059	0.041	
		(0.016)***	(0.012)***	(0.011)***	(0.014)***	
AKM worker exp. effect		0.242	0.190	0.031	0.006	0.047
		(0.014)***	(0.013)***	(0.011)***	(0.014)	(0.059)
AKM residual		0.102	0.016	-0.015	-0.005	-0.008
		(0.012)***	(0.008)**	(0.006)**	(0.008)	(0.014)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Further Controls	No	No	No	No	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	359321	343154	330781	330781	210360	151545
R^2	0.017	0.021	0.293	0.333	0.341	0.633

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 5 for further details.

Table A11: Weighted Regressions with Log Vacancy Duration as Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Log entry wage	0.151					
	(0.015)***					
AKM establishment effect		-0.151	-0.204	-0.187	-0.223	-0.301
		(0.050)***	(0.053)***	(0.036)***	(0.048)***	(0.044)***
AKM worker fixed effect		0.502	0.251	0.078	0.076	
		(0.026)***	(0.028)***	(0.024)***	(0.026)***	
AKM worker exp. effect		0.373	0.270	0.062	0.059	0.152
		(0.022)***	(0.029)***	(0.024)***	(0.030)**	(0.093)
AKM residual		0.106	0.004	-0.025	-0.008	-0.024
		(0.016)***	(0.015)	(0.011)**	(0.014)	(0.021)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	No
Industry FE	No	No	No	Yes	Yes	No
Further Controls	No	No	No	No	Yes	No
Occupation FE (6 digits)	No	No	No	Yes	Yes	No
Individual FE	No	No	No	No	No	Yes
Observations	290822	278606	271198	271198	171426	123824
R^2	0.014	0.021	0.050	0.132	0.142	0.606

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. See footnote of Table 5 for further details. Weights are constructed by running a probit regression for each year in the AMS universe of a dummy for being in the worker sample on dummies for educational requirement of job, region and industry and then taking the inverse of the predicted value of the probit regression. Values above 1000 are windsorized (affecting 0.01 percent of observations in the worker sample).

Table A12: Alternative Specifications for AMS, JOLTS and Posting Duration

	AMS		JOLTS		Posting	
	(1)	(2)	(3)	(4)	(5)	(6)
AKM establishment effect	-4.444	-4.376	-2.017	-3.988	-2.050	-6.544
	(0.758)***	(0.837)***	(0.459)***	(0.833)***	(0.421)***	(1.218)***
AKM worker fixed effect	-2.629	0.146	-0.490	0.681	-0.638	-0.828
	(0.466)***	(0.384)	(0.324)	(0.389)*	(0.305)**	(0.562)
AKM worker exp. effect	-1.896	-0.214	-0.040	-0.046	-0.054	-2.785
	(0.478)***	(0.408)	(0.320)	(0.419)	(0.300)	(0.666)***
AKM residual	-1.031	-0.866	0.166	-0.657	0.043	-1.076
	(0.257)***	(0.233)***	(0.174)	(0.224)***	(0.164)	(0.359)***
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (6 digits)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	406351	406351	363551	363551	363551	363551
R^2	0.126	0.101	0.107	0.124	0.133	0.283

Notes: Authors' regressions with the worker sample for the years 1997-2014. Standard errors are clustered at the establishment level. Columns (1), (3) and (5) reports results with a dummy for whether the vacancy duration was positive times 100 as dependent variable. Columns (2), (4) and (6) report results with duration (not in logs) as dependent variable.

