The Ins and Outs of Vacancies*

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Abstract

This paper uses large-scale high-frequency data on vacancy flows and matched employer-employee data from Austria to document the cyclicality of vacancy flows and their contribution to variation in the vacancy stock. We document four key facts: (1) Vacancy inflows explain at least one-third of the cyclical variation in the vacancy stock, whereas the remainder is explained by vacancy fillings; (2) vacancy lapses, while accounting for about 20% of vacancy outflows, are acyclical and do not contribute to variation in the stock; (3) replacement vacancies, i.e. vacancies posted following a quit of a worker to another firm, are a key driver of vacancy inflows over the business cycle; and (4) the composition of vacancy inflows varies little over the business cycle and cannot account for the cyclical variation in vacancy filling. We set up a search-and-matching model with fixed costs of vacancy posting and on-the-job search, and calibrate it to match the averages of vacancy flows. The calibrated model highlights the crucial role of on-the-job search – particularly replacement hires – in explaining the observed importance of vacancy inflows for cyclical fluctuations in the vacancy rate.

Keywords: Vacancies, Unemployment, Job Search, Recruiting, Business Cycles.
JEL Codes: E24, E32, J63, J64.

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1 Introduction

There is a long and influential literature that decomposes the cyclical variation in the unemployment rate into the flows into and out of unemployment (Elsby, Michaels and Solon, 2009; Shimer, 2012). A general finding is that the outflows are highly cyclical and that, at least for the US, outflows explain at least half of the variation in the unemployment rate over the business cycle. This literature has been highly influential for the modeling and calibration of aggregate labor market dynamics in models with search and matching frictions (Shimer, 2005).

There is a surprising lack of corresponding evidence on the contribution of in- and outflows for the cyclical variation of the stock of *vacancies*. This lack is driven partly by the assumption of free entry in the canonical Diamond-Mortensen-Pissarides (DMP) model, which is widely used as the workhorse model in the literature. The assumption implies that the distinction between flows into and out of the stock of vacancies is not well-defined, as firms are indifferent between keeping an unfilled vacancy open or closing it. Another reason for the lack of evidence, however, is also the lack of longitudinal vacancy data that allows measuring vacancy flows on a consistent basis over a long time period.

This paper tackles this void in the literature, by using large-scale *daily* data on vacancy flows from Austria to document the cyclicality of vacancy flows for the period 1985 to 2019 (see Mueller et al. (2024) for a detailed description of the data). The data are unique as they are sampled from the flow of vacancies and thus do not suffer from any time aggregation issues. This is an important feature of the data as vacancies are usually short-lived, and many vacancies are open and filled within the same month. Moreover, the vacancy data is longitudinal, allowing us to track unfilled vacancies across months. Furthermore, the data record whether vacancies are filled or lapse, i.e., are not filled, but firms give up their recruiting effort. Finally, we match the vacancies to matched employer-employee data in Austria and thus have rich data on firm characteristics posting these vacancies. These unique features along with the long time series provide us with the ideal set up to analyze the cyclicality of vacancy flows and their contribution to the cyclicality of the vacancy stock and its composition. The link between vacancies and firm-level worker flows in the matched employer-employee data is crucial for identifying replacement vacancies.

We apply a decomposition analysis of the time series variation of the stock of vacancies, similar to the one used by Shimer (2012) for the unemployment rate.[1] We find that vacancy inflows explain at least one-third of the time series variation in the vacancy stocks, whereas the remainder is explained by vacancy fillings. Vacancy lapses,

[1]We also apply the decomposition analysis to ins and outs of unemployment and find that the contribution of ins and outs to the cyclical movements in the unemployment rate are similar to the ones in the US.

while accounting for about 20% of vacancy outflows, are acyclical. These patterns are robust to a wide array of robustness checks.

Furthermore, we document the importance of replacement hires for cyclical variation in vacancy inflows. As emphasized by Mercan and Schoefer (2020) and Elsby et al. (2022), replacement hires lead to vacancy chains, where the poaching of one worker can lead to many additional replacement vacancy and hires if replacement hires are also poached from other firms. This mechanism amplifies the cyclical fluctuations in the labor market in terms of vacancies and hires, and ultimately also unemployment. We show that inflows of replacement vacancies account for approximately 44% of the time series variation in vacancy inflows, illustrating the importance of the vacancy chain multiplier effect in micro-level vacancy data. We also show that the cyclical variation in replacement vacancies is not only driven by fewer separations to other employers in recessions, but also by firms being less likely to post a replacement vacancy following a worker separating to another employer.

Finally, we assess to what extent the composition of vacancy inflows varies over the business cycle and whether it can account for variation in vacancy filling. A related literature on the composition of unemployment has found that job finding is not explained by cyclical movements in the composition of the unemployed (Baker, 1992; Kroft et al., 2016; Mueller and Spinnewijn, 2023). While prior research has found little role for composition across industry and size classes for vacancy filling over the business cycle (Mongey and Violante, 2019), it is worthwhile re-examining this proposition in the face of longitudinal vacancy data with a rich set of firm- and vacancy-level characteristics. We find, however, that firm fixed effects in vacancy filling as well as variable firm- and vacancy-level characteristics can account only for a negligible share of the variation in the vacancy filling rate over the business cycle.

To study the implications of our findings for the cyclical dynamics of labor markets, we follow Leduc and Liu (2020) and set up a search-and-matching model with a fixed cost of vacancy posting and variable recruiting intensity. We calibrate the model to match the average vacancy and unemployment rate as well as the average job-finding, vacancy-filling and vacancy inflow rate in the Austrian data. The calibrated model predicts only small variation in vacancy inflows over the business cycle and thus cannot match the importance of inflows for the cyclical variation of the vacancy stock as is documented in our data. An important short-coming of this model is, however, that it does not feature replacement hires, i.e. vacancies for positions where the worker recently quit. We therefore extend the model with on-the-job search and replacement hires, which amplifies the importance of inflows. The model confirms that replacement hires are an important determinant of the variation of the vacancy stock over the business cycle and highlights the importance of business cycle fluctuations in the reposting probability, i.e. the probability to post a vacancy after a poached separation,

for the vacancy chain multiplier effect over the business cycle. These findings have important implications for the cyclical fluctuations in the labor market, as a longer and more cyclical vacancy chain amplifies the fluctuations in the unemployment rate.

Our paper proceeds as follows: Section 2 introduces the data, describes the institutional background, and provides a decomposition of the ins and outs of unemployment in Austria. In Section 3 we apply a similar decomposition analysis of the time series variation to the stock of vacancies. Section 4 develops a new and more refined approach for identifying replacement hires and provides a decomposition of vacancy inflows into the vacancy pool resulting from replacement vacancies and new vacancy inflows. Section 5 assesses the importance of compositional changes of the vacancy pool over the business cycle for the filling rate. Section 6 calibrates a search-theoretic model incorporating both job search and replacement hires exploring the implications of our empirical results for the cyclical dynamics of labor markets, and Section 7 concludes.

2 Data and the Austrian Labor Market

We start by introducing our primary data source: the vacancy database of the Austrian 'Arbeitsmarktservice' (AMS). As Austria's leading job-matching platform, the AMS aims to connect jobseekers and employers, minimizing labor market search frictions. The platform serves both employed and unemployed jobseekers, along with firms posting vacancies of all types, although it is more commonly used by unemployed workers, and most filled vacancies reflect transitions from unemployment to employment (see also Mueller et al. (2024)). The AMS services are free for both jobseekers and employers. In addition to its pivotal role as an intermediary on the Austrian labor market, the AMS manages income support programs (including unemployment insurance benefits and assistance as well as other related transfers) and oversees active labor market policies (see Arbeitsmarktservice (2018)).

2.1 AMS Vacancy Data

The AMS vacancy register database provides comprehensive information on the universe of vacancies posted through the AMS over a span of more than 30 years, from 1987 to 2019. There are two main advantages of the AMS vacancy database (see Mueller et al. (2024) for a detailed description of the data). First, it provides information in the AMS vacancy on the timing (posting, availability, filling) on a *daily* basis. Because vacancy durations are typically quite short – often less than 30 days – the daily information is particularly useful. Second, the AMS vacancy database contains an establishment

identifier that allows a link of the AMS vacancy data to the Austrian social security data (ASSD). In addition, the AMS vacancy database provides information on the characteristics of a vacancy (skill requirements, working hours, and other relevant job-related information). Combined with employer characteristics from the ASSD, these employer and vacancy attributes allow us to explore the extent to which compositional changes drive vacancy inflows and outflows over the business cycle.

Measuring vacancy stocks and flows. An important issue relates to the measurement of vacancy stocks and flows. The measurement concept is obviously determined by the definition of the duration of a vacancy. The AMS vacancy data enable the use of two alternative definitions of vacancy duration. The first duration concept defines the duration of a vacancy as the difference (in days) between the date when the vacancy is filled and the desired start date of the job (= the date when the job becomes "immediately available"). Alternatively, the AMS vacancy data also allows us to measure the duration of a vacancy as the time difference between the date when the vacancy was posted and the date when the vacancy was filled ("Posting duration"). This latter concept encompasses both vacancies that are immediately available and those that are currently open (i.e., firms are inviting applications) but have a future desired start date. One potentially relevant margin for variations of vacancy inflows and outflows over the business cycle is that firms find it challenging to fill vacancies quickly in tight labor markets. As a result, they might begin the recruitment process earlier and post vacancies further in advance of the desired start date. Therefore, observing both the posting date and the desired start date of the job is crucial for our analysis.[2]

Are AMS vacancies representative for the universe of Austrian vacancies? The AMS platform is not Austria's only job-advertisement portal, but it is by far the most significant. Figure 1 illustrates the number of vacancies posted on the AMS platform and compares the stock of AMS vacancies to that of the 'Offene-Stellen-Erhebung' (OStE), a representative quarterly survey conducted by Statistics Austria since 2009. The OStE survey asks establishments about all currently posted vacancies – both those listed on the AMS and those on other platforms – and their characteristics, such as skill requirements and full-time status. Importantly, the OStE survey includes an indicator that identifies whether a given vacancy is posted on the AMS platform, enabling us to

[2]Ideally, vacancy duration should measure the active period of recruitment, similar to how unemployment duration reflects job search efforts: if a firm posts a vacancy but is not actively working to fill the position, it should not be included in the vacancy stock. However, in practice it is difficult to exactly measure the start of the recruiting spell since recruiting effort is not directly observable. Our analysis below will focus on the Posting duration concept (i.e., duration since posting), but we will confirm in the Appendix that the results are very similar for alternative duration concepts.

assess the share of vacancies covered by the AMS over time.[3]

Panel (a) of Figure 1 shows average quarterly vacancy stocks, as measured in the representative OStE survey and in the AMS vacancy data (separately for all vacancies and for immediately available vacancies). According to the OStE survey, there were about 70,000 open vacancies during the period 2009 – 2016, followed by a sharp increase from 2017 on. The stock of AMS vacancies closely tracks the OStE stock, suggesting that the dynamic evolution of AMS vacancies effectively reflects total vacancies in Austria. The solid line in Panel (b) of Figure 1 shows the AMS coverage rate – i.e. the share of OStE vacancies reporting that the vacancy has been posted on the AMS platform – is roughly 60 percent throughout the observation period. Importantly, the share of AMS covered vacancies does not vary over the business cycle. The gray shaded area in Panel (b) shows the ratio of AMS vacancies to the OStE vacancy stock, separately for all AMS vacancies and for immediately available vacancies. By construction, the former lies above the latter and, reassuringly, the solid line capturing the AMS coverage rate reported in the OStE survey, lies in between.[4]

Overall, these results suggest that the subsample of AMS vacancies represents business cycle variations of Austrian vacancies reasonably well and provides us with a meaningful data set to investigate the ins and outs of vacancies over the business cycle on the Austrian labor market.

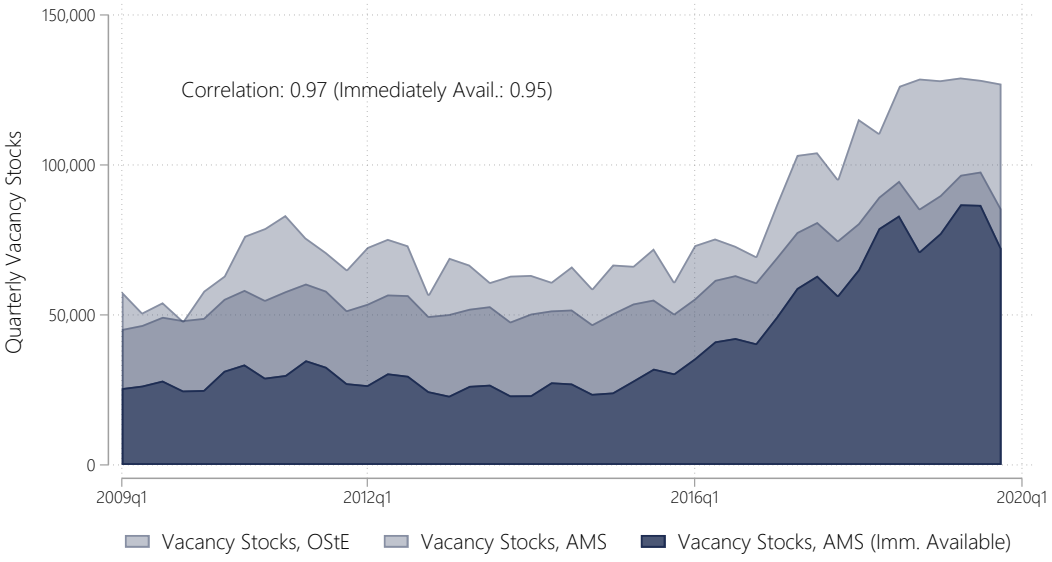
Linking AMS vacancies to social security data. Although the AMS vacancy data lack an establishment identifier in the early years, this identifier becomes available starting in 1994. This allows us to link the vacancy information in the AMS database to the social security register (ASSD), a matched employer-employee dataset that reports establishments' employment (as well as new hires and separations), in addition to workers' earnings and take-up of social insurance benefits (unemployment and disability insurance, sickness-, parental-leave benefits, etc.). Even though, the establishment identifier in the AMS vacancy data and the corresponding establishment identifier in the ASSD are collected for different purposes, the AMS provides an official crosswalk between the two establishment identifiers that allows to match establishments in the

[3]For a detailed comparison of AMS vacancies to vacancies in the OStE survey, see also Edelhofer and Knittler (2013) and Mueller et al. (2024). Compared to the representative OStE survey, AMS vacancies are more concentrated in occupations at the middle of the skill spectrum and have slightly lower education requirements than those not posted via the AMS. However, the coverage rate is very similar for stable or shrinking establishments.

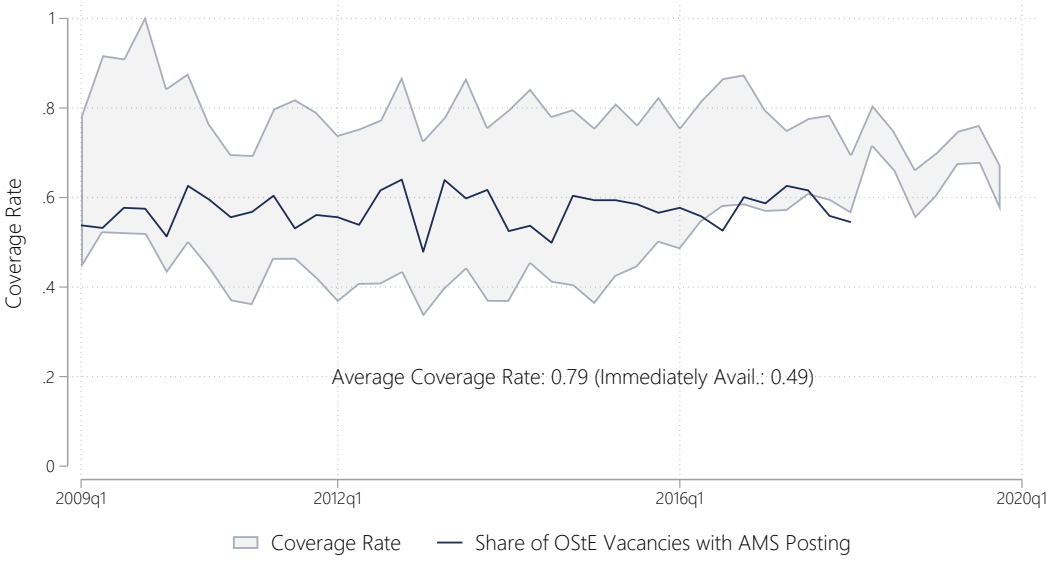
[4]The vacancy concept underlying the OStE survey is more vague than the vacancy concept underlying the AMS register data. The stock of vacancies displayed in Figure 1 includes either all posted AMS vacancies or the subset that are immediately available. In contrast, the OStE stock includes vacancies that are "available within a certain period". This implies that the latter stock is based on a more narrow definition than the concept of all posted AMS vacancies, but based on a broader definition than the immediately available AMS vacancies. It is therefore reassuring that the AMS coverage rate – the share of vacancies that are posted on the AMS platform according to the OStE survey – as measured in the OStE survey lies in between the two definitions.

Figure 1
Comparison of AMS Data with representative Austrian Vacancy Survey

(a) Vacancy Stocks



(b) Coverage Rate



Notes: This figure shows a comparison of vacancy stocks in AMS to vacancy stocks in a representative vacancy survey for Austria ("*Offene-Stellen-Erhebung*", OStE). Quarterly averaged data from 2009 – 2019 (OStE data is only available quarterly and after 2009).

AMS vacancy data to ASSD establishments. Appendix Section A.1 describes the data and the link between the AMS and the ASSD in more detail and Table A.1 provides descriptive statistics for the two samples (i.e., AMS universe and the matched establishment sample), confirming that vacancy rates are very similar across the two samples (see Appendix Figure A.1). Overall, the matched establishment sample is therefore representative for the universe of vacancies posted through the AMS over the business cycle and allows a detailed analysis of the importance of compositional changes of the vacancy pool.

2.2 The Austrian Labor Market

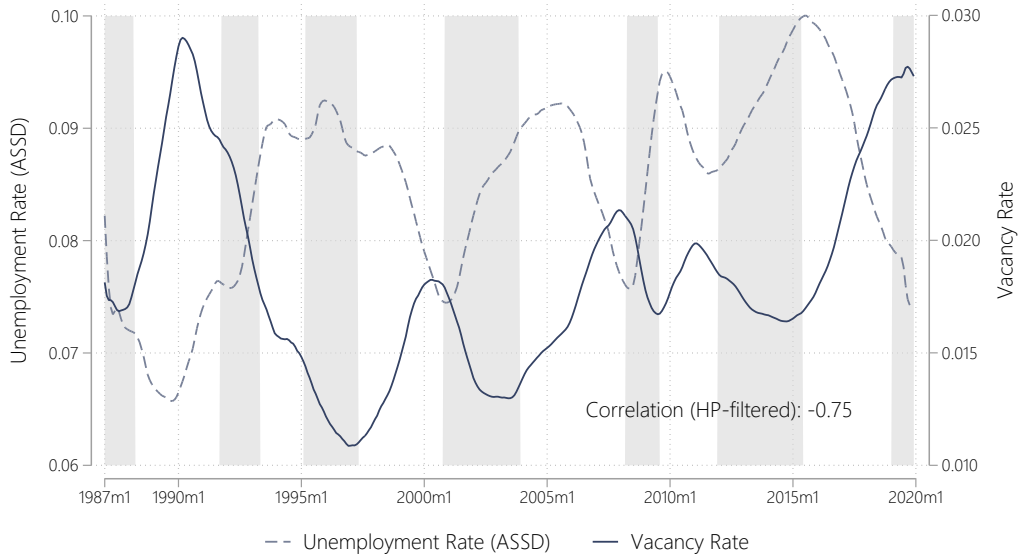
Figure 2 plots the monthly vacancy rate based on AMS vacancy stocks against the unemployment rate based on the ASSD from 1987 – 2019 in Austria. First and foremost, the figure illustrates that the vacancy rate – defined as the ratio of vacancy stocks to the sum of vacancies and employed individuals – exhibits a strong negative correlation with the unemployment rate over the business cycle. During economic expansions, firms tend to increase hiring to meet rising demand, leading to a decrease in the unemployment rate and a corresponding increase in the vacancy rate as job openings rise. Conversely, in recessions (highlighted by the gray shaded areas), the unemployment rate rises as firms reduce their workforce or freeze hiring, resulting in fewer vacancies being posted.[5]

The Beveridge curve in Figure 3 further illustrates the inverse relationship between the unemployment and vacancy rate between 1987 – 2019 in Austria.[6] The Beveridge curve usually reflects that fluctuations in unemployment are driven by changes in the demand for labor (Beveridge, 1944), where typically, more job-openings correspond to lower unemployment rates, and vice versa. However, similarly as in the US (see e.g. Barlevy et al. (2023)), the negative relationship between the unemployment and vacancy rate is not stable over time. There was a gradual outward shift of the Beveridge curve in Austria, especially during the recovery after the Great Recession in 2008, but also during the recovery after the Dotcom bubble in 2000. As shown by Barlevy et al. (2023) these shifts can occur due to various factors, such as changes in labor market frictions, variations in workforce skill sets, and broader economic conditions affecting job availability. For instance, during economic downturns, the curve may shift outward if employers become more selective in their hiring practices, resulting in higher unemployment rates for a given level of the vacancy rate (i.e., there are fewer vacancy fillings).

[5] In Appendix Figure A.2, we plot the relationship between labor market tightness – defined as the ratio of the vacancy rate to the unemployment rate – and the unemployment rate.

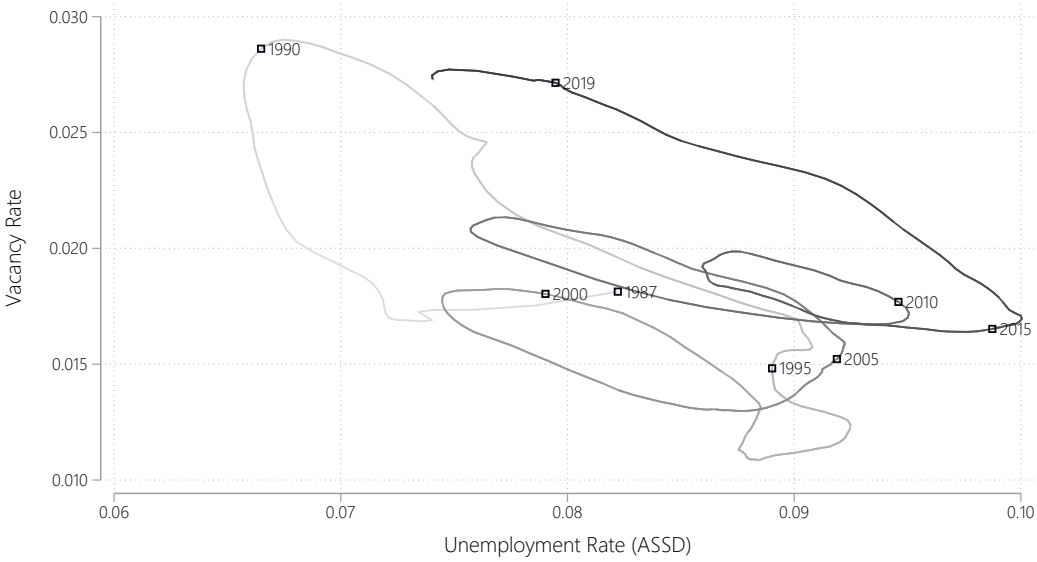
[6] We plot the Beveridge curve using the official OENB unemployment rate and confirm that results are very similar in Appendix Figure A.3.