Table A13: Additional Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AKM establishment effect	-0.209	-0.167	-0.219	-0.233	-0.230	-0.209	-0.199	-0.226	-0.247
	(0.025)***	(0.023)***	(0.020)***	(0.016)***	(0.019)***	(0.019)***	(0.019)***	(0.021)***	(0.025)***
AKM worker fixed effect	0.063	0.044	0.131	0.037	0.036	0.063	0.087	0.030	0.083
	(0.015)***	(0.015)***	(0.018)***	(0.015)**	(0.018)**	(0.018)***	(0.017)***	(0.021)	(0.019)***
AKM worker exp. effect	0.046	0.048	0.093	0.017	0.019	0.056	0.054	0.029	0.054
	(0.015)***	(0.017)***	(0.018)***	(0.015)	(0.017)	(0.017)***	(0.016)***	(0.020)	(0.018)***
AKM residual	-0.030	-0.034	-0.026	-0.064	-0.059	-0.025	-0.025	-0.051	-0.018
	(0.008)***	(0.008)***	(0.009)***	(0.011)***	(0.014)***	(0.009)***	(0.009)***	(0.011)***	(0.010)*
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE (6 digits)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	271198	260180	187391	265784	244725	188962	180131	113980	157217
R^2	0.113	0.113	0.121	0.113	0.112	0.122	0.121	0.127	0.122

Notes: Column (1) reports the baseline results from column 4 in Table 5; Column (2) reports results where the AKM effects were estimated only from E-U-E transitions; Column (3) reports results where the sample is restricted to persons and establishments where AKM effects were estimated for at least 10 worker observations and at least 10 establishment observations; Column (4) reports results where the sample is trimmed below the 1st and above 99th percentile of the distribution of starting wages; Column (5) reports results where the sample is trimmed below the 5th and above 95th percentile of the distribution of starting wages; Column (6) reports results where the sample is restricted to men; Column (7) reports results where the sample is restricted to ages 25-54; Column (8) reports results for the sample of establishments with 10 employees or less; and Column (9) reports results for the sample of establishments with more than 10 employees.

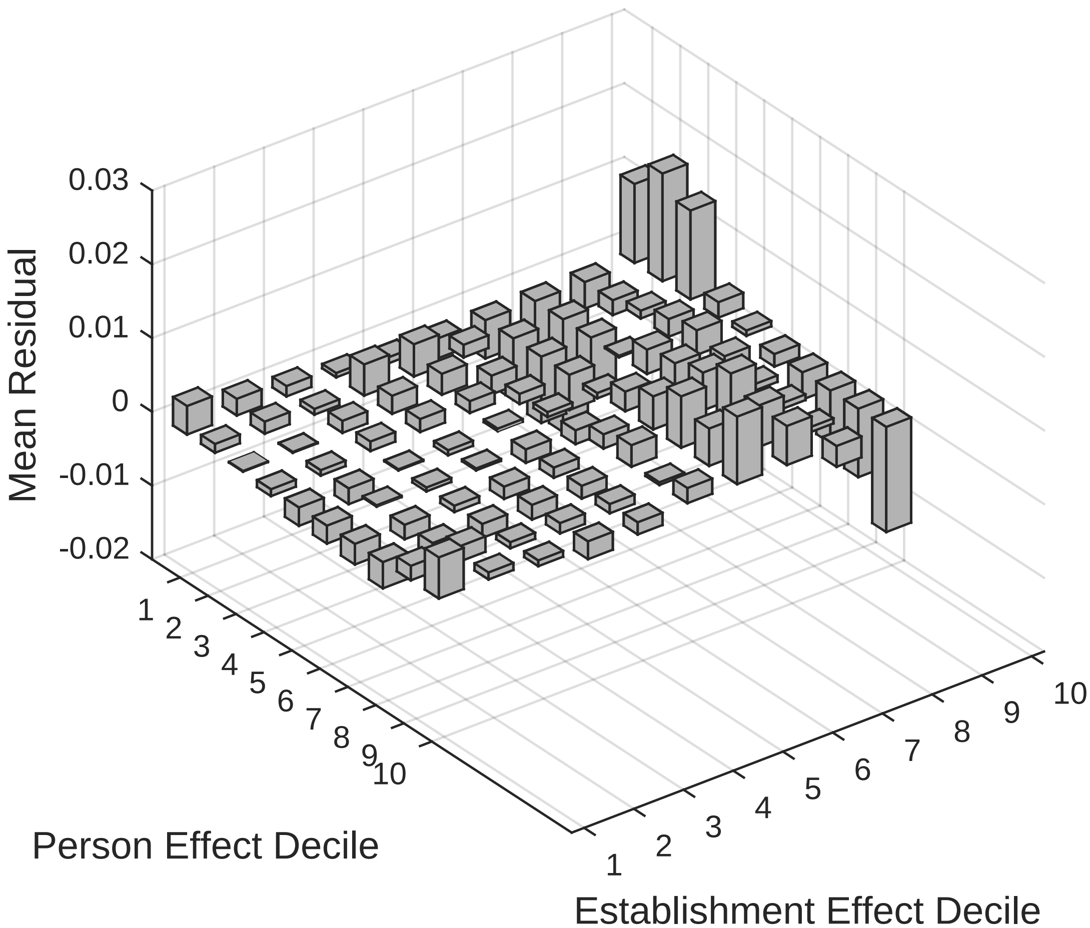


Figure A11: Mean Residuals by Person/Establishment Deciles

B Model Appendix

B.1 Details on Model Extension with Ex-Ante Worker Heterogeneity

To gain some intuition, let's consider first the model without any shocks and assume that $\delta_0(x) = \delta_0$, i.e. the exogenous firm death rate does not depend on firm productivity. In a model without shocks, firms never want to shrink and thus firm death and separations are purely exogenous, i.e. $\delta(x) = \delta_0$ and $s_i = s_0$. Let $J^x(\boldsymbol{L}, \boldsymbol{W})$ be the value function of the firm with productivity x, and W_i the wage bill to which the firm is committed for each type of worker i. As in Kaas and Kircher, one can write $J^x(\boldsymbol{L}, \boldsymbol{W}) = J^x(\boldsymbol{L}, \boldsymbol{0}) - \frac{\sum_{i=1}^N W_i}{1-\beta(1-\delta_0)(1-s_0)}$ where $\frac{\sum_{i=1}^N W_i}{1-\beta(1-\delta_0)(1-s_0)}$ is the net present value of existing wage commitments, which is independent of future hiring decisions. The firms recursive maximization problem can thus be written as

$$J^x(\boldsymbol{L}, 0) = \max_{(\boldsymbol{m},\boldsymbol{V})} xF(\boldsymbol{L}, x) - C(\boldsymbol{V}, \boldsymbol{L}, x) - \sum_{i=1}^{N} D_i(m_i)V_i + \beta(1-\delta_0)J^x(\mathbf{L}^+, 0),$$
$$s.t. L_i^+ = L_i(1-s_0) + m_iV_i, \forall i = 1, ..., N,$$

where $D_i(m_i)V_i = w_i(m_i)\frac{1-\delta_0}{1-\beta(1-\delta_0)(1-s_0)}m_iV_i$ is the net present value of wage commitments paid for the m_iV_i new hires of type i and $w_i(m_i)$ is the wage for worker type i with job filling rate m_i. We refer to the text of Kaas and Kircher for the first order conditions and other details, which follow in exact analogy for each worker type. Free entry of firms implies that $\sum_{x \epsilon X} \pi(x)J^x(\boldsymbol{0}, 1) \leq K$.