Figure 2
Vacancy Rate in AMS Data



Notes: This figure shows the monthly vacancy rate based on AMS vacancy stocks and the monthly unemployment rate based on the ASSD from 1987 – 2019, where we apply a 13-month centered moving average. OECD based Recession Indicators for Austria from FRED (2023).

Figure 3
Beveridge Curve in Austria



Notes: This figure shows the Beveridge curve in Austria based on the monthly vacancy rate using AMS vacancy stocks and the monthly unemployment rate from the ASSD from 1987 – 2019, where we apply a 13-month centered moving average.

Importantly, fluctuations in the vacancy rate – similar to those observed in the unemployment rate as highlighted in Shimer (2012)'s decomposition of the unemployment rate – can be driven by both inflows and/or outflows of vacancies. In the following, we will therefore conduct a similar decomposition for the vacancy rate to understand whether variations stem from inflows or outflows, as this distinction is critical for analyzing labor market dynamics and understanding shifts in the Beveridge curve.

2.3 The Ins and Outs of Unemployment

Following Shimer (2012), we use a similar decomposition of the ins and outs of unemployment in Austria using a simplified two-state model and an extended model that accounts for entry and exit from the labor force in order to document the importance of the job finding and employment exit probability for fluctuations in the unemployment rate in Austria. More specifically, following Shimer (2012), we calculate the hypothetical unemployment rates using average values of the job-finding f_t and the employment exit rate x_t over the sample period

$$\hat{u}_t^f \equiv \frac{\bar{x}_t}{\bar{x}_t + f_t} \quad \text{and} \quad \hat{u}_t^x \equiv \frac{x_t}{x_t + \bar{f}_t} \tag{1}$$

as measures of the contribution of fluctuations in the job finding and employment exit rates to overall fluctuations in the unemployment rate and compare these counterfactual unemployment rates to the steady-state unemployment rate u_{t+1}^{ss} (see Appendix A.3 for details).

Table 1 reports a decomposition analysis of the time series variation of unemployment in Austria for the time period 1987 – 2019, similar to Shimer (2012) using CPS data in the US. In Austria, the job-finding rate accounts for 62% of the fluctuation in the unemployment rate, less than the 77% reported by Shimer (2012) for the US between 1948 and 2010 but in line with results of Elsby, Hobijn and Şahin (2013) for the OECD.[7] Similarly, in a three-state model including entry and exit from the labor force, E-U transitions are somewhat more important in Austria (33%) than in the US (22%) and U-E transitions only account for 39% of the fluctuation in the unemployment rate in Austria, compared to 49% in the US. At the same time, N-E transitions are more important than in the US, such that N-E and U-E transitions together are similarly important as in the US (56% vs. 57% in the US), while E-U and E-N transitions together are less important (29% vs. 17% in the US). Overall, employment exits are more important relative to

[7] In Appendix Tables A.2 and A.3, we show that the importance of the job-finding rate and the employment exit rate are very similar if we restrict the decomposition to years 1987 – 2010 as in Shimer (2012) or to years 1995 – 2019, where we can match our AMS vacancy data to the ASSD. Furthermore, Appendix Figures A.4 – A.7 provide a graphical illustration of the results in Table 1.

Table 1
The Ins and Outs of Unemployment in Austria

	Sample	
	Austria	US Data
A. Job Finding and Employment Exit		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Job Finding Rate f_t	0.62	0.77
Employment Exit Rate x_t	0.39	0.24
B. Entry and Exit from the Labor Force		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Employment-Unemployment λ_t^{EU}	0.33	0.22
Employment-Nonemployment λ_t^{EN}	-0.04	-0.05
Unemployment-Employment λ_t^{UE}	0.39	0.49
Unemployment-Nonemployment λ_t^{UN}	0.14	0.17
Nonemployment-Employment λ_t^{NE}	0.17	0.08
Nonemployment-Unemployment λ_t^{NU}	0.01	0.12

Notes: This table replicates Shimer (2012) for Austria using the ASSD from 1987 – 2019, where the last column shows the corresponding results from Shimer (2012) based on US CPS data for the time period 1948 – 2010.

unemployment outflows in Austria, but the results are generally similar across the two countries.

3 The Ins and Outs of Vacancies

In parallel to the literature on worker flows between labor market states, we develop an empirical framework to measure vacancy flows and stocks. We start with the daily law of motion for the number of vacancies:

$$V_{t,s} = V_{t,s-1} - H_{t,s} - L_{t,s} + N_{t,s}, \tag{2}$$

where $V_{t,s}$ is the vacancy stock at the end of day s in month t, $H_{t,s}$ is the flow of hires, $L_{t,s}$ is the flow of lapsed vacancies (i.e., closed but not filled vacancies) and $N_{t,s}$ is the flow of new vacancies. One can show that the daily law of motion for the vacancy *rate*, $v_{t,s} = \frac{V_{t,s}}{E_{t,s}+V_{t,s}}$, then is:

$$\frac{E_{t,s} + V_{t,s}}{E_{t,s-1} + V_{t,s-1}} v_{t,s} = v_{t,s-1} + (1 - v_{t,s-1}) n_{t,s} - v_{t,s-1}(f_{t,s} + l_{t,s})$$

where $f_{t,s} = \frac{H_{t,s}}{V_{t,s-1}}$ is the daily filling rate, $l_{t,s} = \frac{L_{t,s}}{V_{t,s-1}}$ is the daily lapse rate and $n_{t,s} = \frac{N_{t,s}}{E_{t,s-1}}$ is the daily inflow rate. In principle, this is analogous to the law of motion for the unemployment rate in a two-state model of the labor market, except that $E_{t,s} + V_{t,s}$ is not bounded at 1. Assuming a constant labor force $LF = E_{t,s} + U_{t,s}$, in flow steady state we have that $E_{t,s} = E_{t,s-1}$, $U_{t,s} = U_{t,s-1}$ and $V_{t,s} = V_{t,s-1}$, and thus the flow steady state vacancy rate satisfies:

$$v_{t,s}^{ss} = \frac{n_{t,s}}{n_{t,s} + f_{t,s} + l_{t,s}}.$$

In our empirical work, we will aggregate to monthly averages of daily rates, so the monthly flow steady state is as follows (see Appendix B.1 for details)

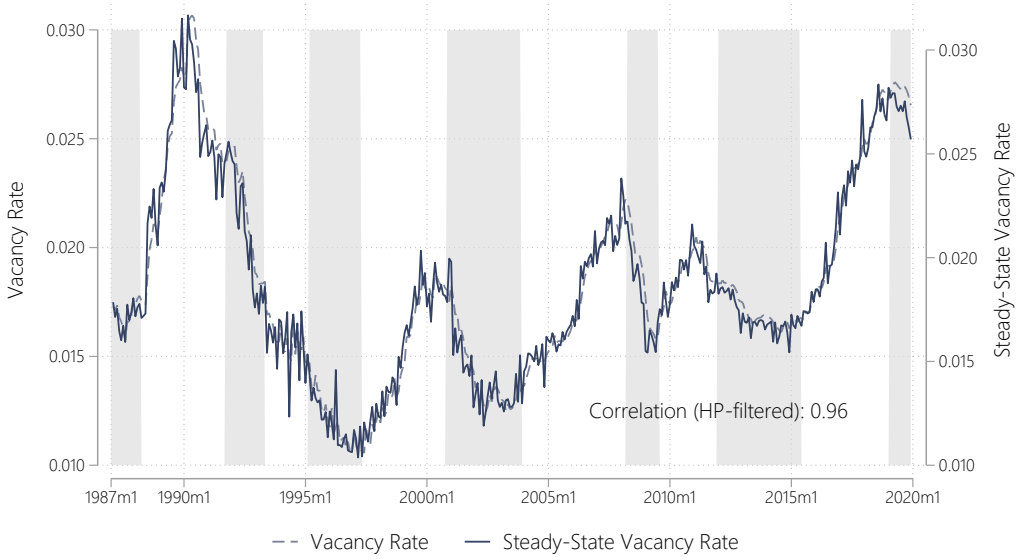
$$v_t^{ss} = \frac{n_t}{n_t + f_t + l_t}. \tag{3}$$

3.1 Measuring Vacancy Flows in the Austrian Vacancy Database

The Austrian vacancy database has several major advantages over other existing databases: First, we measure stocks of vacancies and flows at the daily level and thus our analysis does not suffer from time aggregation issues, which can be substantial as a lot of vacancies are opened and closed within a given month (approximately 70% of filled vacancies in the Austrian data). This allows us to measure daily filling and inflow rates precisely without having to make any assumptions. Second, our database distinguishes among outflows that lead to filled vacancies and outflows of vacancies due to a lapse. As confirmed in private correspondence, the AMS makes a big effort in following up at least every 2 weeks with firms posting vacancies to determine whether a vacancy is filled or still active. Finally, we can match the vacancy database at the establishment level with the Austrian Social Security Database (ASSD), which allows relating worker flows to vacancy flows. As explained in detail below, this allows distinguishing among vacancy inflows (and also outflows) that occur concurrently with separations at the same establishment and thus allow us to infer inflows that are likely intended as a replacement hire for a separated worker. Finally, the AMS database has been consistently collected since 1987 and can be matched to the ASSD since 1994, allowing for an analysis of vacancy flows over a long time series with several full

business cycles.

Figure 4
Comparison of v_t and v_t^{ss} in AMS Data



Notes: This figure shows the monthly vacancy rate based on AMS vacancy stocks and the steady-state vacancy rate from 1987 – 2019, seasonally adjusted using X-13ARIMA-SEATS (Sax and Eddelbuettel, 2018). OECD based Recession Indicators for Austria from FRED (2023).

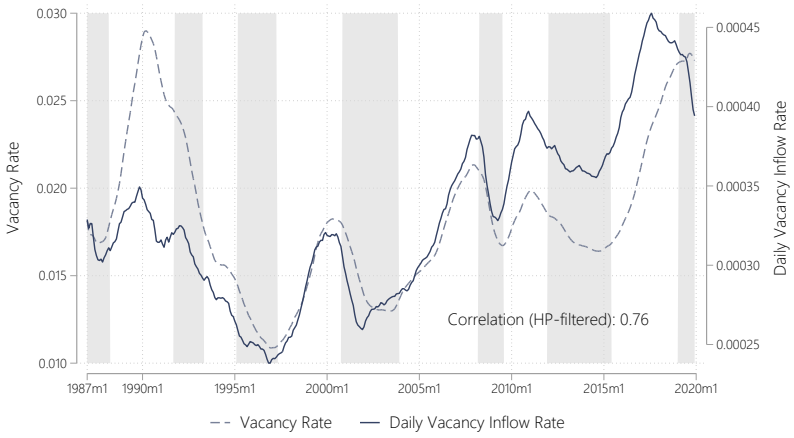
We begin by comparing the steady-state vacancy rate, v_t^{ss}, from equation (3), with the actual empirical vacancy rate, v_t. Figure 4 illustrates that the steady-state vacancy rate is a very good approximation of the actual vacancy rate, which is not surprising giving the high inflow and especially outflow rates in the data. Furthermore, the figure highlights that the vacancy rate typically increases in times of economic expansions and declines in times of recessions, as shown in the gray shaded areas.

As illustrated in equation (3), variations in the (steady-state) vacancy rate can be driven by vacancy inflows, vacancy fillings and vacancy lapses. Figure 5 plots the aggregated daily filling, inflow and lapse rate in the AMS universe from 1987 – 2019. The inflow rate n_t and the vacancy rate v_t in Panel (a) are strongly positively correlated, with a correlation coefficient of 0.76. The filling rate f_t in Panel (b) and the lapse rate l_t in Panel (c) on the other hand, are both strongly negatively correlated with the vacancy rate, with a correlation coefficient of -0.92 and -0.53, respectively.[8] A negative correlation of the outflow rates suggests a positive contribution – in an accounting sense – to the fluctuations in the vacancy rate. Therefore, the evidence here suggests that all three flows contribute to the variation in the vacancy rate. Consequently, we provide a comprehensive and formal decomposition of their relative importance in Section 3.2.

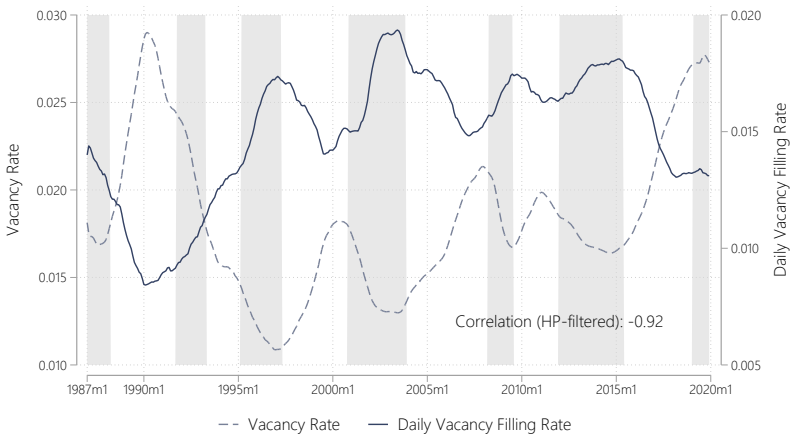
[8]Appendix Figures B.1 – B.4 plot the vacancy rates using an HP filter instead of the moving average and confirm that all results are virtually the same.

Figure 5
Vacancy Inflow, Filling and Lapse Rate in AMS Data

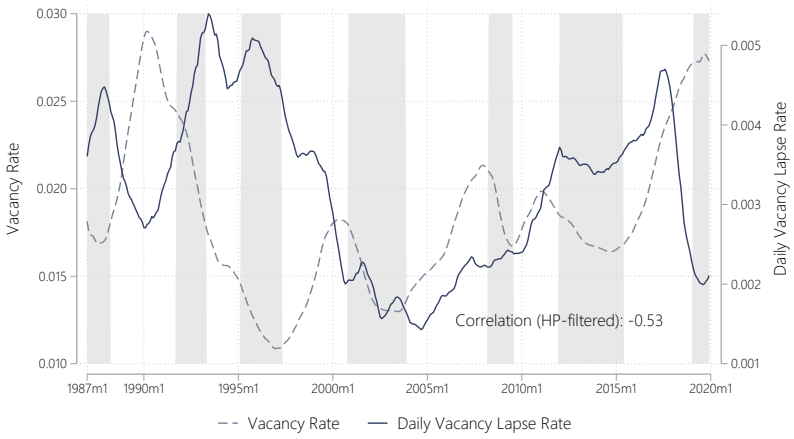
(a) Vacancy Inflow Rate



(b) Vacancy Filling Rate



(c) Vacancy Lapse Rate



Notes: This figure shows the daily vacancy inflow, filling and lapse rate based on AMS data from 1987 – 2019, where we apply a 13-month centered moving average. OECD based Recession Indicators for Austria from FRED (2023).

3.2 The Importance of Ins and Outs for Vacancy Fluctuations

In this section, we apply a decomposition analysis of the time series variation of the stock of vacancies in Austria, similar to the one used by Shimer (2012) for the unemployment rate in the US. More specifically, we decompose the variance of the monthly steady-state vacancy rate from equation (3)

$$v_t^{ss} = \frac{n_t}{n_t + f_t + l_t},$$

using the counterfactual steady-state vacancy rates

$$\begin{aligned} \tilde{v}_t^f &= \frac{\bar{n}}{\bar{n} + f_t + \bar{l}}, \\ \tilde{v}_t^l &= \frac{\bar{n}}{\bar{n} + \bar{f} + l_t}, \\ \tilde{v}_t^n &= \frac{n_t}{n_t + \bar{f} + \bar{l}}, \end{aligned} \tag{4}$$

where $\bar{n}$, $\bar{f}$, and $\bar{l}$ are the averages of the aggregated monthly inflow rate n_t, the filling rate f_t, and the lapse rate l_t, which can be exactly measured on a daily basis for all vacancies in the AMS universe between 1987 and 2019. The counterfactual vacancy rates $\tilde{v}_t^f$, $\tilde{v}_t^f$ and $\tilde{v}_t^f$ measure the fluctuations in the vacancy rate that are due to changes in the inflow rate n_t, due to changes in the filling rate f_t or due to changes in the lapse rate l_t, while holding all other flow rates constant. We decompose the relative importance of these counterfactual vacancy rates by their covariance with the steady-state vacancy rate v_t^{ss}, i.e.,

$$\beta^x = \frac{cov(\tilde{v}_t^x, v_t^{ss})}{var(v_t^{ss})}, \quad \forall \quad x \in \{f, l, n\}. \tag{5}$$

The Ins and Outs of Vacancies in Austrian AMS Data. Table 2 reports the coefficients β^x of a bivariate regression of the counterfactual vacancy rates $v_t^x, x \in \{n, f, l\}$ from equation (4) on the steady-state vacancy rate v_t^{ss} for different samples. Column (1) shows the results of the variance decomposition for all vacancies in the AMS universe over the full-time period 1987 – 2019. While vacancy fillings account for approximately 55% of the time series variation in the vacancy rate, the inflow rate is also important, accounting for about 35% of the variation in the vacancy rate. In contrast, vacancy lapses only account for 9% of the time series variation in the vacancy rate. Columns (2) and (3) of Table 2 confirm that the results are very similar for the matched establishment sample, where we can link establishment identifiers in the AMS vacancy data to establishment identifiers in the ASSD. However, because establishment identifiers

TABLE 2
THE INS AND OUTS OF VACANCIES

	Austrian AMS Data			US Data
	Universe		Matched	JOLTS
	1987 – 2019	1995 – 2019	1995 – 2019	2001 – 2019
Variation in Steady-State Vacancy Rate v_t^{ss} due to...				
Vacancy Inflows $\tilde{v}_t^n$	0.345	0.484	0.429	0.454
	(0.032)	(0.025)	(0.033)	(0.026)
Vacancy Fillings $\tilde{v}_t^f$	0.547	0.500	0.556	0.596
	(0.020)	(0.020)	(0.026)	(0.024)
Vacancy Lapses $\tilde{v}_t^l$	0.092	0.012	–0.002	0.004
	(0.015)	(0.021)	(0.021)	(0.001)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$. AMS universe covers the time period 1987 – 2019, the matched establishment universe covers the time period 1995 – 2019, and JOLTS data covers the time period 2001 – 2019. We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000. Newey-West standard errors are given in parentheses below the respective estimate.

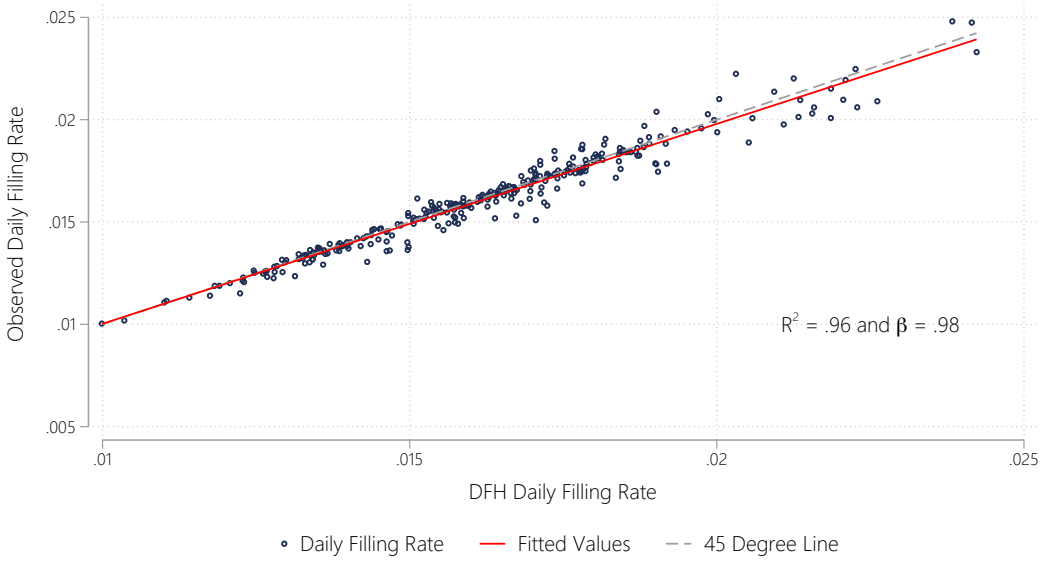
in the AMS data are only available from 1994, we restrict the variance decomposition to the time period 1995 – 2019. As shown in Column (2), the inflow rate is slightly more important if we exclude years before 1995, accounting for approximately 43 – 48% of the time series variation in both the AMS universe and the matched establishment sample.

The lapse rate appears to contribute very little to the overall variation in the vacancy rate. While we find that the lapse rate is negatively correlated to the vacancy rate (see Figure 5), our estimates of the contribution to the business cycle variation in vacancy rates range from 0% to 9%, depending on the time period and sample. We conclude that vacancy lapses are not an important margin for business cycle variation in vacancy rates, even if on average about 15 – 20% of vacancy end in a lapsed status. This is an important finding, as the AMS vacancy database is unique in this aspect that it identifies lapses directly in the data and distinguishes fillings from lapses.[9]

[9] As mentioned above, 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

Comparison with US JOLTS Data. How do the results of the variance decomposition using the universe of all vacancies in the AMS data for Austria compare to the US? JOLTS data is available on a monthly basis from 2001 – 2019. We therefore impute daily filling rates in the JOLTS data based on the Davis, Faberman and Haltiwanger (2013) (DFH) approach (see Appendix B.2.2 for details). Figure 6 compares the observed daily filling rate in the AMS universe to the imputed filling rate based on the DFH approach and shows that the imputed filling rates are very similar to the observed daily filling rates with a slope coefficient of 0.98 and an R^2 of 0.96, confirming the validity of the DFH approach. Column (4) of Table 2 compares the importance of vacancy fillings and inflows in Austria to the US for the restricted time period 2001 – 2019. Remarkably, both the filling rate and the inflow rate are similarly important in the US. More specifically, the inflow rate accounts for approximately 45% of the time series variation in the US, whereas in Austria it is between 43% and 48% in the more recent time period from 1995 – 2019. The filling rate is slightly more important in the US (60%) compared to Austria (50% to 56%), but overall still quite similar. Finally, vacancy lapses in JOLTS contribute less than 0.5% to the variation in vacancy rates. This is not surprising given that lapses in JOLTS are inferred from the total layoff rate in the JOLTS data, which is much lower in the level than the lapse rate in the AMS data.