Now, let's turn to the model with firm-level shocks and where exogenous firm death rates depend on firm-level productivity, i.e. $\delta_0(x)$.[41] In analogy to Kaas and Kircher, we solve the social planner version of the problem.[42] The social value of the firm of type x satisfies the Bellman equation

$$\begin{aligned} G^x(\boldsymbol{L}, y; \boldsymbol{M}) \quad = \quad & \max_{(\boldsymbol{m},\boldsymbol{V},\boldsymbol{s},\delta)} \Big\{ F(\boldsymbol{L}, y, x) - \sum_{i=1}^{N} b_iL_i - \sum_{i=1}^{N} \mu_i \left[L_i + \lambda(m_i)V_i\right] - f \\ & -C(\boldsymbol{V}, \boldsymbol{L}, y, x) + \beta(1-\delta)E_yG^x(\boldsymbol{L^+}, y^+; \boldsymbol{M}) \Big\} \end{aligned} \tag{5}$$

$$s.t. \qquad L_i^+ = L_i(1-s_i) + m_iV_i, \forall i = 1, ..., N,$$

[41] Unlike Kaas and Kircher, we abstract from aggregate shocks, as this is not the focus of our analysis.

[42] For the type of production function and vacancy cost functions considered in the calibration below, it is easy to show that the proof of Kaas and Kircher that the decentralized economy is efficient carries over the case with ex-ante heterogeneous workers.

and subject to $\delta \in [\delta_0(x), 1]$, $s_i \in [s_0, 1]$, $m_i \in [0, 1]$, and $V_i \geq 0$, $\forall i = 1, ..., N$, and where $\boldsymbol{M} = (\mu_1, \mu_2, ..., \mu_N)$ are the social values of each type of worker tied to the firm in a given period. In our calibration, we set $f = 0$ and thus all firm exit is exogenous, i.e. $\delta = \delta_0(x)$. As discussed in detail in Kaas and Kircher, the firm's social flow value consists of the output of the firm minus the opportunity cost of employment ($b_i L_i$), the social cost of workers tied to the firm, including the unemployed applying to the firm ($\mu_i [L_i + \lambda(m_i) V_i]$), fixed operating costs (f) and vacancy posting costs ($C(\boldsymbol{V}, \boldsymbol{L}, y, x)$). Positive entry requires that $\sum_{x \epsilon X} \pi(x) G^x(\boldsymbol{0}, 1; \boldsymbol{M}) = K$, which is satisfied in all calibrations that we explore. We solve the model, by first forming an initial guess of $\boldsymbol{M}$, then solving the Bellman equation above, and then iterating on $\boldsymbol{M}$ until the resource constraints of the economy are satisfied with equality (i.e., workers of all types are either employed or unemployed searching for a job).

B.2 Calibrated Parameter Values and Additional Model Simulation Results

Table B1: Calibrated Parameter Values

Parameter	Value	Description	Target/Source
c	0.11	Vacancy cost scale parameter	Weekly job filling rate of 0.102
γ	0.5	Vacancy cost elastiticity	Job filling rates by employment growth & Elasticity of hiring to job filling of 0.18
k	4.8	Matching function scale parameter	Weekly job finding rate of 3.3 percent
r	0.56	Matching function elasticity	Elasticity of job finding to tightness of 0.72
K	2.4	Entry cost	Normalization
β	0.999	Discount factor	Kaas and Kircher
b	0.1	Unemployment income	Kaas and Kircher
s_0	0.48%	Quite rate	Kaas and Kircher
x_1	0.37	Firm productivity of firm type 1	Kaas and Kircher
x_2	0.74	Firm productivity of firm type 2	Kaas and Kircher
x_3	1.17	Firm productivity of firm type 3	Kaas and Kircher
x_4	2.03	Firm productivity of firm type 4	Kaas and Kircher
x_5	4.14	Firm productivity of firm type 5	Kaas and Kircher
σ_1	98.820%	Firm share at birth of firm type 1	Kaas and Kircher
σ_2	1.000%	Firm share at birth of firm type 2	Kaas and Kircher
σ_3	0.153%	Firm share at birth of firm type 3	Kaas and Kircher
σ_4	0.025%	Firm share at birth of firm type 4	Kaas and Kircher
σ_5	0.002%	Firm share at birth of firm type 5	Kaas and Kircher
$\delta_{0,1}$	1.710‰	Exogenous exit rate of firm type 1	Kaas and Kircher
$\delta_{0,2}$	0.270‰	Exogenous exit rate of firm type 2	Kaas and Kircher
$\delta_{0,3}$	0.160‰	Exogenous exit rate of firm type 3	Kaas and Kircher
$\delta_{0,4}$	0.088‰	Exogenous exit rate of firm type 4	Kaas and Kircher
$\delta_{0,5}$	0.016‰	Exogenous exit rate of firm type 5	Kaas and Kircher
$\bar{y}$	0.312	Transitory productivity range	Kaas and Kircher
π_y	0.027	Adjustment probability	Kaas and Kircher