Figure 6
DFH Filling Rate vs. Observed Daily Filling Rate in AMS Data



Notes: This figure compares the daily filling rate based on the Davis, Faberman and Haltiwanger (2013) approach to the directly observed daily filling rate in the AMS data from 1994 – 2019. See Appendix B.2.2 for details.

sites (Albrecht, Decreuse and Vroman, 2023).

Further Robustness. Appendix Section B.2 provides various robustness checks, confirming the robustness of our baseline results. More specifically, Appendix Tables B.1 – B.3 illustrate that the variance decomposition is robust across various filters and to using an X-13ARIMA-SEATS seasonal adjustment (Sax and Eddelbuettel, 2018), instead of our baseline 13-month centered moving average. Furthermore, Appendix Table B.4 shows that using the actual vacancy rate v_t instead of the steady-state vacancy rate v_t^{ss} does not affect our conclusion. Finally, Appendix Table B.5 confirms that even when using different vacancy duration concepts (JOLTS and AMS instead of the Posting duration) results remain very similar and Appendix Table B.6 validates the results for US JOLTS data with different filtering methods.

4 Replacement Hiring and Vacancy Inflows

As emphasized by Mercan and Schoefer (2020) and Elsby et al. (2022), replacement hires create vacancy chains, where the poaching of a single worker can trigger multiple additional vacancy inflows if those replacements are also recruited from other firms. In order to document the importance of replacement hires for the cyclical variation in vacancy inflows, we further distinguish between vacancy inflows of new positions (new jobs), $N^n_{t,s}$, and inflows for workers who quit their job (existing jobs), $N^r_{t,s}$, such that $N_{t,s} = N^r_{t,s} + N^n_{t,s}$ and $V_{t,s} = V_{t,s-1} - H_{t,s} - L_{t,s} + N^r_{t,s} + N^n_{t,s}$. The monthly flow-steady state vacancy rate then can be written as

$$v^{ss}_{t,s} = \frac{n^r_{t,s} + n^n_{t,s}}{n^r_{t,s} + n^n_{t,s} + f_{t,s} + l_{t,s}}. \tag{6}$$

where n_t, l_t, and f_t are the inflow, lapse and filling rate defined in Section 3. Similarly, we can differentiate among hires for existing jobs, $H^r_{t,s}$, and hires for newly created jobs $H^n_{t,s}$ such that $H_t = H^r_{t,s} + H^n_{t,s}$ and $f_{t,s} = f^r_{t,s} + f^n_{t,s}$, where $f^r_{t,s} = \frac{H^r_{t,s}}{V_{t,s-1}}$ and $f^n_{t,s} = \frac{H^n_{t,s}}{V_{t,s-1}}$.

4.1 Identifying Replacement Vacancies using Daily Worker Flows

One main advantage of our linked employer-employee-vacancy data is that we are able to use firm-specific worker flows on a daily basis in order to identify replacement hires and their corresponding vacancy inflows, in order to understand the relative importance of vacancy inflows from newly created vacancies that are due to replacement of workers who quit their job. While the AMS vacancy database does not offer a breakdown between these two type of hires, we can leverage the merge of the Austrian vacancy database with the Austrian matched employed data (ASSD) to identify, which vacancies are likely linked to a replacement of a worker who quit.

Traditionally, measures of replacement hires are based on worker quits, as firms facing quits often report stable employment because contemporaneous hires exactly offset earlier separations (c.f., Mercan and Schoefer, 2020; Elsby et al., 2022). These measures range from directly using quits to proxy replacement vacancies in Mercan and Schoefer (2020) to a more refined version in Elsby et al. (2022), who use the minimum of an establishment's quits and its gross hires at a quarterly frequency or the number of hires accounted for by establishments that hold employment (near-)constant, for various inaction windows.

We develop a new and more refined approach for identifying replacement hires that takes advantage of the precise record of daily worker flows in the ASSD. More specifically, using detailed micro-level data from the ASSD that covers individual labor market histories of all private-sector employees in Austria on a daily basis, we develop a novel measure that uses daily worker flows of similar worker types between different establishments to sequentially infer replacement hires. The idea of the approach is that if hires are closely preceded by separations of the same worker type in a given establishment, the incoming worker can be assumed to be replacing the worker separating from the same establishment. Empirically, we will use different time windows around the hiring date of the worker and two definitions of separations in order to proxy for vacated but viable jobs in the data. In our baseline, we identify hires as replacement hires if we observe a separation of the same worker type (blue/white collar) between 31 days before and 14 days after the hiring date.[10] In order to mitigate the risk of misclassifying hires as replacement hires, we focus on contemporary hires and separations of workers with the *same* employment contract, i.e., we distinguish between blue and white collar workers in the same establishment, and various robustness checks confirm the validity and robustness of our novel approach.[11] To proxy voluntary separations (quits) as in Mercan and Schoefer (2020) and Elsby et al. (2022), our first measure of replacement hires uses only separations into employment, while our broader measure that takes into account 'vacant jobs' following Qiu (2023) uses all separations of the same worker type closely around the hiring date in the same establishment.

Conceptually, our approach is very similar to Elsby et al. (2022), who use the minimum of an establishment's quits and its gross hires at a quarterly frequency. But in contrast to the fixed quarterly frequency in Elsby et al. (2022), we use a dynamic time window around the hiring date that takes into account the timing of individual-level hires and separations based on daily flows of workers with the same employment

[10] Appendix Figure C.1 shows the distribution of the days between the separation and the hiring date and confirms that approximately 80% of all replacement hires happen in a very narrow time window of +/-14 days around the separation date.

[11] Importantly, we confirm that results are very similar if we focus on small firms and industries with lower turnover, where we are more confident to correctly identify replacement hires using our worker-flow approach.

contract.[12] Our worker-flow approach is also consistent with the idea that replacement hires hold employment in an establishment (near-)constant: Because the identification of a replacement hire in our worker-flow approach always requires a (close) separation of the same worker type, replacement hires hold employment constant not only at the establishment but at the establishment-worker type level. At the same time, we allow for *additional* hires that change an establishment's employment through non-replacement hires. Appendix Figures C.2 and C.3 plot DFH hockey-stick figures separately for replacement and non-replacement hires and confirm that growing establishments have higher hires rates for non-replacement hires but not for replacement hires. Finally, as in Mercan and Schoefer (2020) for Germany, Appendix Tables F.1 and F.2, as well as Appendix Figures F.1, confirm that separations into employment are replaced almost one-to-one by new hires at the establishment level in Austria. Taken together, these results suggest that we can credibly infer aggregate replacement hires from individual-level worker flows across establishments in the ASSD and relate these to the corresponding vacancy flows in the AMS.[13]

4.2 The Importance of Replacement Vacancies for Vacancy Inflows

In this section, we provide a decomposition of the vacancy inflows into the vacancy pool resulting from replacement vacancies and new vacancy inflows. That is, we compute a counterfactual vacancy rate,

$$\tilde{v}_t^{n,R} = \frac{n_t^R + \bar{n}^N}{n_t^R + \bar{n}^N + \bar{f} + \bar{l}}, \tag{7}$$

where we only allow the inflow rate due to replacement vacancies n_t^R to vary over time and similarly for inflows for new vacancies n_t^N (see Appendix C for details). We then compute the importance of replacement inflows relative to total inflows for variations in the steady-state vacancy rate by dividing the covariance of the steady steady-state vacancy rate with the counterfactual steady-state vacancy rate due to replacement inflows from (7) by the covariance of total vacancy inflows from Table 2, i.e.,

$$\frac{cov(\tilde{v}_t^{n,R}, v_t^{ss})}{cov(\tilde{v}_t^{n}, v_t^{ss})}. \tag{8}$$

[12] Suppose all separations happen on March 31 and all hires take place on April 1. While there are no replacement hires in Elsby et al. (2022), in our worker-flow approach all hires are replacement hires. However, Appendix Figure C.4 illustrates that the aggregate business cycle dynamics are very similar for both approaches in Austria.

[13] Appendix Tables D.1 and D.2 additionally show that replacement vacancies have on average a shorter vacancy duration and a higher vacancy filling probability, suggesting that there is more pressure to fill these vacancies compared to non-replacement vacancies.

An alternative and more direct decomposition is on the level of total inflows, where we look at the covariance of total inflows, N_t, with replacement inflows, N_t^R. The decomposition of the level has the advantage that it is linear and thus exact. Finally, we can also do a variance decomposition at the hires level, where we look at the covariance of total hires, H_t, with the level of replacement hires, H_t^R. The advantage of this last decomposition is that it is not restricted to the vacancy universe and can be applied to the universe of hires in the Austrian Social Security Database (ASSD). Note that we exclude recall hires from total hires to keep the analysis comparable to the vacancy inflows. Table C.1 in the Appendix shows the same decomposition when including recall hires. Recall hires interestingly don't correlate much with the time variation in total hires, with a marginal effect of -0.09 and an average share of 25% of all hires.

Table 3
The Importance of Replacement Vacancies for Vacancy Inflows

	Rate		
Variation due to Replacements in ...	v_t^{ss}	n_t	h_t
Marginal Effect	0.356	0.284 (0.009)	0.442 (0.023)
Replacement Share	0.187	0.187	0.178
Excess Sensitivity	1.904	1.519	2.477

Notes: Column 1 shows the relative importance of replacement inflows for variation in the steady-state vacancy rate from equation (8). Column 2 shows the marginal effects of a bivariate regression of replacement inflows, n_t^R, on total vacancy inflows, n_t. Column 3 shows the marginal effects of a bivariate regression of replacement hires, h_t^R, on total hires, h_t, excluding recalled hires. Excess sensitivity is defined as the ratio of the marginal effects relative to the average share of replacement vacancies/hires over the sample period. Columns 1 and 2 use the matched establishment universe for the time period 1995 – 2019, Column 3 uses the ASSD universe for the time period 1995 – 2019. We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000. Newey-West standard errors are given in parentheses below the respective estimate.

Excess Sensitivity of Replacement Vacancies. In Table 3, we use separations of the same worker type (blue/white collar) into employment in order to identify replacement vacancies using our novel approach detailed in Section 3.1. On average, about 19% of all vacancy inflows are identified replacement vacancies in the matched establishment sample. However, inflows of replacement vacancies account for approximately 36% of

the time series variation in the steady-state vacancy rate. As a consequence, there is a substantial excess sensitivity of replacement hires – defined as the ratio of the marginal effect to the average share – of approximately 1.9. The results are similar when we use separations into employment *and* non-employment to identify replacement vacancies and replacement hires in Appendix Table C.7. The average shares of replacement vacancies are substantially larger, with an average of about 38% when using this broader definition of replacement hires. The excess sensitivity is therefore somewhat smaller when using the broader definition including separations into non-employment, with an excess sensitivity of 1.2 compared to 1.9 in Table 3. This suggests that most of the cyclical variation in replacement vacancies and hires is driven by quits to another employer.

Table 3 also illustrates that when we do a variance decomposition of the cyclical variation of hires h_t, replacement hires explain a share that is somewhat larger than the share in the decomposition of vacancy inflows n_t. This shows that the restriction to the AMS matched establishment sample for vacancy flows does not limit the general validity of our conclusions. Of course, hires are a different concept than vacancy inflows and the results may be different not only because of the different nature of the sample, but also because of differential vacancy filling rates. For this reason, Panel F. of Tables C.3 and C.4 in the Appendix report the same hires decomposition in the AMS matched establishment sample finding very similar results, showing that the different concept – vacancies vs. hires – does not affect our conclusions on the importance of replacement vacancies and hires.

Further Robustness. In addition, Appendix Section C.2 investigates the robustness of the importance of replacement vacancies for vacancy inflows and hires. Panel B. of Appendix Table C.6 shows that our results are not driven by seasonal and high-turnover industries. Appendix Table C.8 indicates that we find limited evidence of substantial differences across various measures of firm quality. However, excess sensitivity appears somewhat larger in small firms, where replacement hires are more precisely identified (see Appendix Tables C.9 and C.10). Furthermore, Appendix Table C.11 presents the complete results of the variance decomposition underlying Table 3 for various filtering methods and confirm that replacement inflows play a similarly significant role in explaining variation in the vacancy rate over the business cycle across these methods.

4.3 The Importance of Reposting for Replacement Inflows

Mercan and Schoefer (2020) show that separations into employment are replaced almost one-to-one by new hires at the establishment level.[14] They therefore assume that the reposting probability – the probability that a poached worker is replaced by the firm – in their model is constant and equal to 1. However, we will provide evidence using two different measures that the reposting probability is highly cyclical, which has important implications in our calibrated search model discussed below.

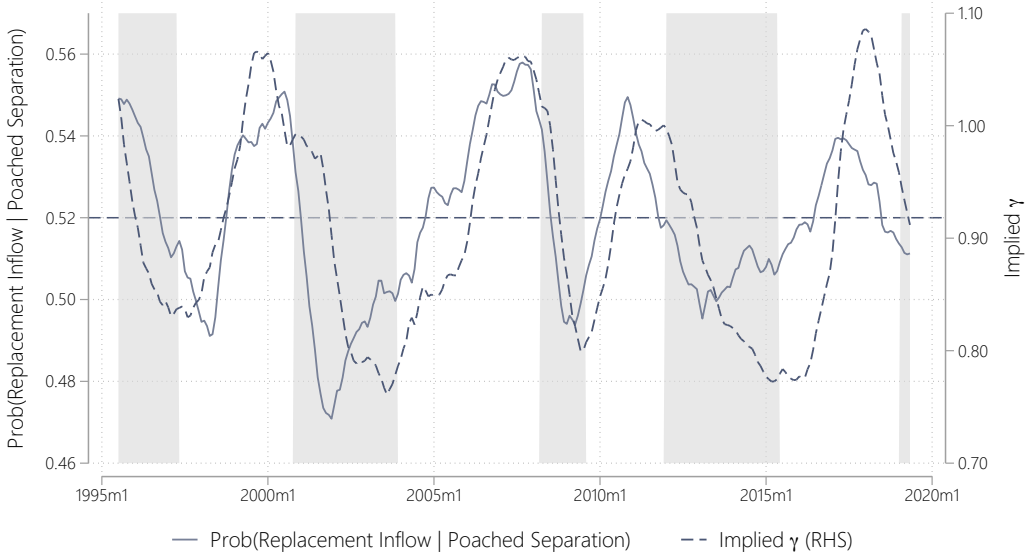
First, we will introduce a direct empirical measure of the vacancy reposting probability based on our novel approach to identify replacement hires and taking advantage of our linked vacancy-employer data at the establishment level. Because we both observe poached separations (defined as separations into employment) as well as vacancy inflows that we identify as replacement hires/vacancies (see Section 3.1 for a discussion of how we identify replacement hires), we can calculate the reposting probability Prob(Replacement Inflow | Poached Separation) as the number of replacement vacancy inflows divided by the number of poached separations in a given month. The solid line in Figure 7 plots the empirical reposting probability for the years 1995 – 2019 in our matched establishment sample. On average, approximately 52% of poached separations lead on to a vacancy inflow in the same establishment.[15] However, the reposting probability varies substantially over the business cycle, with lower reposting probabilities in downturns than in expansions. This finding is consistent with a model, where firms have a fixed cost of reposting an existing job and a value of a filled vacancy that is lower during recessions.

Second, we derive a model based measure of the reposting probability γ that is consistent with our calibrated model below and can be readily calculated using our linked vacancy-employer data. In our model in Section 6, we will assume that – as in Mercan and Schoefer (2020) and Leduc and Liu (2020) – there is an exogenous rate of obsolence ρ at which jobs become obsolete (i.e., rate of job destruction), and that firms are matched to workers at the vacancy-filling rate $q(\theta)$, where θ is the labor market tightness. For a given poached separation, the job is therefore reposted with probability γ and filled with probability $(1-\rho)q(\theta)$. Hence, we can calculate the implied reposting

[14] We replicate and confirm the results of Mercan and Schoefer (2020) for Austria in Appendix Section F.1, see Appendix Tables F.1 and F.2 for the event-study regressions in the ASSD.

[15] The observed average reposting probability might be somewhat underestimated because some vacancies are potentially not posted on the AMS platform. We will discuss this in more detail, when we introduce our second (model-based) measure of the reposting probability. However, it is important to note that the emphasis here is on the *cyclicality* of the reposting probability and, as illustrated in Figure 1, there is no evidence that the share of vacancies posted on the AMS platform varies over the business cycle.

Figure 7
Empirical Measure of the Reposting Probability



Notes: This figure shows the replacement probability Prob(Replacement Inflow | Poached Separation) and the implied γ based on

$$f^R = \gamma(1-\rho)q(\theta)$$

using monthly AMS and ASSD data from 1995 – 2019. We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000. See text for details.

probability γ in our data using

$$\gamma = \frac{f^R}{(1-\rho)q(\theta)}, \tag{9}$$

where empirically f^R are replacement vacancy fillings (i.e., replacement hires) divided by the number of poached separations, ρ is the vacancy lapse rate and $q(\theta)$ is the empirical vacancy-filling rate. The dashed line in Figure 7 plots the implied reposting probability γ. While the implied reposting probability is only slightly smaller than 1 in the data (consistent with our replication of Mercan and Schoefer (2020)), there is substantial variation over the business cycle with lower reposting probabilities during recessions, as indicated by the gray shaded areas.

Both of our empirical measures of the reposting probability indicate that the likelihood of a firm reposting a job vacated due to a poached separation is cyclical. Furthermore, we illustrate the importance of the reposting probability for vacancy inflows N_t and hires H_t using a variance decomposition of replacement inflows and hires into a reposting probability and the number of poached workers using our matched establishment sample in Table 4. More specifically, replacement vacancies and hires as a share of employment, R_t, are given by $R_t = p_t \cdot P_t$, where p_t is the conditional probability

Table 4
The Importance of Reposting for Replacement Hires

	Replacement	
	N_t	H_t
Prob(Replacement | Poached Separation)	0.366	0.333
	(0.030)	(0.017)
Poached Separations	0.634	0.667
	(0.030)	(0.017)

Notes: This table shows a variance decomposition of replacement inflows and replacement hires into a reposting probability and the number of poached workers using AMS and ASSD data for the time period 1995 – 2019. More specifically, replacement vacancies and hires as a share of employment, R_t, are given by

$$R_t = p_t \cdot P_t,$$

where p_t is the conditional probability of replacing a poached worker and P_t are poached workers as a share of employment in month t. We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000.

of replacing a poached worker and P_t are poached workers as a share of employment in month t. As highlighted in Table 4, the reposting probability accounts for roughly one-third of the variation in replacement hires and vacancy inflows in the data, which illustrates that replacement hires not only depend on the number of poached separations, but also on the willingness of a firm to repost a vacated job. We will therefore assess the implications of a cyclical reposting probability for the importance of vacancy inflows and the vacancy chain multiplier in our calibrated search model below.

5 Vacancy Composition and Vacancy Outflows

In this section, we assess the importance of compositional changes of the vacancy pool over the business cycle for the filling rate. More specifically, given detailed vacancy and firm characteristics including firm-level identifiers over a long time period, our data allows documenting whether the composition of the vacancy pool changes over the business cycle (Hershbein and Kahn, 2018; Modestino, Shoag and Ballance, 2020) and whether the composition of vacancies explain variation of job-filling rates over

the business cycle (Mongey and Violante, 2019).[16] We start by descriptively showing that characteristics of vacancies vary over the business cycle, in line with upskilling in periods of low vacancy rates (Hershbein and Kahn, 2018; Modestino, Shoag and Ballance, 2020) and changes in the pool of unemployed documented for the US (Baker, 1992; Mueller, 2017; Mueller and Spinnewijn, 2023). However, differences in the filling rate across different vacancies and firms are too small to explain meaningful variation in the aggregate monthly vacancy filling rate over the business cycle, as we will confirm using a formal variance decomposition of the vacancy filling rate.

Vacancy Characteristics over the Business Cycle. We start by descriptively showing that vacancy characteristics of vacancies that are posted at different points in time vary with the business cycle. Figures D.1 – D.7 in Appendix Section D.1 confirm that the share of high-skill vacancies increases during recessions, where vacancy rates are low (and unemployment rates are high). Furthermore, Figure D.10(b) illustrates that the share of replacement vacancies decreases during recessions. Together with the results in Tables D.1 and D.2 that replacement vacancies have on average shorter vacancy duration and higher vacancy filling probabilities, this suggests that compositional changes over the business cycle might explain variation in the filling rate over the business cycle, not only through an upskilling of vacancies but also a shift towards non-replacement vacancies in recessions.

Non-Importance of Compositional Changes for Filling Rate. In this section, we assess the importance of compositional changes of the vacancy pool over the business cycle more formally using a variance decomposition of the monthly filling rate. More specifically, based on daily firm-specific filling rates $f_{i,t,d}$, we compute a firm-level monthly filling rate $f_{i,t}$ and estimate the fixed-effects model

$$f_{i,t} = \psi_i + \delta_t + \Gamma' X_{i,t} + \varepsilon_{i,t}, \tag{10}$$

where ψ_i are firm fixed-effects and δ_t are time fixed-effects. Γ is a vector of coefficients and $X_{i,t}$ is a vector of control variables controlling for firm characteristics (firm size, firm location and industry) and vacancy characteristics (education levels, employment extent, job duration, types of jobs). Additionally, we control for firm-specific monthly DFH employment growth, and whether the vacancy is identified as a replacement vacancy. We then use the estimated coefficients from equation (10), to decompose the

[16] A main advantage of our data set compared to e.g. Burning glass data in the US, which is only available for years 2007 and 2010-now, is the longer time period from 1995 – 2019 and the availability of firm-level identifiers that allows to distinguish within and across firm variation in addition to detailed vacancy characteristics.

observed monthly filling rate f_t according to

$$f_t \approx \overline{\hat{\psi}}_t + \hat{\delta}_t + \overline{\hat{\chi}}_t, \tag{11}$$

where the firm-fixed effect and the partial prediction of the covariates are a weighted average using the monthly vacancy stocks as weights (see Appendix D.3 for details). In order to assess the importance of compositional changes in the vacancy pool for the filling rate over the business cycle, we report results for the variance decomposition

$$\underbrace{\frac{cov(f_t, f_t)}{var(f_t)}}_{=1} = \underbrace{\frac{cov(f_t, \overline{\hat{\psi}}_t)}{var(f_t)}}_{\text{Firm FE}} + \underbrace{\frac{cov(f_t, \hat{\delta}_t)}{var(f_t)}}_{\text{Time FE}} + \underbrace{\frac{cov(f_t, \overline{\hat{\chi}}_t)}{var(f_t)}}_{\text{Characteristics}} \tag{12}$$

where we use weighted averages of estimated firm fixed effects $\hat{\psi}_i$, the estimated time fixed effects $\hat{\delta}_t$, and the firm-specific partial prediction of the monthly filling rate $f_{i,t}$ based on the vacancy and firm characteristics $\hat{\chi}_{i,t} = \hat{\Gamma}' X_{i,t}$ from the fixed-effects model (10).

Table 5
(Non-)Importance of Compositional Changes for Vacancy Fillings

Variation in	Monthly Filling Rate f_t					
due to...	Firm FE	Characteristics $\hat{\chi}_t$				Time FE
	$\hat{\psi}_t$	Vacancy	Firm	Growth	Repl.	$\hat{\delta}_t$
Variance Share	0.0257	0.0358***	-0.0930***	0.0331***	-0.0002	1.010***
	(0.0188)	(0.0137)	(0.0098)	(0.0059)	(0.0013)	(0.0198)

Notes: This table shows a variance decomposition of the observed monthly vacancy filling rate according to equation (12) in the matched establishment sample for the time period 1995 – 2019. We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000. More specifically, the coefficients measure variation in the monthly filling rate f_t that is due to the firm fixed-effect $\hat{\psi}_t$, the time fixed-effect $\hat{\delta}_t$, and the partial prediction of the vacancy and firm characteristics $\hat{\chi}_t$, see text for details.

Table 5 reports the results of the variance decomposition of the monthly filling rate from equation (12) for the matched establishment sample over the time period 1995 – 2019 and shows that compositional changes in the vacancy pool cannot explain any meaningful variation in the monthly filling rate. In contrast, the estimated time

fixed-effect accounts for all the time series variation in the aggregate filling rate, with a coefficient close to 1.[17] We also find that shifts in the employment growth distribution only explain a small share of the variation in job filling rates, in line with results in JOLTS microdata by Mongey and Violante (2019). In sum, despite our rich firm- and vacancy-level data and some evidence of compositional changes in the vacancy characteristics over the business cycle, systematic differences in the filling rate across different vacancy and firm characteristics are too small to explain meaningful variation in the filling rate over the business cycle.

6 Vacancy Flows and Replacement Hires in a Search Model

Our empirical results demonstrate the importance of replacement hires for cyclical variation in vacancy inflows. As emphasized by Mercan and Schoefer (2020) and Elsby et al. (2022), replacement hires lead to vacancy chains, where the poaching of one worker can lead to many additional replacement vacancy and hires if replacement hires are also poached from other firms. This mechanism amplifies the cyclical fluctuations in the labor market in terms of vacancies and hires, and ultimately also unemployment.

To highlight the crucial role of job search – particularly replacement hires – in explaining the observed importance of vacancy inflows for cyclical fluctuations in the vacancy rate, we calibrate a search-theoretic model incorporating both job search and replacement hires and using empirical moments from the Austrian vacancy and social security data. As we highlighted above, the reposting probability – i.e., the probability that an idle vacancy is reposted – is not constant but varies across the business cycle. We will therefore also assess the implications of a cyclical reposting probability (as observed in the data) for the importance of vacancy inflows and the vacancy chain multiplier in our calibrated search model and illustrate that a cyclical reposting probability will be crucial for the volatility of the vacancy chain multiplier in the model.

Vacancy Rate Decomposition and Vacancy Chains in a Calibrated Search Model. This section proposes a simple extension of the standard DMP model, allowing for fixed costs in vacancy creation, endogenous recruiting effort, as well as on-the-job search and replacement hires. Following Leduc and Liu (2020) and Mercan and Schoefer (2020), we assume random matching with CRS matching function $M = M(S, aV)$, where $S = u + \sigma(1 - u)$ is aggregate search effort, σ is the employed workers' search effectiveness (relative to unemployed) and a is a measure of recruiting effort. The

[17] Appendix Figures D.11 and D.12 plot the average time and firm fixed effect over the sample period. Furthermore, Appendix Tables D.3 and D.4 confirm the robustness of these results to using different filters (Table D.3) and using vacancy duration as an outcome (Table D.4).

implied job-finding rate for unemployed is $\lambda(\theta) = M/S$ and for employed $\sigma\lambda(\theta)$, where $\theta = \frac{aV}{S}$ is labor market tightness.[18] Firms exert recruiting effort a at cost $k(a)$, with $k(0) \geq 0$, $k'(a) > 0$ and $k''(a) > 0$, and are matched to workers at rate $aq(\theta)$, where $\lambda(\theta) = \theta q(\theta)$. Finally, firms face a fixed vacancy creation cost x, which is i.i.d. and drawn from distribution $F(\cdot)$. Wages are determined by Nash Bargaining with worker bargaining share α and vacancies are determined endogenously by the condition that there are zero profits from vacancy creation: $n = F(V)$. Appendix Section E describes the full model in detail, in the main text we only highlight the relevance of on-the-job search and replacement hires for the empirically observed importance of vacancy inflows and the implications of a cyclical reposting probability.

We calibrate the initial steady-state to match the average vacancy and unemployment rate as well as the average job-finding, vacancy-filling and vacancy inflow rate in the Austrian data (see Appendix Section E.3 for details). Using a negative productivity shock from the initial steady state with $p_0 = 1$ to $p_1 = 0.96$, we will then perform a similar vacancy rate decomposition as in the data using our calibrated search model. More specifically, because in flow steady state

$$\tilde{v}_t = \frac{\tilde{n}_t}{\tilde{n}_t + \tilde{f}_t + \tilde{l}_t},$$

with

$$\begin{aligned} \tilde{n}_t &= \frac{(1-\rho)(\delta + (1-\delta)\sigma\lambda(\theta_t)) + n_t}{v_t + (1-u_t)} \\ \tilde{f}_t &= (1-\rho)aq(\theta_t) \\ \tilde{l}_t &= \rho \end{aligned} \tag{13}$$

we have the model analogues to equation (4) above

$$\tilde{v}^f = \frac{\tilde{n}_0}{\tilde{n}_0 + \tilde{f}_1 + \tilde{l}_0} \tag{14}$$

$$\tilde{v}^n = \frac{\tilde{n}_1}{\tilde{n}_1 + \tilde{f}_0 + \tilde{l}_0} \tag{15}$$

for a baseline calibration $t = 0$ and a counterfactual steady state calibration $t = 1$ following a negative productivity shock from $p = 1$ to $p' = 0.96$.[19] Furthermore, we can express the vacancy chain multiplier – i.e., the number of additional vacancy inflows

[18] We normalize the matching function such that $\lambda(1) = 1$.

[19] Note that in the model, rates are denoted by $\sim$ and we assume a constant and exogenous rate of job destruction ρ in our model, consistent with our empirical finding that vacancy lapses are not an important margin for business cycle variation in vacancy rates.

for a given poached separation – as (see Appendix E.5 for the derivation)

$$\phi_t = \frac{\gamma\left(\rho + (1-\rho)q(\theta_t)\right)}{1-(1-\rho)\Big(\big(1-q(\theta_t)\big) + (1-\Psi_t)\gamma_t q(\theta_t)\Big)} \tag{16}$$

where $\Psi_t = u_t/S_t$ is the probability to meet an unemployed job-searcher and γ_t is the reposting probability. To illustrate equation (16), suppose that we have no on-the-job search – i.e., $\Psi = 1$ – and a reposting probability $\gamma = 1$. In this case, the vacancy chain multiplier ϕ is exactly equal to one and a separation leads to exactly one additional vacancy inflow. However, for cases with $\Psi < 1$ (and $\gamma < 1$), the vacancy multiplier will be larger than 1.

Vacancy Rate Decomposition in Calibrated Search Model. We start by reporting the results for the vacancy rate decomposition in the calibrated search model for a negative productivity shock from $p_0 = 1$ to $p_1 = 0.96$. The first column in Table 6 shows that the vacancy rate in the initial steady state equals $\tilde{v}_0 = 0.0360$.[20] In the model without on-the-job search – i.e., a relative search efficiency of employed workers $\sigma = 0.001$ – and a constant reposting probability $\gamma_0 = \gamma_1 = 1$ in Panel A., the vacancy rate decreases to $\tilde{v}_1 = 0.0299$, following a negative productivity shock by 4%. However, as illustrated in columns (3) and (4), the reduction in the vacancy rate $\tilde{v}$ is primarily driven by vacancy fillings $\tilde{v}_1^f$, while vacancy inflows $\tilde{v}_1^n$ remain unaffected. In contrast, in a model with on-the-job search (and, therefore, replacement hires) with relative search efficiency $\sigma = 0.050$, the vacancy rate is more responsive to a negative productivity shock. While the counterfactual vacancy rate due to variations in vacancy fillings $\tilde{v}_1^f$ decreases to approximately 0.0300, as in the model without job search, vacancy inflows $\tilde{v}_1^n$ also adjust, resulting in a larger overall reduction in the vacancy rate. This reduction in the vacancy inflow rate is driven by a lower job-finding rate of employed workers $\sigma\lambda(\theta)$, which decreases the necessity for firms to replace vacated jobs due to poached separations in equation (13). Overall, we find that in our calibrated model with on-the-job search and replacement hires, vacancy inflows account for approximately 27% of the decrease in the vacancy rate.[21]

Comparing the results with a constant reposting probability in Panel A. to a model with a cyclical reposting probability, where γ decreases from $\gamma_0 = 1$ to $\gamma_1 = 0.93$ in line with our empirical evidence, we see that the cyclical reposting probability does

[20] Because we (implicitly) match the vacancy rate in our calibration, the initial vacancy rate is the same across all model specifications in Table 6, which facilitates the comparison for different values of relative search efficiency σ and the reposting probability γ.

[21] This share is still slightly below the 34.5% that we find for the universe of the AMS data between 1987 and 2019 in Table 2. However, in our steady-state comparison, we abstract from transitional dynamics, which might be important to capture the magnitude of vacancy inflows in the model.

not affect the importance of vacancy inflows. This result is driven by the fact that, in the steady state, the decrease in replacement vacancy inflows is exactly offset by an increase in new vacancy inflows n_t in equation (13) (see also Table E.3). As a consequence, even though vacancy inflows decrease by the same amount, the pool of vacancy inflows is different – with fewer replacement vacancies and more new vacancy inflows in a model with a cyclical reposting probability – consistent with the lower share of replacement vacancies during recessions in Appendix Figure D.10. However, and as we will illustrate in the following, a cyclical reposting probability has important implications for the vacancy chain multiplier.

Table 6
Vacancy Rate Decomposition and the Vacancy Chain Multiplier in Calibrated Search Model

	Vacancy Rate $\tilde{v}$				Multiplier ϕ	
	$p_0 = 1$	$p_1 = 0.96$			$p_0 = 1$	$p_1 = 0.96$
	$\tilde{v}_0$	$\tilde{v}_1$	$\tilde{v}_1^f$	$\tilde{v}_1^n$	ϕ_0	ϕ_1
Panel A. Constant Reposting Probability: $\gamma_0 = 1, \gamma_1 = 1$						
$\sigma = 0.001$	0.0360	0.0299	0.0300	0.0360	1.0101	1.0084
	—	1.0000	0.9929	0.0085	—	-0.0017
$\sigma = 0.050$	0.0360	0.0280	0.0298	0.0339	1.4963	1.4107
	—	1.0000	0.7790	0.2654	—	-0.0572
Panel B. Cyclical Reposting Probability: $\gamma_0 = 1, \gamma_1 = 0.93$						
$\sigma = 0.001$	0.0360	0.0299	0.0300	0.0360	1.0101	0.9375
	—	1.0000	0.9929	0.0085	—	-0.0723
$\sigma = 0.050$	0.0360	0.0280	0.0298	0.0339	1.4963	1.2752
	—	1.0000	0.7790	0.2654	—	-0.1478

Notes: Decomposition of the vacancy rate $\tilde{v}$ and the implied vacancy chain multiplier ϕ in a calibrated search model following a negative productivity shock for different values of relative search efficiency σ and the reposting probability γ. The counterfactual vacancy rates $\tilde{v}^f$ and $\tilde{v}^n$ are defined in equation (14) and (15). The vacancy chain multiplier ϕ is calibrated according to equation (16). Panel A. shows the results with a constant reposting probability, while Panel B. shows the results for a cyclical reposting probability. See main text and Appendix E for details.

Vacancy Chain Multiplier in Calibrated Search Model. As shown in equation (16), the vacancy chain multiplier ϕ captures the number of additional vacancy inflows generated by a single poached separation, since poaching one worker can trigger multiple replacement vacancies if replacement hires are also poached from other firms. The last two columns in Table 6 report the implied vacancy chain multiplier ϕ in our calibrated search model. As noted earlier, the vacancy chain multiplier is exactly equal to 1 in a model without job search, since there are essentially no vacancy chains – new hires are drawn entirely from the pool of unemployed. More interestingly, in the model with job search, the implied multiplier in the initial steady state is equal to 1.5, implying that one poached separation triggers on average 0.5 additional vacancy inflows.[22] Following a negative productivity shock from $p_0 = 1$ to $p_1 = 0.96$ and a constant reposting probability, the vacancy chain multiplier decreases by approximately 6% to 1.4 in Panel A. Hence, vacancy chains become shorter during recessions. However, allowing for a cyclical reposting probability in Panel B., increases the volatility of the vacancy chain multiplier substantially. While the vacancy chain multiplier only decreases by approximately 6% with a constant reposting probability, the vacancy chain multiplier with a cyclical reposting probability is much more volatile – with a decrease of approximately 15% for the same productivity shock. Thus, the cyclical reposting probability documented in the data has significant implications for the vacancy chain multiplier, thereby affecting cyclical fluctuations in the labor market regarding vacancies and hires, and ultimately unemployment.[23]

7 Conclusion

This paper uses large-scale high-frequency data on vacancy flows and matched social security data from Austria to provide evidence on the contribution of in- and outflows for the cyclical variation of the stock of vacancies. Using a decomposition analysis of the time series variation of the stock of vacancies, similar to the one used by Shimer (2012) for the unemployment rate, we document that vacancy inflows explain at least one-third of the cyclical variation in the vacancy stock, whereas the remainder is explained by vacancy fillings. Vacancy lapses, while accounting for about 20% of vacancy outflows, are acyclical and do not contribute to variation in the stock. We highlight

[22] This is slightly lower than the calibrated vacancy chain length of 1.88 in Mercan and Schoefer (2020). However, the longer vacancy chain length in Mercan and Schoefer (2020) is mostly a result of the lower unemployment rate in their calibration. With an unemployment rate of $u = 0.087$ instead of $u = 0.057$, their calibrated vacancy chain length is $E(C) = 1.56$ and very close to our vacancy chain multiplier in Table 6.

[23] As illustrated in Table E.3, in our steady-state model, the unemployment rate is not more volatile in a model with a cyclical reposting probability. However, in a model with transitional dynamics – which is currently a work in progress –, an overshooting of the unemployment rate could yield an amplification of the unemployment rate volatility consistent with Elsby et al. (2022).

that replacement vacancies, i.e. vacancies posted following a quit of a worker to another firm, are a key driver of vacancy inflows over the business cycle. Furthermore, taking advantage of the detailed matched employer-employee data, we show that the composition of vacancy inflows varies little over the business cycle and cannot account for the cyclical variation in vacancy filling, similar to studies on cyclical movements in the composition of the unemployed (Baker, 1992; Kroft et al., 2016; Mueller and Spinnewijn, 2023). Using a search-and-matching model with fixed costs of vacancy posting and on-the-job search calibrated it to match the averages of vacancy flows, we highlight the crucial role of on-the-job search – particularly replacement hires – in explaining the observed importance of vacancy inflows for cyclical fluctuations in the vacancy rate. The model confirms that replacement hires are an important determinant of the variation of the vacancy stock over the business cycle and highlights the importance of business cycle fluctuations in the reposting probability, i.e. the probability to post a vacancy after a poached separation, for the vacancy chain multiplier effect over the business cycle. In sum, these findings have important implications for the modeling and calibration of aggregate labor market dynamics in models with search and matching frictions, as a longer and more cyclical vacancy chain amplifies the fluctuations in the unemployment rate.

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Online Appendix of: The Ins and Outs of Vacancies*

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A Data and the Austrian Labor Market

A.1 AMS Vacancy Data

The AMS vacancy data covers all vacancies posted through the AMS (approx. 60% of all vacancies in Austria) for the time period 1987 – 2019. The data consists of two different data deliveries with slightly different information.[1] While firm identifiers are only available from 1994 onwards, the data set allows to construct aggregate time series starting already in 1987. In addition, exact posting and filling dates are only available from 2007. However, daily AMS duration is available for the full sample period, which allows to approximate the daily posting and filling dates based on the monthly inflow and outflow dates together with daily AMS duration.

A.1.1 Matched Establishment Sample

In order to match AMS firm identifiers (`btr`) to ASSD establishment identifiers (`benr`), we match AMS establishment identifiers to the ASSD using an official cross-walk, where we restrict to entries with a high reliability (based on propensity scores in the official cross-walk). We define two matched subsamples for our analysis (in addition to the AMS and ASSD universe):

- **Matched Establishment Universe**: a sample mirroring the AMS universe, where we include
  - AMS Firm Identifiers: only firms with a 1:1, 1:m or m:1 firm identifier change over deliveries,
  - ASSD Firm Identifiers: *all* firms in the AMS-ASSD cross-walk.
- **Restrictive Establishment Sample**: a more restrictive sample, where we include
  - AMS Firm Identifiers: only firms with a 1:1, 1:m or m:1 firm identifier change over deliveries,
  - ASSD Firm Identifiers: *only* firms with a 1:1, 1:m or m:1 match in the AMS-ASSD cross-walk.

Establishments with multiple matches in the AMS/ASSD will be aggregated: Having constructed a firm-level cross-walk that maps AMS firms to ASSD firms, we aggregate

[1] The first data delivery contains all vacancy inflows until February 2014, an update delivered by the AMS extends the sample period until December 2019. We identify firm identifier changes across data deliveries using the overlapping time period, that is covered in both data sets. More specifically, if the same vacancy (identified using the unique vacancy identifier and the posting date of the vacancy) was posted by a different firm identifier in the two data deliveries, we consider this firm to be the same. This allows to match AMS establishment identifier changes across data deliveries.

vacancy data from the AMS as well as employment data from the ASSD across different establishments within a match group. These match groups potentially consist of multiple AMS/ASSD firms, e.g., in the case of 1:m or m:1 matches. Table A.1 summarizes the different samples, and Figure A.1 shows different vacancy rates for all samples. Importantly, the dynamics of the vacancy, inflow, filling, and lapse rate are very similar in all samples.

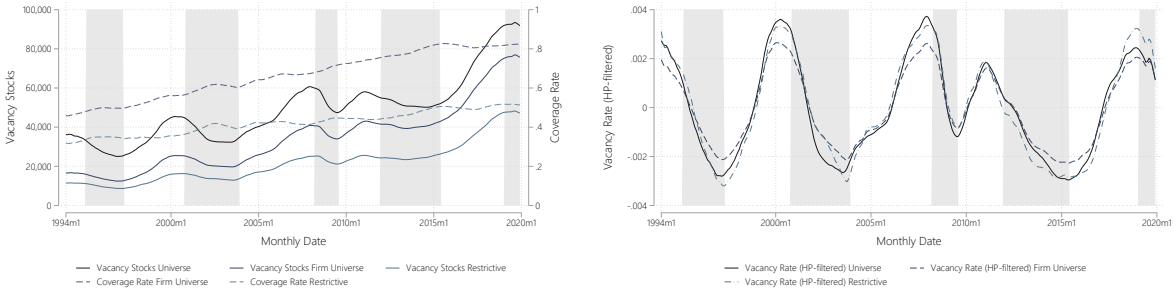
Table A.1
Number of Vacancies and Firms in Matched Firm Samples

Sample	Vacancies	Firms		
		AMS	ASSD	Adjusted
AMS Universe	**8,840,476 (100%)**	**360,818 (100%)**	**- (-)**	**- (-)**
- excluding m:m AMS Firm ID Changes	7,724,930	351,485	-	-
- excluding AMS Firms that are not in Crosswalk	6,215,584	193,612	318,282	164,643
- excluding AMS Firms w/o ASSD counterpart	6,211,000	193,307	318,282	164,338
Matched Firm Universe	**6,211,000 (70%)**	**193,307 (54%)**	**318,282 (-)**	**164,338 (-)**
- excluding m:m AMS-ASSD matches	3,971,292	156,009	250,097	151,489
Restrictive Firm Sample	**3,971,292 (45%)**	**156,009 (43%)**	**250,097 (-)**	**151,489 (-)**

Notes: The table shows the number of vacancies as well as the number of AMS and ASSD firms in the matched firm samples.