Table B2: Additional Simulation Results of Model of Kaas and Kircher with $\gamma = 0.5$

	Data	Baseline	KK	RR=0.98	$\bar{y} = 0.5$	$\pi_y = 0.5$	$s0 = 0.01$	$\epsilon = 0.5$
Key Model Elasticities:								
Vac. dur. to starting wage	0.16	-17.9	-43.8	-239.5	-12.6	-19.3	-14.6	-11.3
Hiring to job filling rate	0.18	0.15	0.33	0.14	0.13	0.16	0.15	0.15
Calibration Targets:								
Replacement Rate (RR)		0.72	0.70	0.98	0.70	0.72	0.70	0.72
Job Filling Rate	0.10	0.10	0.30	0.10	0.10	0.10	0.10	0.10
Job Finding Rate	0.03	0.03	0.11	0.03	0.03	0.03	0.03	0.03

Notes: All simulations use a value of $\gamma = 0.5$. KK refers to the parameters in the baseline calibration of Kaas and Kircher (2015), which targets the weekly job filling and job finding rate for U.S. data.

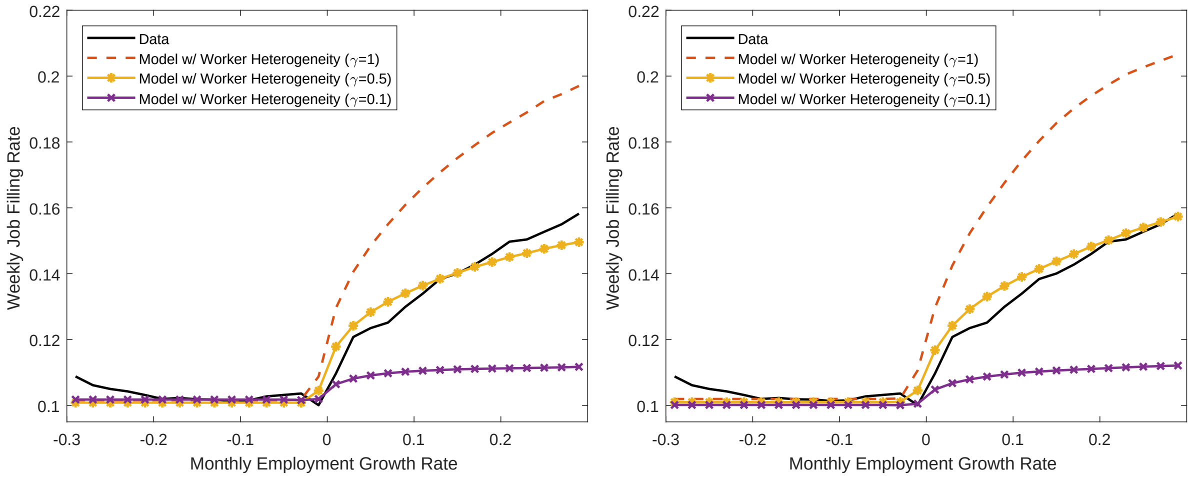


Figure B1: Weekly Job Filling Rates by Employment Growth in Data and Model with Ex-Ante Worker Heterogeneity without (Left Panel) and with (Right Panel) Positive Assortative Matching