Figure A.1
AMS Universe vs. Matched Firm Samples

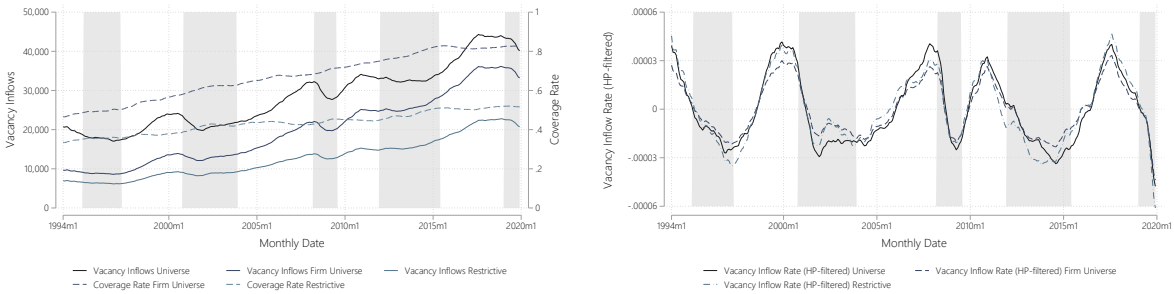
(a) Vacancy Stocks and Vacancy Rate



Mean Coverage: 0.67 (Firm Universe) 0.42 (Restrictive); Correlation: 0.99 (Firm Universe) 0.99 (Restrictive)

Correlation: 0.99 (Firm Universe) 0.98 (Restrictive)

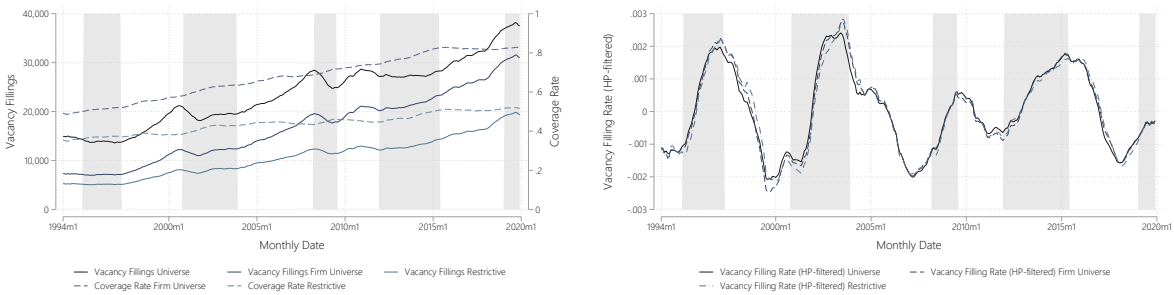
(b) Vacancy Inflows and Inflow Rate



Mean Coverage: 0.67 (Firm Universe) 0.43 (Restrictive); Correlation: 0.99 (Firm Universe) 0.99 (Restrictive)

Correlation: 0.99 (Firm Universe) 0.96 (Restrictive)

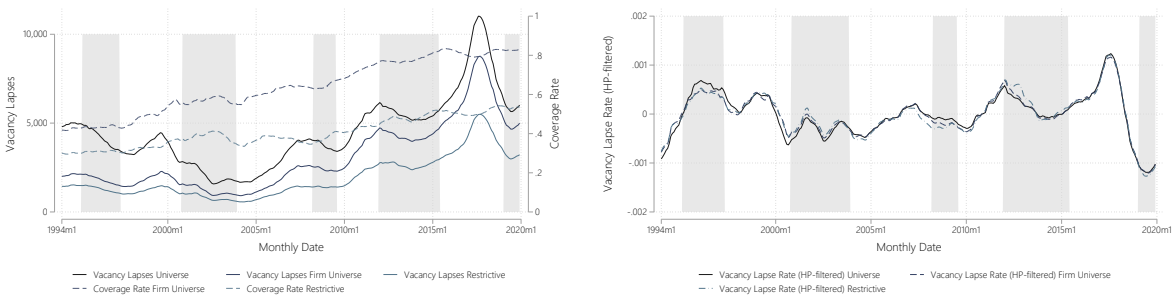
(c) Vacancy Fillings and Filling Rate



Mean Coverage: 0.68 (Firm Universe) 0.44 (Restrictive); Correlation: 0.99 (Firm Universe) 0.99 (Restrictive)

Correlation: 0.99 (Firm Universe) 0.98 (Restrictive)

(d) Vacancy Lapses and Lapse Rate



Mean Coverage: 0.64 (Firm Universe) 0.40 (Restrictive); Correlation: 0.96 (Firm Universe) 0.97 (Restrictive)

Correlation: 0.98 (Firm Universe) 0.97 (Restrictive)

Notes: This figure compares the matched firm samples to the AMS universe for the time period 1994–2019.

A.1.2 Identifying Administrative Firm Identifier Changes in ASSD.

Using a worker-flow approach on a daily basis, we identify administrative firm identifier changes in the ASSD and create a consistent firm identifier and exclude hires/separations from takeovers / spinoffs when considering replacement hires. More specifically, a firm is identified as an administrative change if more than 50% of the workers end (or start) their employment spell on the same day and start (or end) a new employment spell within 28 days around the end (or start) date of the previous (or subsequent) employment spell in the same firm.[2] We restrict to firms that have at least 6 employed workers at the outflow (or inflow) date. In addition, a worker flow of more than 50 workers is considered as an administrative change, irrespective of the share of workers. We classify administrative changes into four different categories, depending on the entry and exit date of the (original) firm identifier, based on daily firm-level employment:[3]

- **Renames**: Firm A exits, Firm B enters $\Rightarrow$ Firm A becomes B.
- **Takeover** (of Firm A): Firm A exits, Firm B does not enter $\Rightarrow$ Firm B acquires A.
- **Spinoff** (of Firm B): Firm A does not exit, Firm B enters $\Rightarrow$ Firm B emerges from A.
- **Multi-Establishment**: Firm A does not exit, Firm B does not enter.

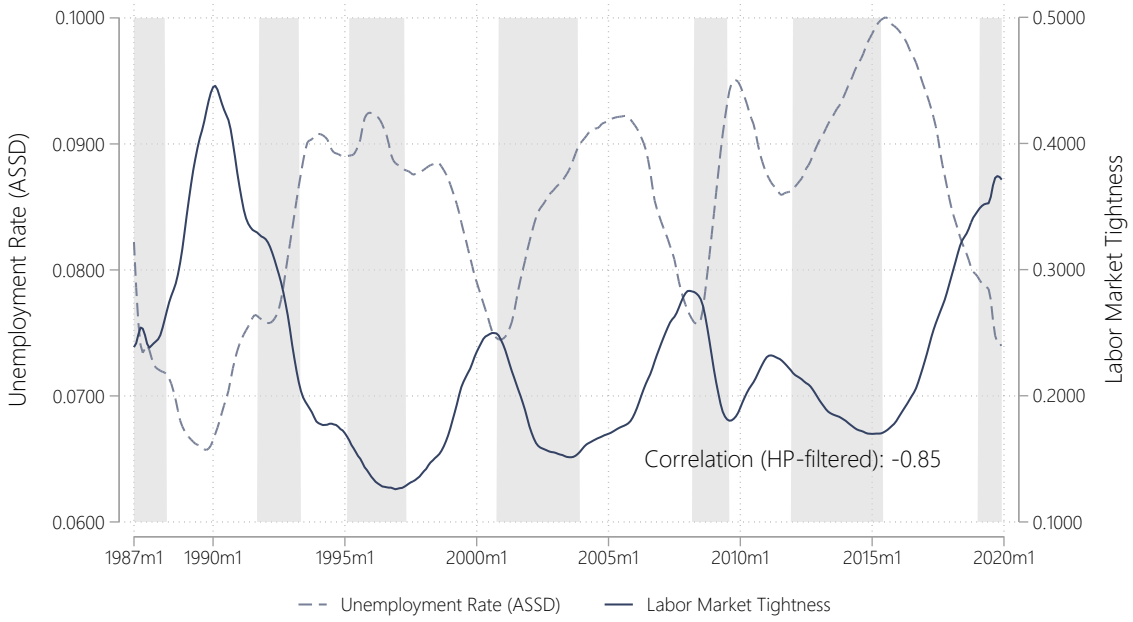
Using all firm identifiers that are classified as an administrative rename, we identify consecutive renames and generate an adjusted firm identifier that contains all ASSD firm identifiers uniquely (i.e., an original ASSD firm identifier is only part of one adjusted firm identifier).

[2] This implies that we also identify administrative changes, where an outflow is identified as an administrative change, but the inflow is not (because inflows are less than 50% of the employed) and vice versa.

[3] An entry/exit date is defined as an interruption in daily employment of more than 28 days.

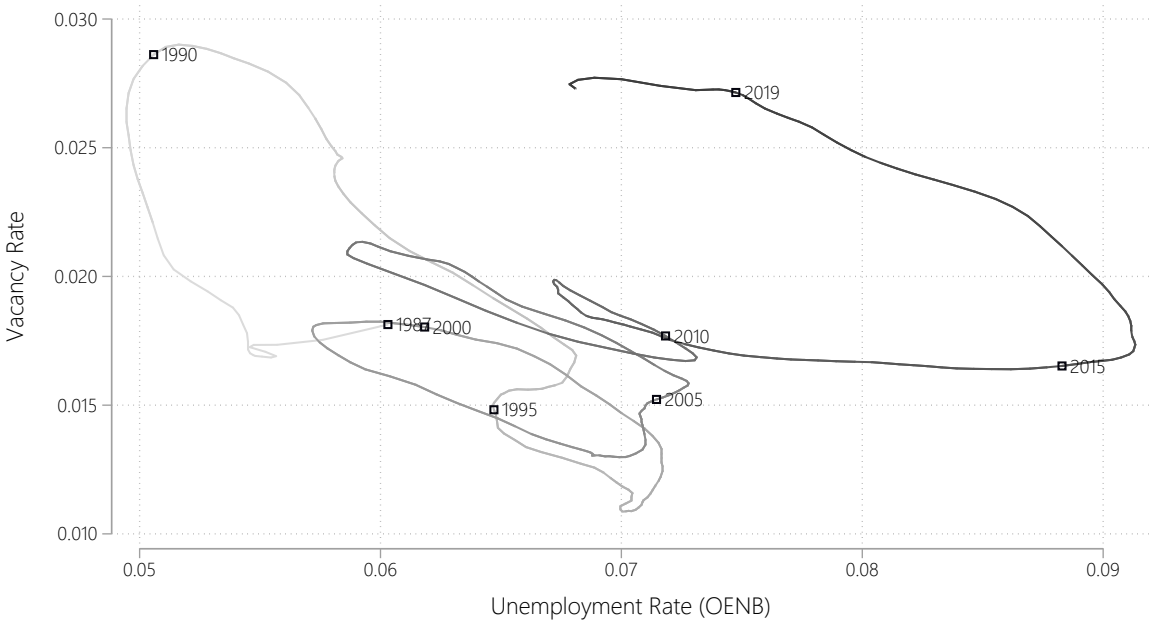
A.2 The Austrian Labor Market

Figure A.2
Labor Market Tightness



Notes: This figure shows the monthly labor market tightness based on AMS vacancy stocks and the monthly unemployment rate based on the ASSD from 1987 – 2019, where we apply a 13-month centered moving average.

Figure A.3
Beveridge Curve in Austria using OENB Uemployment Rate



Notes: This figure shows the Beveridge Curve in Austria based on the monthly vacancy rate using AMS vacancy stocks and the monthly unemployment rate from the OENB from 1987 – 2019, where we apply a 13-month centered moving average.

A.3 The Ins and Outs of Unemployment

Job Finding and Employment Exit. Following Shimer (2012), we use a similar decomposition of the unemployment rate in Austria using a simplified two-state model. More specifically, let F_t be the job finding probability and X_t the employment exit probability during period t. Assume that all unemployed workers find a job according to a Poisson process with arrival rate $f_t \equiv -\log(1 - F_t)$ and all employed workers lose their job according to a Poisson process with arrival rate $x_t \equiv -\log(1 - X_t)$. Given the law of motion for unemployment

$$u_{t+1} = (1 - F_t)u_t + n_{t+1}, \tag{A.1}$$

where n_{t+1} is the number of unemployment inflows in period $t + 1$,[4] the job finding probability is then given as

$$F_t = 1 - \frac{u_{t+1} - n_{t+1}}{u_t}. \tag{A.2}$$

In addition, using data on unemployment, employment and the job finding probability from (A.2), the unemployment exit rate is implicitly given by

$$u_{t+1} = \frac{\left(1 - \exp\left(-(f_t + x_t)\right)\right)x_t}{(f_t + x_t)}\Big(e_t + u_t\Big) + \exp\left(-(f_t + x_t)\right)u_t. \tag{A.3}$$

Note that, if unemployment is constant during period t (i.e. there is no possibility of both finding and losing a job within a period), then (A.3) becomes

$$u_{t+1} = \tilde{X}_t e_t + (1 - \tilde{F}_t)u_t, \tag{A.4}$$

where assuming $\tilde{F}_t = F_t$ implies that $\tilde{X}_t = n_{t+1}/e_t$. According to Shimer (2012), this is a good approximation when the time period is sufficiently small (e.g. weekly or monthly). As in Shimer (2012) we use seasonally adjusted data series and an HP filter with smoothing parameter 10^5.

Figure A.4 replicates Figure 1 in Shimer (2012) and shows the the job finding probability F_t and the employment exit probability X_t according to equations (A.2) and (A.3) based on the *daily* number of unemployed and employed workers as well as the number of unemployment inflows in the ASSD. In addition, Panel (b) compares plots the approximation $\tilde{X}_t$ not accounting for time aggregation bias. Figure A.5 replicates Figure 2 of Shimer (2012) and shows the hypothetical unemployment rates

[4] In Shimer (2012), the number of inflows equal the number of short-term unemployed, i.e. $n_{t+1} = u^s_{t+1}$.

using average values of f_t and x_t over the sample period

$$\hat{u}_t^f \equiv \frac{\bar{x}_t}{\bar{x}_t + f_t} \quad \text{and} \quad \hat{u}_t^x \equiv \frac{x_t}{x_t + \bar{f}_t} \tag{A.5}$$

as measures of the contribution of fluctuations in the job finding and employment exit rates to overall fluctuations in the unemployment rate and compares these counterfactual unemployment rates to the actual unemployment rate $u_{t+1}/(u_{t+1} + e_{t+1})$.[5]

With entry and exit from the labor force. In this section, we extend the simple two-state model above to account for entry and exit from the labor force. Let n_t be the 3×3 discrete time Markov transition matrix with the full month transition probabilities n_t^{AB} between state A and B. In order to account for time aggregation bias, let λ_t^{AB} again denote the Poisson arrival rate of a shock that moves worker from state $A \in \{E, U, N\}$ to state $B \neq A$ during the time interval $[t, t+1)$. According to Shimer (2012), we can calculate the matrix λ_t (under certain conditions) as

$$\lambda_t = p_t \tilde{\mu}_t p_t^{-1}, \tag{A.6}$$

where p_t is the matrix of eigenvalues of n_t and $\tilde{\mu}_t$ is a diagonal matrix with diagonal elements equal to the natural logarithm of the eigenvalues of n_t (i.e. we only need the eigenvalues of n_t). Having calculated the Poisson arrival rate matrix λ_t, we can calculate the full month transition probabilities adjusted for time aggregation bias as

$$\Lambda^{AB} = 1 - \exp\left(-\lambda_t^{AB}\right) \tag{A.7}$$

Figure A.6 replicates Figure 4 in Shimer (2012) and plots the job finding probability F_t and the employment exit probability X_t against the transition probabilities Λ_t^{AB}. Figure A.7 replicates Figure 5 in Shimer (2012) and plots the counterfactual unemployment rates using the six transition rates λ_t^{AB} according to equation (7) in Shimer (2012) against the actual unemployment rate.

[5] This assumes constant (steady-state) unemployment $u_t = u_{t+1}$.

Table A.2
The Ins and Outs of Unemployment in Austria, 1987 – 2010

	Austria	US Data
A. Job Finding and Employment Exit		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Job Finding Rate f_t	0.61	0.90
Employment Exit Rate x_t	0.40	0.10
B. Entry and Exit from the Labor Force		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Employment-Unemployment λ_t^{EU}	0.34	0.17
Employment-Nonemployment λ_t^{EN}	-0.04	-0.05
Unemployment-Employment λ_t^{UE}	0.37	0.51
Unemployment-Nonemployment λ_t^{UN}	0.13	0.16
Nonemployment-Employment λ_t^{NE}	0.18	0.09
Nonemployment-Unemployment λ_t^{NU}	0.03	0.13

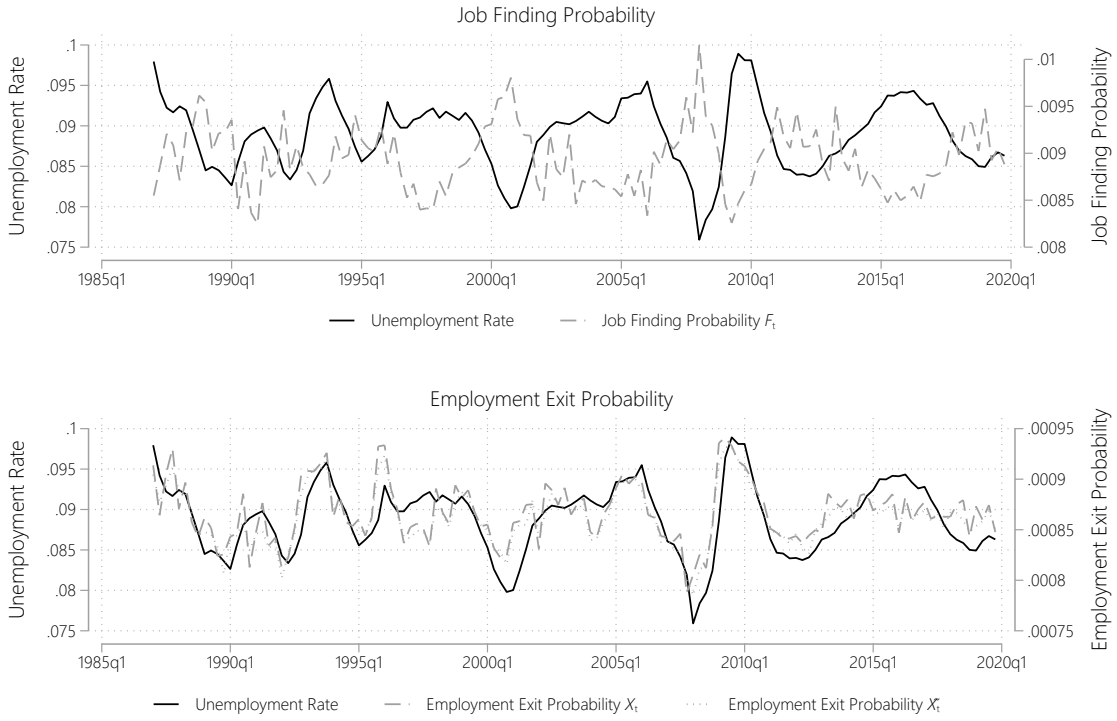
Notes: This table replicates Shimer (2012) for Austria using the ASSD from 1987 – 2010, where the last column shows the corresponding results based on US CPS data from Shimer (2012) for the time period 1987 – 2010.

Table A.3
The Ins and Outs of Unemployment in Austria, 1995 – 2019

	Austria	US Data
A. Job Finding and Employment Exit		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Job Finding Rate f_t	0.64	0.90
Employment Exit Rate x_t	0.36	0.10
B. Entry and Exit from the Labor Force		
Variation in Steady-State Unemployment Rate u_{t+1}^{ss} due to...		
Employment-Unemployment λ_t^{EU}	0.26	0.17
Employment-Nonemployment λ_t^{EN}	-0.03	-0.05
Unemployment-Employment λ_t^{UE}	0.38	0.51
Unemployment-Nonemployment λ_t^{UN}	0.14	0.16
Nonemployment-Employment λ_t^{NE}	0.23	0.09
Nonemployment-Unemployment λ_t^{NU}	0.02	0.13

Notes: This table replicates Shimer (2012) for Austria using the ASSD from 1995 – 2019, where the last column shows the corresponding results based on US CPS data from Shimer (2012) for the time period 1987 – 2010.

Figure A.4
Ins and Outs of Unemployment in Austria
Job Finding and Employment Exit Probabilities without Entry and Exit from Labor Force



Notes: The figure replicates Figure 1 of Shimer (2012) and shows job finding (top panel) as well as employment exit probabilities (bottom panel) against the actual unemployment rate based on quarterly averages of daily ASSD data for the time period 1987 – 2020. The job finding probability F_t is calculated according to equation (A.2) and the employment exit probability X_t is constructed using equation (A.3). $\tilde{X}_t$ is constructed without accounting for time aggregation using equation (A.4). All time series are seasonally adjusted and detrended using a HP filter with smoothing parameter 10^5 as in Shimer (2012).

Figure A.5

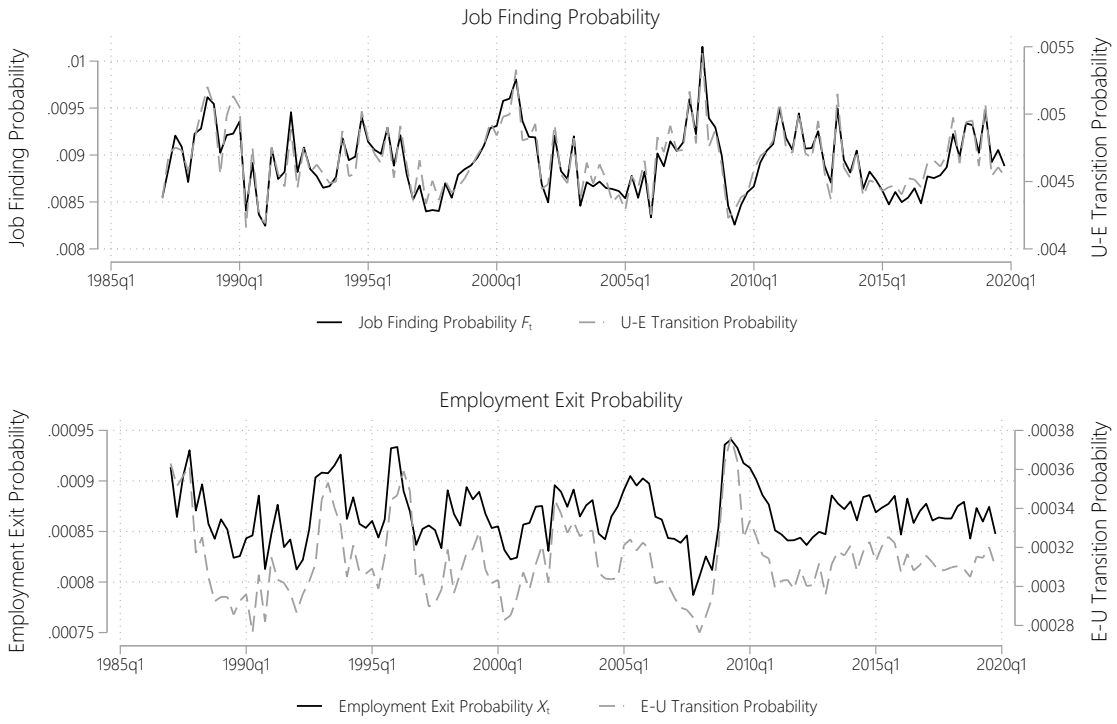
Ins and Outs of Unemployment in Austria

Contributions of Fluctuations in Job Finding and Employment Exit Rates without Entry and Exit from Labor Force



Notes: This figure plots the contributions of fluctuations in the job finding and the employment exit rate following Shimer (2012) for Austria from 1987 – 2019.

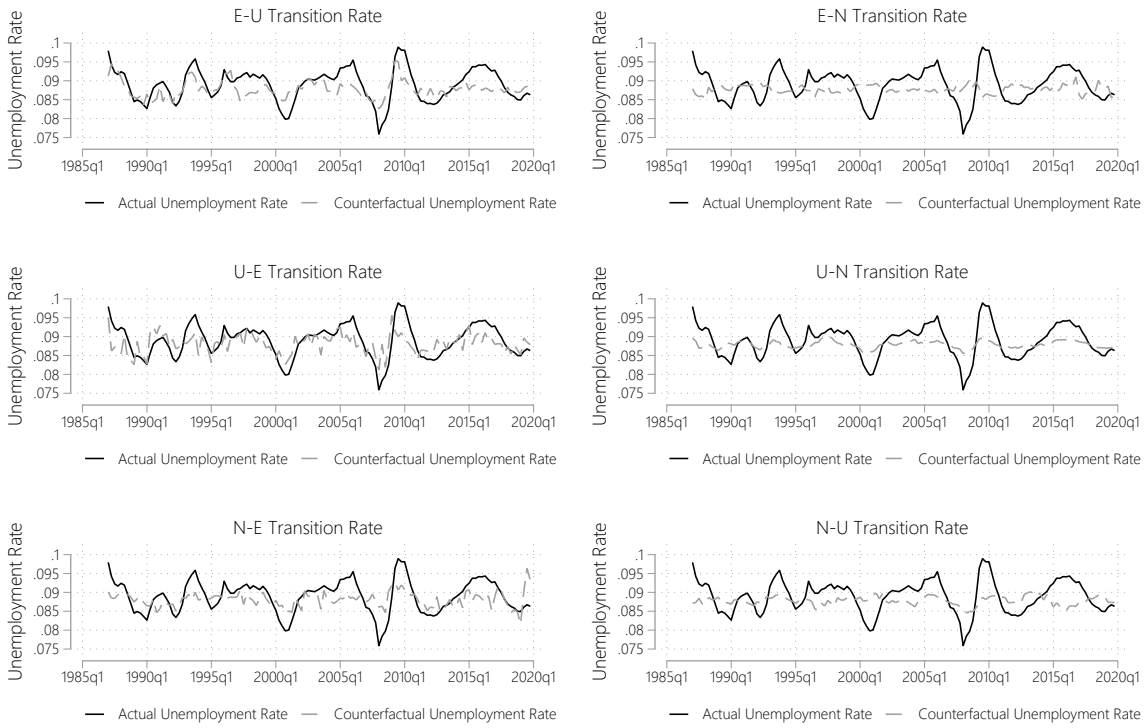
Figure A.6
Ins and Outs of Unemployment in Austria
Job Finding and Employment Exit Probabilities
with Entry and Exit from Labor Force



Notes: This figure plots the job finding and the employment exit rate following Shimer (2012) for Austria from 1987 – 2019.

Figure A.7

Ins and Outs of Unemployment in Austria
Contributions of Fluctuations in Job Finding and Employment Exit Rates with Entry and Exit from Labor Force



Notes: The figure replicates Figure 5 of Shimer (2012) and shows the contributions of fluctuations in the instantaneous transition rates to fluctuations in the actual unemployment rate based on quarterly averages of daily ASSD data for the time period 1987 – 2020. The counterfactual unemployment rates are calculated only varying the corresponding transition rate, keeping all other transition rates constant at the average rate over the full sample period. All time series are seasonally adjusted and detrended using a HP filter with smoothing parameter 10^5 as in Shimer (2012).

B The Ins and Outs of Vacancies

B.1 Measuring Vacancy Flows in the Austrian Vacancy Database

We start with

$$V_{t,s} = V_{t,s-1} - H_{t,s} - L_{t,s} + N_{t,s}, \tag{B.1}$$

and then divide by $E_{t,s-1} + V_{t,s-1}$ to get to vacancy *rate*:

$$\begin{aligned}\frac{V_{t,s}}{E_{t,s-1}+V_{t,s-1}} &= \frac{V_{t,s-1}}{E_{t,s-1}+V_{t,s-1}} - \frac{V_{t,s-1}}{E_{t,s-1}+V_{t,s-1}}\frac{H_{t,s}}{V_{t,s-1}} \\ &\quad - \frac{V_{t,s-1}}{E_{t,s-1}+V_{t,s-1}}\frac{L_{t,s}}{V_{t,s-1}} + \frac{E_{t,s-1}}{E_{t,s-1}+V_{t,s-1}}\frac{N_{t,s}}{E_{t,s-1}} \\ \frac{E_{t,s}+V_{t,s}}{E_{t,s-1}+V_{t,s-1}}v_{t,s} &= v_{t,s-1} - v_{t,s-1}\frac{H_{t,s}}{V_{t,s-1}} - v_{t,s-1}\frac{L_{t,s}}{V_{t,s-1}} + (1-v_{t,s-1})\frac{N_{t,s}}{E_{t,s-1}},\end{aligned} \tag{B.2}$$

where $H_{t,s}$ is the number of filled vacancies in month t on day s, $L_{t,s}$ the number of lapsed vacancies and $N_{t,s}$ is the number of new vacancies. Define

$$\begin{aligned} f_{t,s} &\equiv \frac{H_{t,s}}{V_{t,s-1}} \\ l_{t,s} &\equiv \frac{L_{t,s}}{V_{t,s-1}} \\ n_{t,s} &\equiv \frac{N_{t,s}}{E_{t,s-1}} \\ v_{t,s} &\equiv \frac{V_{t,s}}{E_{t,s}+V_{t,s}}, \end{aligned} \tag{B.3}$$

where $E_{t,s}$ is replaced by E_{t-1} due to lack of daily employment data. Therefore,

$$\frac{E_{t,s}+V_{t,s}}{E_{t,s-1}+V_{t,s-1}}v_{t,s} - v_{t,s-1} = (1-v_{t,s-1})n_{t,s} - v_{t,s-1}(f_{t,s}+l_{t,s}). \tag{B.4}$$

In flow steady state (i.e., assuming constant population and labor force), we have that $E_{t,s} = E_{t,s-1}$, $U_{t,s} = U_{t,s-1}$ and $V_{t,s} = V_{t,s-1}$. Let's also assume that all rates are constant within a month. Therefore, the vacancy rate in flow steady state in month t is:

$$v_t^{ss} = \frac{n_t}{n_t + f_t + l_t} \tag{B.5}$$

The monthly rates are defined as

$$
\begin{aligned}
f_t &= \sum_{i=1}^{D_t} \frac{V_{t,i-1}}{\sum_{i=1}^{D_t} V_{t,i-1}} f_{t,i} \\
l_t &= \sum_{i=1}^{D_t} \frac{V_{t,i-1}}{\sum_{i=1}^{D_t} V_{t,i-1}} l_{t,i} \\
n_t &= \sum_{i=1}^{D_t} \frac{E_{t,i-1}}{\sum_{i=1}^{D_t} E_{t,i-1}} n_{t,i} \\
v_t &= \sum_{i=1}^{D_t} \frac{E_{t,i} + V_{t,i}}{\sum_{i=1}^{D_t} E_{t,i} + V_{t,i}} v_{t,i} \\
v_t^{ss} &= \frac{n_t}{n_t + f_t + l_t}
\end{aligned}
\tag{B.6}
$$

where $E_{t,s}$ is replaced by E_{t-1} due to lack of daily employment data.

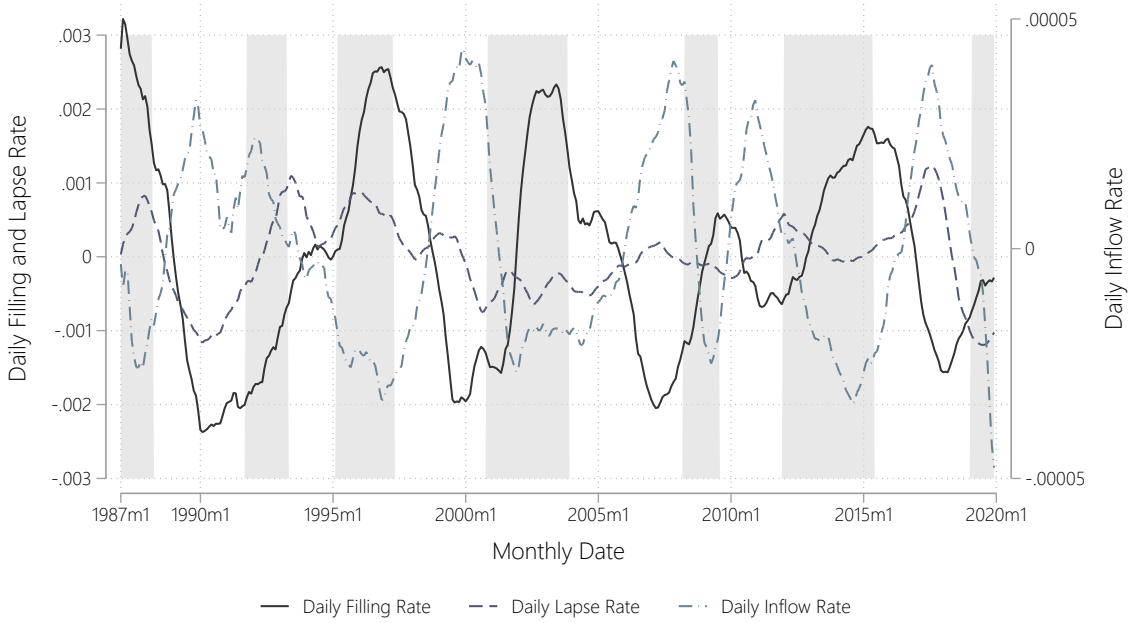
We filter the monthly time series using Christiano-Fitzgerald, Hamilton, Hodrick-Prescott and Baxter-King Filter. We define and compute counterfactual steady state vacancy rates:

$$
\begin{aligned}
\tilde{v}_t^f &= \frac{\bar{n}}{\bar{n} + f_t + \bar{l}} \\
\tilde{v}_t^l &= \frac{\bar{n}}{\bar{n} + \bar{f} + l_t} \\
\tilde{v}_t^n &= \frac{n_t}{n_t + \bar{f} + \bar{l}}
\end{aligned}
\tag{B.7}
$$

where $\bar{f}$, $\bar{l}$ and $\bar{n}$ are overall averages.

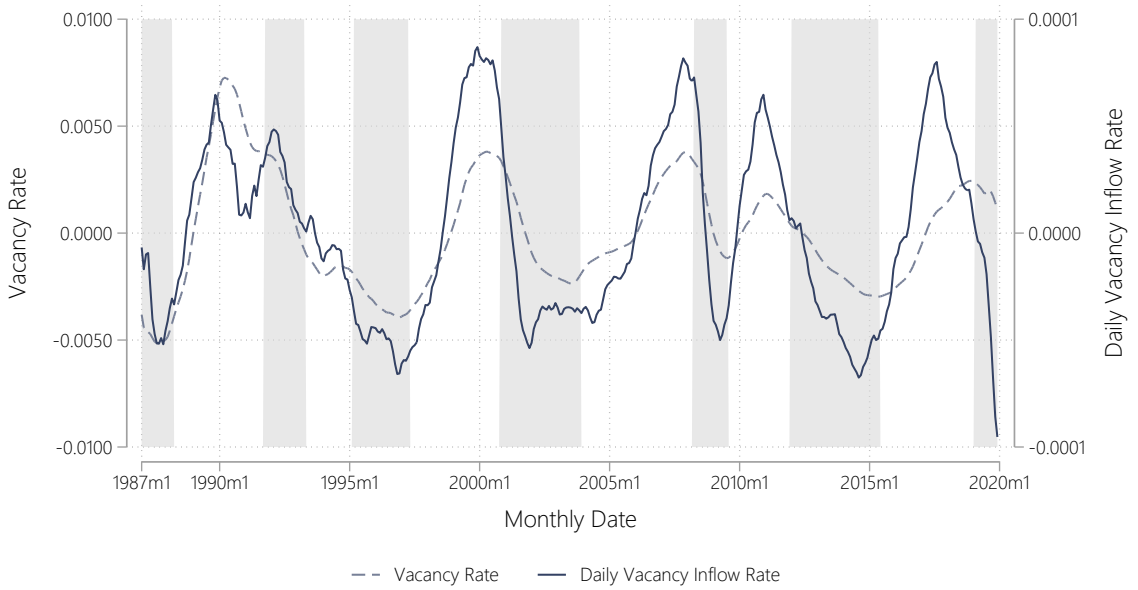
Finally, we decompose the variance of v_t^{ss} using bivariate regression of counterfactuals $\tilde{v}_t^x$, where $x \in \{n, f, l\}$, onto v_t^{ss}. More specifically, we calculate bivariate log-log regressions of $\log(f_t)$, $\log(l_t)$, $\log(n_t)$ and the rescaled versions $\frac{f_t}{f_t+l_t}\log(f_t)$, $\frac{l_t}{f_t+l_t}\log(l_t)$ on $\log(v_t)$ to get better understanding of their relationship.

Figure B.1
Vacancy Rates using HP Filter



Notes: This figure shows the daily vacancy inflow, filling and lapse rate based on AMS data from 1987 – 2019. OECD based Recession Indicators for Austria from FRED (2023). We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000.

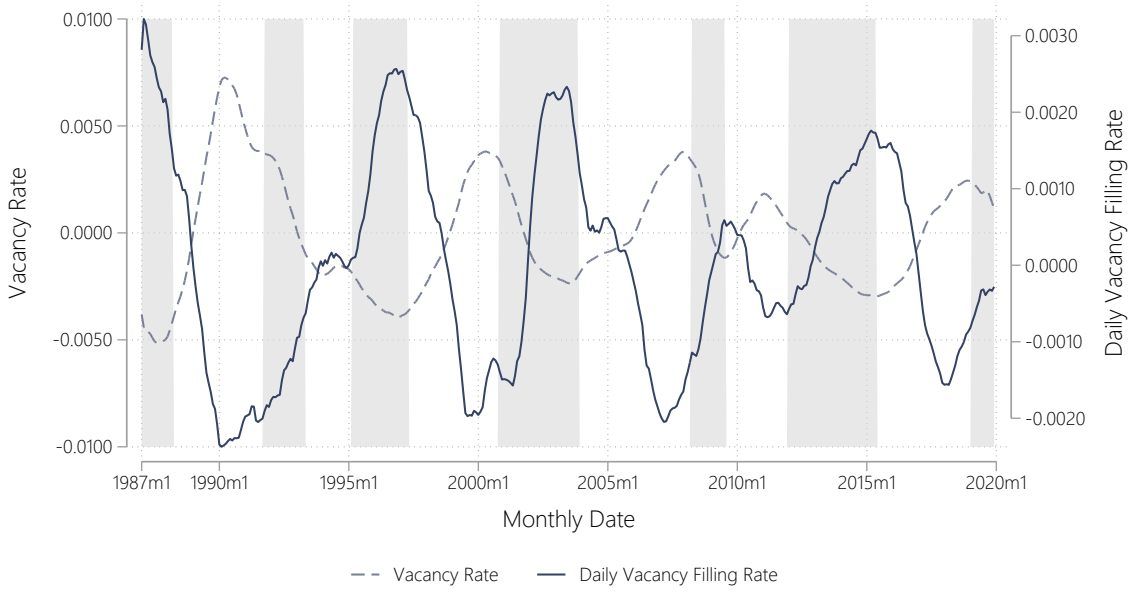
Figure B.2
Vacancy Inflow Rate using HP Filter



Correlation (HP-filtered): 0.76

Notes: This figure shows the daily vacancy inflow rate based on AMS data from 1987 – 2019. OECD based Recession Indicators for Austria from FRED (2023). We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000.

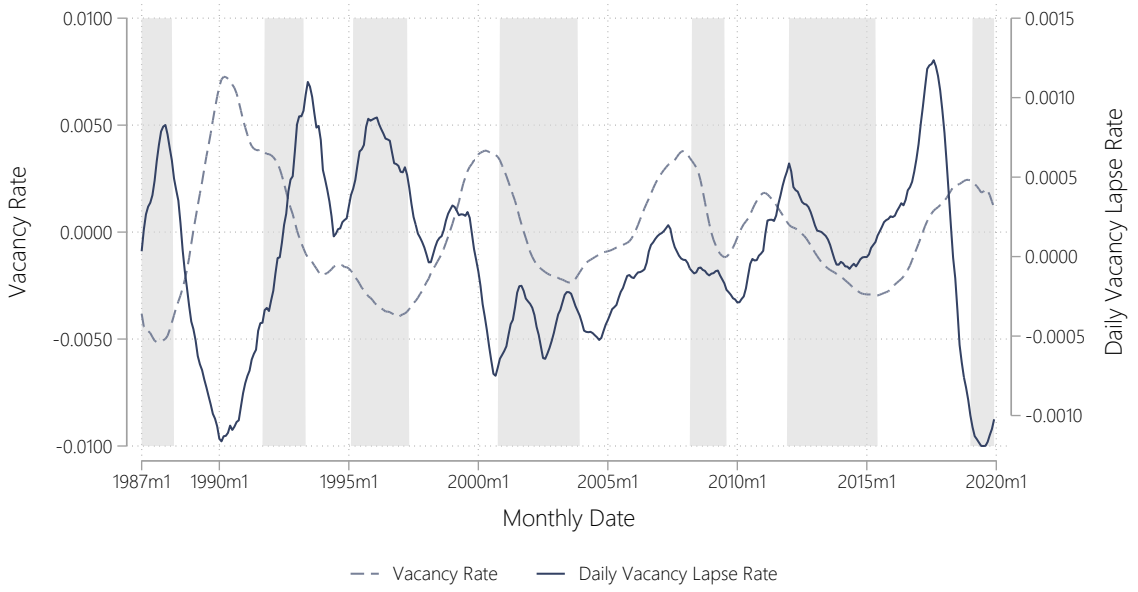
Figure B.3
Vacancy Filling Rate using HP filter



Correlation (HP-filtered): -0.92

Notes: This figure shows the daily vacancy filling rate based on AMS data from 1987 – 2019. OECD based Recession Indicators for Austria from FRED (2023). We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000.

Figure B.4
Vacancy Lapse Rate using HP Filter



Correlation (HP-filtered): -0.53

Notes: This figure shows the daily vacancy lapse rate based on AMS data from 1987 – 2019. OECD based Recession Indicators for Austria from FRED (2023). We apply a 13-month centered moving average and detrend the monthly time series using an HP-filter with smoothing parameter 900,000.

B.2 The Importance of Ins and Outs for Vacancy Fluctuations

B.2.1 Variance Decomposition in AMS Data

Table B.1
The Ins and Outs of Vacancies in AMS:
Different Filtering Methods 1987 – 2019

	Vacancy Rate (AMS)		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Unfiltered	0.539***	0.0152	0.451***
	(0.0733)	(0.0239)	(0.0729)
Christiano-Fitzgerald	0.475***	0.0641***	0.374***
	(0.0225)	(0.0247)	(0.0463)
Hamilton	0.404***	0.0268	0.444***
	(0.0542)	(0.0286)	(0.0558)
Hodrick-Prescott	0.547***	0.0921***	0.345***
	(0.0199)	(0.0150)	(0.0319)
Baxter-King	0.523***	0.0507**	0.411***
	(0.0259)	(0.0235)	(0.0573)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters using AMS data for the time period 1987 – 2019 (1990 – 2019 for Hamilton, 1990 – 2016 for Baxter-King). We apply a 13-month centered moving average and detrend the monthly time series using different filters. HP smoothing parameter is 900,000.

Table B.2
The Ins and Outs of Vacancies in AMS:
Different Filtering Methods 1990 – 2016

	Vacancy Rate (AMS)		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Christiano-Fitzgerald Restr.	0.495***	0.0253	0.427***
	(0.0285)	(0.0255)	(0.0543)
Hamilton Restr.	0.395***	0.0237	0.455***
	(0.0525)	(0.0290)	(0.0537)
Hodrick-Prescott Restr.	0.548***	0.0818***	0.375***
	(0.0231)	(0.0185)	(0.0386)
Baxter-King Restr.	0.523***	0.0507**	0.411***
	(0.0259)	(0.0235)	(0.0573)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters using AMS data for the (common) time period 1990 – 2016. We apply a 13-month centered moving average and detrend the monthly time series using different filters. HP smoothing parameter is 900,000. Because Baxter-King is only available for 1990 – 2016, we shortened the time series for comparison.

Table B.3
THE INS AND OUTS OF VACANCIES IN AMS:
SEASONAL ADJUSTMENT (X-13ARIMA-SEATS)

	Vacancy Rate (AMS)		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Christiano-Fitzgerald	0.465***	0.0684***	0.366***
	(0.0259)	(0.0260)	(0.0495)
Hamilton	0.422***	0.0204	0.428***
	(0.0448)	(0.0271)	(0.0539)
Hodrick-Prescott	0.526***	0.0944***	0.334***
	(0.0246)	(0.0147)	(0.0313)
Baxter-King	0.500***	0.0506**	0.429***
	(0.0315)	(0.0247)	(0.0573)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters using AMS data for the time period 1987 – 2019 (1990 – 2019 for Hamilton, 1990 – 2016 for Baxter-King). We apply an X-13ARIMA-SEATS seasonal adjustment (Sax and Eddelbuettel, 2018) – instead of our baseline 13-month centered moving average – and detrend the monthly time series using different filters. HP smoothing parameter is 900,000.

Table B.4
The Ins and Outs of Vacancies in AMS:
Vacancy Rate v_t (instead of v_t^{ss})

	Vacancy Rate (AMS)		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Christiano-Fitzgerald	0.512***	0.0682***	0.357***
	(0.0206)	(0.0256)	(0.0509)
Hamilton	0.439***	0.0273	0.451***
	(0.0552)	(0.0291)	(0.0599)
Hodrick-Prescott	0.558***	0.0923***	0.331***
	(0.0171)	(0.0146)	(0.0331)
Baxter-King	0.527***	0.0522**	0.373***
	(0.0232)	(0.0225)	(0.0577)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the vacancy rate v_t, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters using AMS data for the time period 1987 – 2019 (1990 – 2019 for Hamilton, 1990 – 2016 for Baxter-King). We apply a 13-month centered moving average and detrend the monthly time series using different filters. HP smoothing parameter is 900,000.

Table B.5
THE INS AND OUTS OF VACANCIES IN AMS:
ALTERNATIVE DURATION CONCEPTS

	AMS			**Posting**			**JOLTS**		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Christiano-Fitzgerald	0.481***	0.00247	0.429***	0.525***	-0.0156	0.503***	0.558***	0.00511	0.436***
	(0.0311)	(0.0162)	(0.0357)	(0.0339)	(0.0183)	(0.0280)	(0.0305)	(0.0161)	(0.0286)
Hamilton	0.295***	0.0263	0.428***	0.259***	-0.0305	0.531***	0.333***	0.0113	0.434***
	(0.0399)	(0.0297)	(0.0617)	(0.0382)	(0.0271)	(0.0387)	(0.0456)	(0.0330)	(0.0518)
Hodrick-Prescott	0.405***	0.0490***	0.486***	0.500***	0.0122	0.484***	0.532***	0.0408**	0.416***
	(0.0236)	(0.0182)	(0.0401)	(0.0204)	(0.0213)	(0.0254)	(0.0195)	(0.0206)	(0.0263)
Baxter-King	0.421***	-0.000313	0.546***	0.486***	-0.0226	0.544***	0.525***	-0.00275	0.484***
	(0.0378)	(0.0184)	(0.0412)	(0.0287)	(0.0194)	(0.0245)	(0.0264)	(0.0190)	(0.0258)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters and duration concepts using AMS data for the time period 1995 – 2019 (1998 – 2019 for Hamilton Filter, 1998 – 2016 for Baxter-King). We apply a 13-month centered moving average and detrend the monthly time series using different filters. HP smoothing parameter is 900,000. Because for years 1987 – 1993 only posting duration concept is available, we shortened the time series for comparison.

B.2.2 Variance Decomposition in JOLTS Data

DFH+ Methodology. Davis, Faberman and Haltiwanger (2013) (DFH) solve their key equations

$$\begin{aligned} V_t &= ((1-f_t)(1-l_t))^{D_t} V_{t-1} + \frac{N_t}{D_t} \sum_{i=1}^{D_t} ((1-f_t)(1-l_t))^{D_t - i} \\ H_t &= f_t V_{t-1} \sum_{i=1}^{D_t} ((1-f_t)(1-l_t))^{i-1} + f_t \frac{N_t}{D_t} \sum_{i=1}^{D_t} (D_t - i)((1-f_t)(1-l_t))^{i-1} \end{aligned} \tag{B.8}$$

using an iterative approach described in Appendix B.2 of Mongey and Violante (2019). V_t, V_{t-1}, D_t and H_t are observed, N_t and f_t are obtained by assuming $l_t = 0$ or setting the lapse rate equal to the layoff rate (the exact lapse rate is not important).

We can also use the equations from DFH but use the fact that we observe lapses (L_t) and inflows (N_t). Let's rewrite the equations (B.8) as:

$$V_t = (1-\tilde{f}_t)^{D_t} V_{t-1} + \frac{N_t}{D_t} \sum_{i=1}^{D_t} ((1-\tilde{f}_t))^{D_t - i} \tag{B.9}$$

where $(1-\tilde{f}_t) = (1-f_t)(1-l_t)$, and

$$H_t = f_t V_{t-1} \sum_{i=1}^{D_t} ((1-\tilde{f}_t))^{i-1} + f_t \frac{N_t}{D_t} \sum_{i=1}^{D_t} (D_t - i)((1-\tilde{f}_t))^{i-1} \tag{B.10}$$

which can be re-arranged to:

$$f_t = \frac{H_t}{V_{t-1} \sum_{i=1}^{D_t} ((1-\tilde{f}_t))^{i-1} + \frac{N_t}{D_t} \sum_{i=1}^{D_t} (D_t - i)((1-\tilde{f}_t))^{i-1}}. \tag{B.11}$$

We can then estimate f_t and l_t as follows:

1. Given V_t, V_{t-1}, D_t and N_t, we can solve equation (B.9) for $\tilde{f}_t$ for each t.
2. Given H_t, V_{t-1}, D_t, N_t and $\tilde{f}_t$, we can solve equation (B.11) for f_t for each t.
3. Given $\tilde{f}_t$ and f_t, we can solve for l_t for each t.

Table B.6
The Ins and Outs of Vacancies in JOLTS:
Different Filtering Methods

	Vacancy Rate (JOLTS)		
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$
Christiano-Fitzgerald	0.629^{***}	0.00462^{***}	0.424^{***}
	(0.0266)	(0.0008)	(0.0232)
Hamilton	0.572^{***}	0.00460^{***}	0.358^{***}
	(0.0433)	(0.0006)	(0.0244)
Hodrick-Prescott	0.596^{***}	0.00375^{***}	0.454^{***}
	(0.0244)	(0.0009)	(0.0255)
Baxter-King	0.631^{***}	0.00508^{***}	0.442^{***}
	(0.0350)	(0.0011)	(0.0339)

Notes: This table shows results of a bivariate regression of vacancy rate counterfactuals $\tilde{v}_t^x$, $x \in \{n, f, l\}$ on the steady-state vacancy rate v_t^{ss}, i.e., $\beta^x = cov(v_t^x, v_t^{ss})/var(v_t^{ss})$ for different filters using JOLTS data for the time period 2001 – 2019 (2004 – 2019 for Hamilton, 2004 – 2016 for Baxter-King). We apply a 13-month centered moving average and detrend the monthly time series using different filters. HP smoothing parameter is 900,000. We impute daily filling rates in the JOLTS data based on the Davis, Faberman and Haltiwanger (2013) (DFH) approach (see Appendix B.2.2 for details).

C Replacement Hiring and Vacancy Inflows

In this section, we use the identified replacement and non-replacement vacancies to further decompose the steady-state vacancy rate into parts driven by the two types of vacancies. In particular, we can decompose the effect of the filling, lapse and inflow rate into two parts respectively. To do this we define the steady-state vacancy rate and the counterfactuals which we already used before. In the following $\bar{x}$ represents the average of the variable x.

$$\begin{aligned} v_t^{ss} &= \frac{n_t}{n_t + f_t + l_t} \\ \tilde{v}_t^{f} &= \frac{\bar{n}}{\bar{n} + f_t + \bar{l}} \\ \tilde{v}_t^{l} &= \frac{\bar{n}}{\bar{n} + \bar{f} + l_t} \\ \tilde{v}_t^{n} &= \frac{n_t}{n_t + \bar{f} + \bar{l}}. \end{aligned} \tag{C.1}$$

To isolate the effect replacement and non-replacement flows have on the vacancy rate we define the following counterfactuals.

$$\begin{aligned} \tilde{f}_t^X &= \frac{H_t^X}{V_t} \\ \tilde{l}_t^X &= \frac{L_t^X}{V_t} \qquad for\ X \in \{N, R\} \\ \tilde{n}_t^X &= \frac{N_t^X}{E_t}. \end{aligned} \tag{C.2}$$

Using these, we can construct six additional counterfactuals which only utilize variation originating from the respective replacement or non-replacement flow.

$$\begin{aligned} \tilde{v}_t^{fX} &= \frac{\bar{n}}{\bar{n} + \tilde{f}_t^X + \bar{\tilde{f}}_t^Y + \bar{l}} \\ \tilde{v}_t^{lX} &= \frac{\bar{n}}{\bar{n} + \bar{f} + \tilde{l}_t^X + \bar{\tilde{l}}_t^Y} \qquad for\ X, Y \in \{N, R\}\ and\ X \neq Y \\ \tilde{v}_t^{nX} &= \frac{\tilde{n}_t^X + \bar{\tilde{n}}_t^Y}{\tilde{n}_t^X + \bar{\tilde{n}}_t^Y + \bar{f} + \bar{l}}. \end{aligned} \tag{C.3}$$

Thereafter, we follow the same approach as before, we filter the time series and compute the fraction of total v_t^{ss} variance the counterfactual can explain, i.e. the coefficients give $\frac{Cov(y, v_t^{ss})}{Var(v_t^{ss})} \quad for\ y \in \{\tilde{v}_t^{f}, \tilde{v}_t^{fN}, \tilde{v}_t^{fR}, \tilde{v}_t^{l}, \tilde{v}_t^{lR}, \tilde{v}_t^{lN}, \tilde{v}_t^{n}, \tilde{v}_t^{nN}, \tilde{v}_t^{nR}\}$.

C.1 Identifying Replacement Hires and Vacancies using Worker Flows

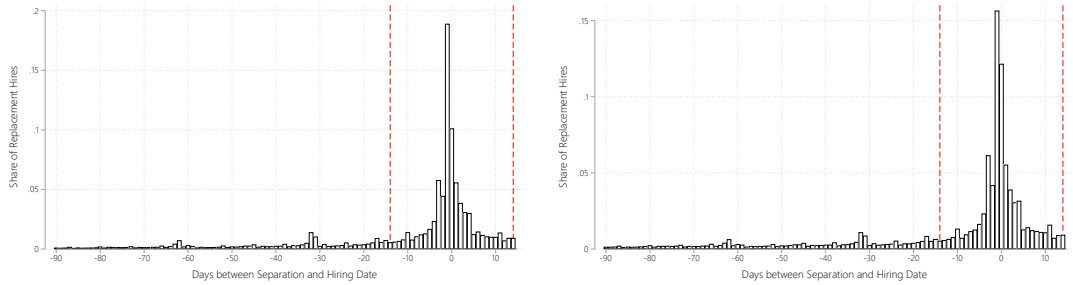
We identify replacement hires as hires that happen shortly after a separation of the same worker type in the same firm, using daily worker flows for the universe of workers in the ASSD. More specifically, for each daily hire, we (sequentially) identify the closest separation of the same worker type in the same firm in order to identify replacement hires. Our baseline specification uses separations into employment that happen 32 days before and 14 days after the hire in the same firm separately for blue and white collar workers (worker types). However, results are very robust to different time windows. Figure C.1 confirms that most of the separations happen in a very narrow time window around the hiring date.

Conceptually, our approach is very similar to Elsby et al. (2022), who use the minimum of an establishment's quits and its gross hires at a quarterly frequency. For instance, by construction, our replacement hire identification always gives the minimum of quits (approximated by E-E separations) and hires over a given time period. But in contrast to Elsby et al. (2022), we use a dynamic time window, while Elsby et al. (2022) use a (fixed) quarterly frequency (which does not take into account the timing of hires/separations within the quarter).[6] Our approach is also consistent with their second approach, where they consider replacement hires as "the total number of hires accounted for by establishments that hold employment (near-)constant, for various inaction windows". Given that we only use hires that follow a separation, we only consider hires as a replacement hire if they hold employment constant, but we allow for *additional* non-replacement hires and separations that change an establishment's employment. Figure C.4 illustrates that results are very similar for both approaches in the aggregate. In addition, Figure C.2 confirms that growing establishments have a higher hires rate for non-replacement hires but not for replacement hires.

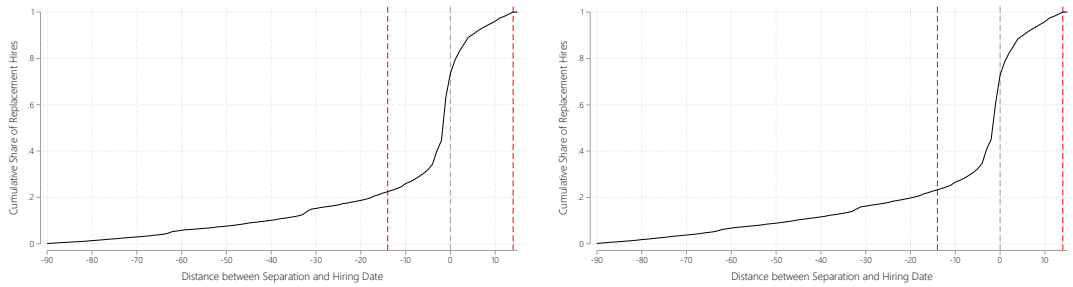
[6]Suppose all separations happen on March 31 and all hires take place on April 1. Strictly speaking, there are no replacement hires in Elsby et al. (2022), while in our baseline approach all hires are replacement hires.

Figure C.1
Days between Separation and Hiring Date for Replacement Hires

(a) Probability Density Function

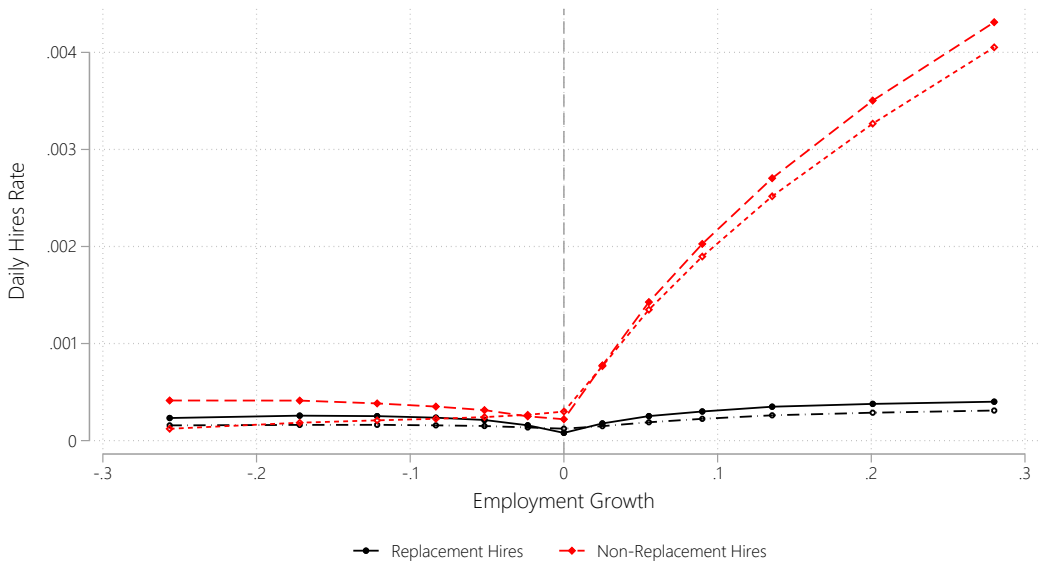


(b) Cumulative Density Function



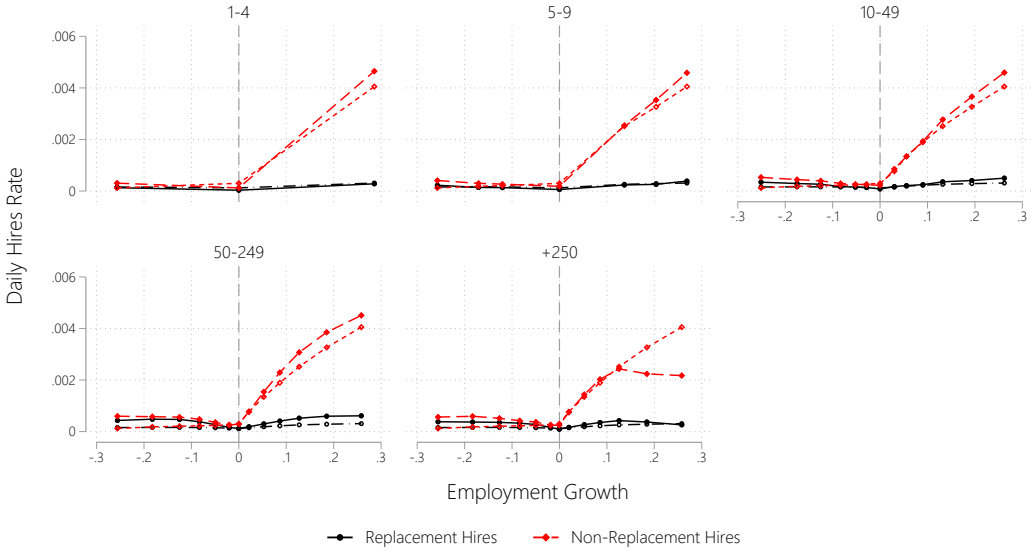
Notes: This figure shows the probability and cumulative density function of the number of days between separation and hiring date for identified replacement hires in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations of the same worker type into employment (LHS) or separations of the same worker type (RHS) in the same firm -90 – 14 days around the date of the new hire.

Figure C.2
Daily Hires Rate by Monthly Employment Growth



Notes: Daily hires rate by monthly DFH employment growth in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations into employment in the same firm -30 – 14 days around the date of the new hire. Solid dots include time fixed effects, while hollow dots additionally control for firm fixed effects.

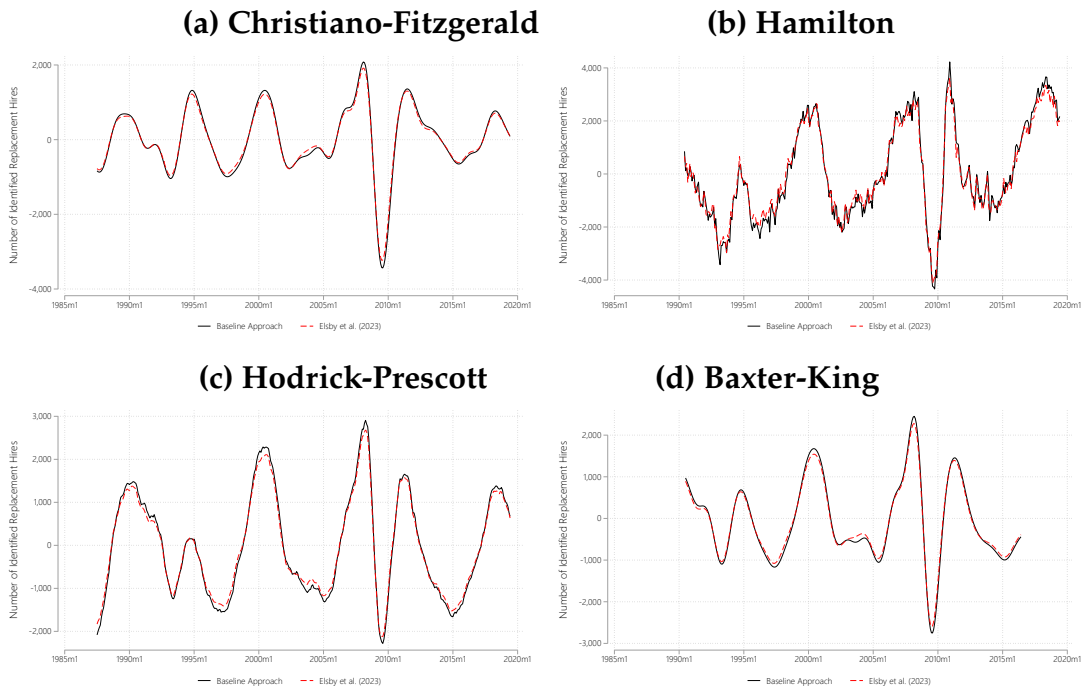
Figure C.3
Daily Hires Rate by Monthly Employment Growth and Firm Size



Notes: Daily hires rate by monthly DFH employment growth in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations into employment in the same firm -30 – 14 days around the date of the new hire. Solid dots include time fixed effects, while hollow dots additionally control for firm fixed effects.

Figure C.4

Identified Replacement Hires: Comparison with Elsby et al. (2022)



Notes: Number of identified replacement hires H^R using our baseline approach compared to the approach of Elsby et al. (2022) in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations into employment in the same firm -30 – 14 days around the date of the new hire. We apply a 13-month centered moving average as well as different filters as indicated in different rows. Elsby et al. (2022) use the minimum of an establishment's quits and its gross hires at a quarterly frequency, while we use their approach on a monthly frequency. However, the results are the same if we use a quarterly frequency.

C.2 The Importance of Replacement Vacancies for Vacancy Inflows

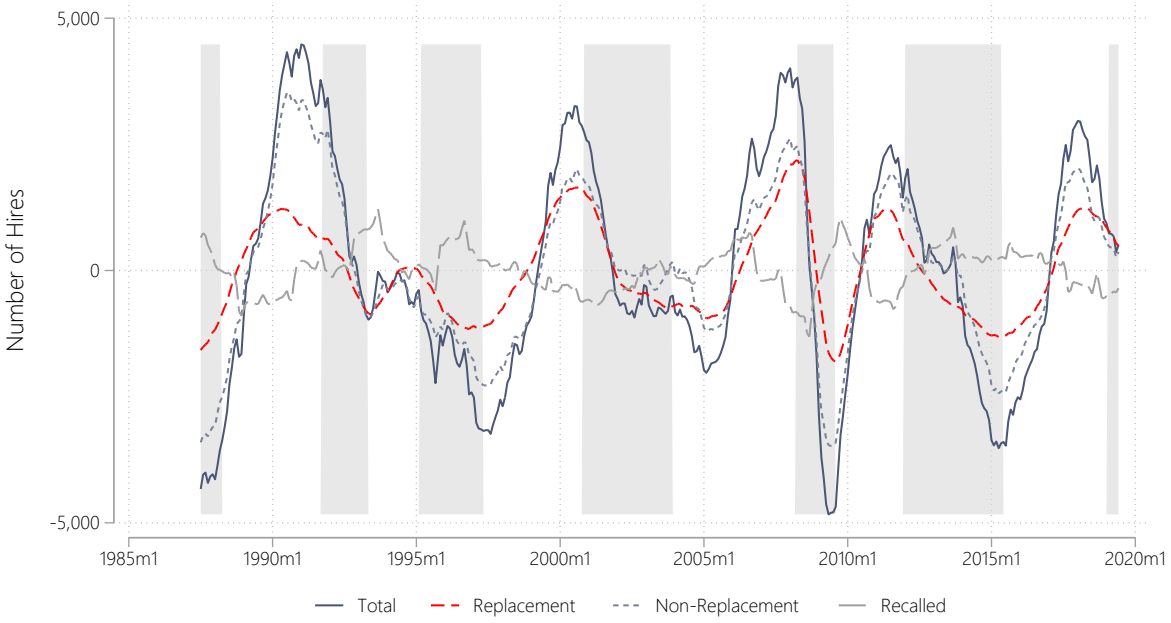
Table C.1
Replacement Hires over the Business Cycle

	Number of Hires H_t		
	H_t^N	H_t^R	H_t^{Recall}
A. Separations of same Worker Type into Employment			
Hodrick-Prescott	0.707***	0.385***	-0.0919***
	(0.0122)	(0.0205)	(0.0156)
Average Share	0.61	0.14	0.25
B. All Separations of same Worker Type			
Hodrick-Prescott	0.452***	0.640***	-0.0919***
	(0.0121)	(0.0215)	(0.0156)
Average Share	0.40	0.36	0.25

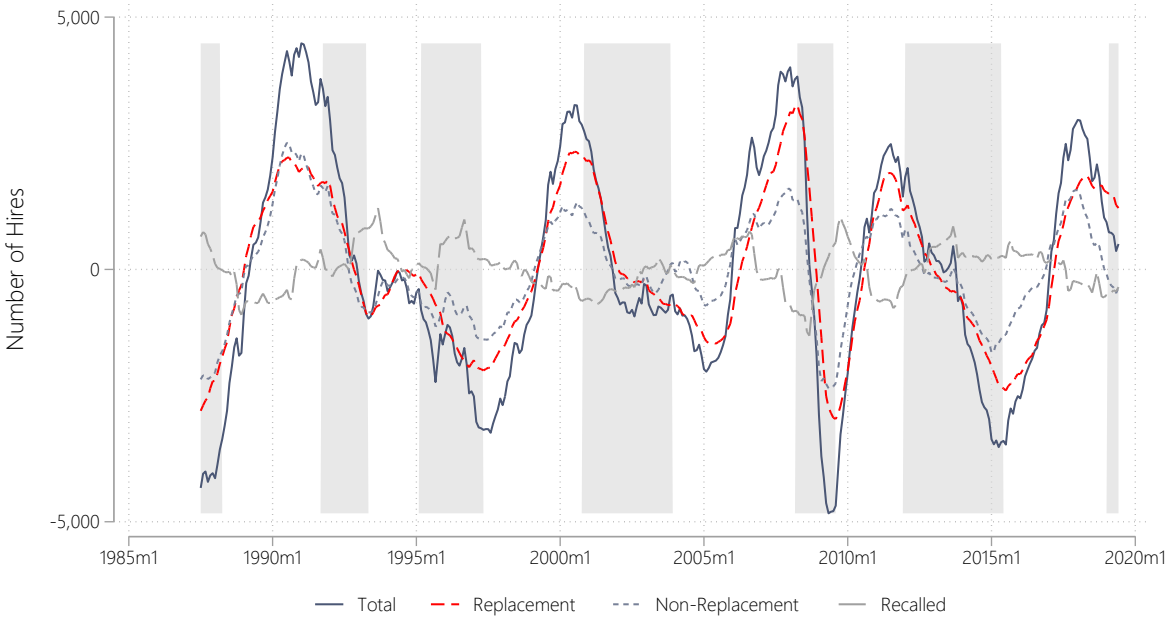
Notes: This table shows a variance decomposition of the absolute number of hires H_t into replacement H^R, non-replacement H^N hires, and recalled hires H^{Recall} in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations of the same worker type (Panel A.) or separations of the same worker type into employment (Panel B.) in the same firm -30 – 14 days around the date of the new hire. We apply a 13-month centered moving average as well as an HP filter. HP smoothing parameter is 900,000.

Figure C.5
Replacement Hire over the Business Cycle

(a) Separations of same Worker Type into Employment



(b) All Separations of same Worker Type



Notes: This table shows a variance decomposition of the absolute number of hires H_t into replacement H^R, non-replacement H^N hires, and recalled hires in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations of the same worker type (into employment) in the same firm around the date of the new hire. We apply a 13-month centered moving average and a HP filter, with HP smoothing parameter 900,000.

Table C.2
Replacement Hires over the Business Cycle
Separately for Hires from Employment and Non-Employment

	Number of Hires H_t				
	H_t^N		H_t^R		H_t^{Recall}
	$H_t^{N,N}$	$H_t^{N,E}$	$H_t^{R,N}$	$H_t^{R,E}$	
A. Separations of same Worker Type into Employment					
Hodrick-Prescott	0.395***	0.312***	0.189***	0.196***	-0.0919***
	(0.0282)	(0.0187)	(0.0078)	(0.0133)	(0.0156)
Average Share	0.42	0.19	0.08	0.06	0.25
B. All Separations of same Worker Type					
Hodrick-Prescott	0.256***	0.196***	0.327***	0.313***	-0.0919***
	(0.0209)	(0.0127)	(0.0082)	(0.0197)	(0.0156)
Average Share	0.28	0.12	0.22	0.13	0.25

Notes: This table shows a variance decomposition of the absolute number of hires H_t into replacement H^R, non-replacement H^N hires, and recalled hires in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using all separations of the same worker type (Panel A.) or separations of the same worker type into employment (Panel B.) in the same firm -32 – 14 days around the date of the new hire. We apply a 13-month centered moving average and an HP filter, with HP smoothing parameter 900,000.

Table C.3
Replacement Hires over the Business Cycle
Robustness for Separations of same Worker Type into Employment

	Number of Hires H_t		
	H_t^N	H_t^R	H_t^{Recall}
A. Baseline Results			
Hodrick-Prescott	0.707***	0.385***	-0.0919***
	(0.0122)	(0.0205)	(0.0156)
Average Share	0.61	0.14	0.25
B. Long Time Window (-90 – 14 Days)			
Hodrick-Prescott	0.662***	0.430***	-0.0919***
	(0.0135)	(0.0225)	(0.0156)
Average Share	0.59	0.16	0.25
C. Short Time Window (-14 – 14 Days)			
Hodrick-Prescott	0.750***	0.342***	-0.0919***
	(0.0111)	(0.0185)	(0.0156)
Average Share	0.63	0.12	0.25
D. Excl. Recruitment Agencies, Public/Seasonal Sector			
Hodrick-Prescott	0.770***	0.357***	-0.128***
	(0.0131)	(0.0156)	(0.0159)
Average Share	0.63	0.13	0.24
E. Small Firms (10-49 Employed)			
Hodrick-Prescott	0.846***	0.293***	-0.139***
	(0.0222)	(0.0265)	(0.0333)
Average Share	0.63	0.10	0.26
F. Matched Firm Sample			
Hodrick-Prescott	0.644***	0.438***	-0.0823***
	(0.0156)	(0.0267)	(0.0220)
Average Share	0.61	0.14	0.25

Notes: This table shows a variance decomposition of the absolute number of hires H_t into replacement H^R, non-replacement H^N hires, and recalled hires in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations of the same worker type into employment in the same firm around the date of the new hire. We apply a 13-month centered moving average and an HP filter, with HP smoothing parameter 900,000. The table shows robustness results for different samples.

Table C.4
Replacement Hires over the Business Cycle
Robustness for all Separations of same Worker Type

	Number of Hires H_t		
	H_t^N	H_t^R	H_t^{Recall}
A. Baseline Results			
Hodrick-Prescott	0.452***	0.640***	-0.0919***
	(0.0121)	(0.0215)	(0.0156)
Average Share	0.40	0.36	0.25
B. Long Time Window (-90 – 14 Days)			
Hodrick-Prescott	0.367***	0.725***	-0.0919***
	(0.0144)	(0.0233)	(0.0156)
Average Share	0.33	0.42	0.25
C. Short Time Window (-14 – 14 Days)			
Hodrick-Prescott	0.521***	0.571***	-0.0919***
	(0.0109)	(0.0195)	(0.0156)
Average Share	0.44	0.31	0.25
D. Excl. Recruitment Agencies, Public/Seasonal Sector			
Hodrick-Prescott	0.520***	0.608***	-0.128***
	(0.0122)	(0.0163)	(0.0159)
Average Share	0.42	0.33	0.24
E. Small Firms (10-49 Employed)			
Hodrick-Prescott	0.652***	0.486***	-0.139***
	(0.0196)	(0.0240)	(0.0333)
Average Share	0.48	0.25	0.26
F. Matched Firm Sample			
Hodrick-Prescott	0.401***	0.681***	-0.0823***
	(0.0183)	(0.0333)	(0.0220)
Average Share	0.39	0.37	0.25

Notes: This table shows a variance decomposition of the absolute number of hires H_t into replacement H^R, non-replacement H^N hires, and recalled hires in the ASSD universe from 1987 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement hires using separations of the same worker type in the same firm around the date of the new hire. We apply a 13-month centered moving average and an HP filter, with HP smoothing parameter 900,000. The table shows robustness results for different samples.

Table C.5
Replacement Vacancy Inflows over the Business Cycle

	Number of Inflows N_t	
	N_t^N	N_t^R
A. Baseline Time Window: -30 – 14 Days		
Christiano-Fitzgerald	0.629***	0.371***
	(0.0258)	(0.0258)
Hamilton	0.655***	0.342***
	(0.0194)	(0.0195)
Hodrick-Prescott	0.642***	0.358***
	(0.0182)	(0.0182)
Baxter-King	0.600***	0.400***
	(0.0178)	(0.0178)
Average Share	0.78	0.22
B. Long Time Window: -90 – 14 Days		
Christiano-Fitzgerald	0.579***	0.421***
	(0.0326)	(0.0326)
Hamilton	0.605***	0.394***
	(0.0242)	(0.0243)
Hodrick-Prescott	0.590***	0.410***
	(0.0231)	(0.0231)
Baxter-King	0.541***	0.459***
	(0.0217)	(0.0217)
Average Share	0.73	0.27
C. Short Time Window: -14 – 14 Days		
Christiano-Fitzgerald	0.659***	0.341***
	(0.0220)	(0.0220)
Hamilton	0.683***	0.313***
	(0.0170)	(0.0170)
Hodrick-Prescott	0.671***	0.329***
	(0.0156)	(0.0156)
Baxter-King	0.634***	0.366***
	(0.0155)	(0.0155)
Average Share	0.80	0.20

Notes: This table shows a variance decomposition of the absolute number of vacancy inflows N_t into replacement N^R, non-replacement N^N hires in the matched firm universe from 1998 – 2019, excluding administrative firm identifier changes. More specifically, we identify replacement inflows using separations of same worker type into employment in the same firm around the date of the new hire. We apply a 13-month centered moving average as well as different filters as indicated in different rows. The table shows robustness results for different time windows. We restrict to blue/white collar employment and exclude minor employment.

Table C.6
The Importance of Replacement Vacancies for Vacancy Inflows using Separations of same Worker Type into Employment

	Rate		
Variation due to Replacements in . . .	v_t^{ss}	n_t	h_t
A. All Replacement Vacancies and Hires			
Marginal Effect	0.354	0.285	0.442
		(0.009)	(0.023)
Replacement Share	0.187	0.187	0.178
Excess Sensitivity	1.893	1.524	2.477
B. Excl. Seasonal and High-turnover Industries			
Marginal Effect	0.321	0.243	0.360
		(0.008)	(0.020)
Replacement Share	0.164	0.164	0.162
Excess Sensitivity	1.957	1.482	2.221

Notes: Column 1 shows the relative importance of replacement inflows for variation in the steady-state vacancy rate from equation (8). Column 2 shows the marginal effects of a bivariate regression of replacement inflows, n_t^R, on total vacancy inflows, n_t. Column 3 shows the marginal effects of a bivariate regression of replacement hires, h_t^R, on total hires, h_t, excluding recalled hires. Excess sensitivity is defined as the ratio of the marginal effects relative to the average share of replacement vacancies/hires over the sample period. Data is monthly data and HP smoothing parameter is 900,000. Columns 1 and 2 use the AMS matched firm universe for the time period 1995 – 2019, Column 3 uses the ASSD universe for the time period 1995 – 2019. Newey-West standard errors are given in parentheses below the respective estimate.

Table C.7
The Importance of Replacement Vacancies for Vacancy Inflows using all Separations of same Worker Type (incl. Non-Employment)

	Rate		
Variation due to Replacements in ...	v_t^{ss}	n_t	h_t
A. All Replacement Vacancies and Hires			
Marginal Effect	0.467	0.389	0.646
		(0.012)	(0.023)
Replacement Share	0.380	0.380	0.448
Excess Sensitivity	1.229	1.024	1.443
B. Excl. Seasonal and High-turnover Industries			
Marginal Effect	0.418	0.321	0.540
		(0.011)	(0.017)
Replacement Share	0.351	0.351	0.412
Excess Sensitivity	1.191	0.915	1.313

Notes: Column 1 shows the marginal effects of a bivariate regression of vacancy rate counterfactual $\tilde{v}_t^{n,R}$ on the steady-state vacancy rate v_t^{ss} relative to the marginal effects of a bivariate regression coefficient of vacancy rate counterfactual $\tilde{v}_t^{n}$ on the steady-state vacancy rate v_t^{ss}. Column 2 shows the results of the marginal effects of a bivariate regression of replacement inflows, N_t^R, on total inflows, N^t. Column 3 shows the results of the marginal effects of a bivariate regression of replacement hires, H_t^R, on total inflows, H^t. Excess sensitivity is defined as the ratio of the marginal effects relative to the average share of replacement vacancies/hires. Data is monthly data and HP smoothing parameter is 900,000. Columns 1 and 2 use the AMS matched firm universe for the time period 1995 – 2019. Column 3 uses the ASSD universe for the time period 1995 – 2019.

Table C.8
The Importance of Replacement Vacancies for Vacancy Inflows by Poaching Rank, Starting Wage and AKM Effects

	Rate		
Variation due to Replacements in ...	v_t^{ss}	n_t	h_t
A. Above Median Poaching Rank			
Marginal Effect	0.393	0.343	0.421
		(0.010)	(0.017)
Replacement Share	0.240	0.240	0.188
Excess Sensitivity	1.638	1.429	2.243
B. Below Median Poaching Rank			
Marginal Effect	0.307	0.225	0.444
		(0.008)	(0.032)
Replacement Share	0.147	0.147	0.170
Excess Sensitivity	2.088	1.531	2.615
C. Above Median Starting Wage			
Marginal Effect	0.398	0.316	0.426
		(0.011)	(0.026)
Replacement Share	0.207	0.207	0.177
Excess Sensitivity	1.923	1.527	2.406
D. Below Median Starting Wage			
Marginal Effect	0.295	0.234	0.444
		(0.008)	(0.022)
Replacement Share	0.160	0.160	0.181
Excess Sensitivity	1.844	1.463	2.456
E. Above Median Firm AKM Effect			
Marginal Effect	0.398	0.332	0.396
		(0.011)	(0.022)
Replacement Share	0.222	0.222	0.173
Excess Sensitivity	1.793	1.495	2.295
F. Below Median Firm AKM Effect			
Marginal Effect	0.283	0.223	0.437
		(0.007)	(0.021)
Replacement Share	0.153	0.153	0.162
Excess Sensitivity	1.850	1.458	2.703

Notes: This Table reports results from Table C.7 for different firm quality samples based on the poaching rank, average starting wage and firm AKM effect. See Notes of Table C.7 for details.

Table C.9
The Importance of Replacement Vacancies for Vacancy Inflows by Poaching Rank, Starting Wage and AKM Effects for large Firms

	Rate		
Variation due to Replacements in ...	v_t^{ss}	n_t	h_t
A. Above Median Poaching Rank			
Marginal Effect	0.466	0.424	0.424
		(0.009)	(0.018)
Replacement Share	0.321	0.321	0.200
Excess Sensitivity	1.452	1.321	2.125
B. Below Median Poaching Rank			
Marginal Effect	0.364	0.259	0.452
		(0.010)	(0.032)
Replacement Share	0.194	0.194	0.179
Excess Sensitivity	1.876	1.335	2.523
C. Above Median Starting Wage			
Marginal Effect	0.509	0.393	0.432
		(0.013)	(0.027)
Replacement Share	0.284	0.284	0.188
Excess Sensitivity	1.792	1.384	2.302
D. Below Median Starting Wage			
Marginal Effect	0.328	0.265	0.446
		(0.009)	(0.022)
Replacement Share	0.206	0.206	0.191
Excess Sensitivity	1.592	1.286	2.337
E. Above Median Firm AKM Effect			
Marginal Effect	0.475	0.385	0.404
		(0.012)	(0.023)
Replacement Share	0.292	0.292	0.184
Excess Sensitivity	1.627	1.318	2.200
F. Below Median Firm AKM Effect			
Marginal Effect	0.320	0.259	0.438
		(0.008)	(0.022)
Replacement Share	0.196	0.196	0.172
Excess Sensitivity	1.633	1.321	2.540

Notes: This Table reports results from Table C.7 for different firm quality samples based on the poaching rank, average starting wage and firm AKM effect. See Notes of Table C.7 for details.

Table C.10

The Importance of Replacement Vacancies for Vacancy Inflows by Poaching Rank, Starting Wage and AKM Effects for small Firms

	Rate		
Variation due to Replacements in ...	v_t^{ss}	n_t	h_t
A. Above Median Poaching Rank			
Marginal Effect	0.209	0.164	0.408
		(0.006)	(0.012)
Replacement Share	0.114	0.114	0.161
Excess Sensitivity	1.833	1.439	2.530
B. Below Median Poaching Rank			
Marginal Effect	0.220	0.160	0.384
		(0.007)	(0.027)
Replacement Share	0.099	0.099	0.145
Excess Sensitivity	2.222	1.616	2.651
C. Above Median Starting Wage			
Marginal Effect	0.195	0.141	0.426
		(0.007)	(0.025)
Replacement Share	0.097	0.097	0.151
Excess Sensitivity	2.010	1.454	2.827
D. Below Median Starting Wage			
Marginal Effect	0.230	0.181	0.390
		(0.006)	(0.017)
Replacement Share	0.113	0.113	0.155
Excess Sensitivity	2.035	1.602	2.512
E. Above Median Firm AKM Effect			
Marginal Effect	0.196	0.150	0.385
		(0.007)	(0.022)
Replacement Share	0.105	0.105	0.151
Excess Sensitivity	1.867	1.429	2.546
F. Below Median Firm AKM Effect			
Marginal Effect	0.231	0.177	0.418
		(0.006)	(0.017)
Replacement Share	0.111	0.111	0.149
Excess Sensitivity	2.081	1.595	2.808

Notes: This Table reports results from Table C.7 for different firm quality samples based on the poaching rank, average starting wage and firm AKM effect. See Notes of Table C.7 for details.

Table C.11
The Ins and Outs of Vacancies using Replacement Hires
Variance Decomposition for Different Filtering Methods

	Vacancy Rate v_t^{ss}				
	$\tilde{v}_t^f$	$\tilde{v}_t^l$	$\tilde{v}_t^n$		
			$\tilde{v}_t^{n,T}$	$\tilde{v}_t^{n,N}$	$\tilde{v}_t^{n,R}$
A. Separations of same Worker Type into Employment					
Christiano-Fitzgerald	0.633***	-0.0524***	0.460***	0.282***	0.177***
	(0.0412)	(0.0170)	(0.0339)	(0.0297)	(0.0135)
Hamilton	0.251***	-0.0340	0.440***	0.298***	0.143***
	(0.0392)	(0.0278)	(0.0450)	(0.0399)	(0.0108)
Christiano-Fitzgerald	0.633***	-0.0524***	0.460***	0.282***	0.177***
	(0.0412)	(0.0170)	(0.0339)	(0.0297)	(0.0135)
Baxter-King	0.555***	-0.0493***	0.516***	0.332***	0.184***
	(0.0379)	(0.0185)	(0.0333)	(0.0294)	(0.0140)
Average Share				.813	.187
B. All Separations of same Worker Type					
Christiano-Fitzgerald	0.633***	-0.0524***	0.460***	0.232***	0.227***
	(0.0412)	(0.0170)	(0.0339)	(0.0282)	(0.0169)
Hamilton	0.251***	-0.0340	0.440***	0.261***	0.178***
	(0.0392)	(0.0278)	(0.0450)	(0.0343)	(0.0160)
Hodrick-Prescott	0.562***	0.00163	0.410***	0.218***	0.192***
	(0.0260)	(0.0242)	(0.0391)	(0.0324)	(0.0125)
Baxter-King	0.555***	-0.0493***	0.516***	0.275***	0.242***
	(0.0379)	(0.0185)	(0.0333)	(0.0286)	(0.0173)
Average Share				.62	.38

Notes: This table shows results of bivariate regression of counterfactuals $\tilde{v}_t^x$, where $x \in \{n, f, l\}$ onto v_t^{ss} for different filters using AMS data for the time period 1995 – 2019 (1998 – 2019 for Hamilton, 1998 – 2016 for Baxter-King). HP smoothing parameter is 900,000.

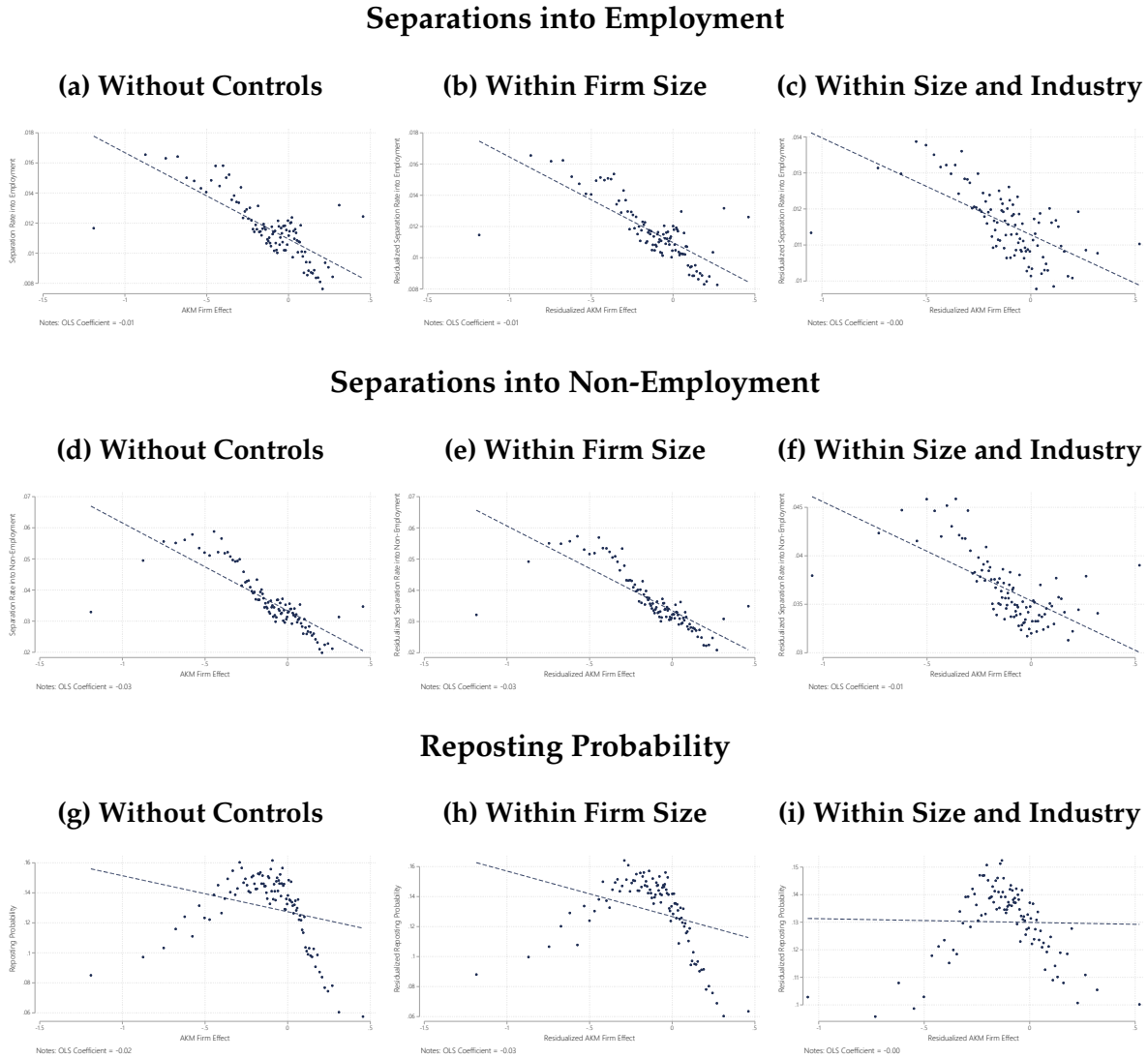
C.3 The Importance of Reposting for Replacement Inflows

Table C.12
The Importance of Reposting for Replacement Hires by Firm Quality

	Replacement	
	N_t	H_t
A. High Entry Wage Firms		
Prob(Replacement | Poached Hire)	0.390	0.336
	(0.041)	(0.014)
Poached Hires	0.610	0.664
	(0.041)	(0.014)
B. Low Entry Wage Firms		
Prob(Replacement | Poached Hire)	0.376	0.320
	(0.024)	(0.025)
Poached Hires	0.624	0.680
	(0.024)	(0.025)
C. High Poaching Rank Firms		
Prob(Replacement | Poached Hire)	0.471	0.356
	(0.041)	(0.015)
Poached Hires	0.529	0.644
	(0.041)	(0.015)
D. Low Poaching Rank Firms		
Prob(Replacement | Poached Hire)	0.293	0.301
	(0.023)	(0.022)
Poached Hires	0.707	0.699
	(0.023)	(0.022)

Notes: This table shows a variance decomposition of replacement inflows and replacement hires into a reposting probability and the number of poached workers using AMS and ASSD data for the time period 1995 – 2019. More specifically, replacement vacancies and hires as a share of employment R_t are given by $R_t = p_t \cdot P_t$, where p_t is the conditional probability of replacing a poached worker and P_t are poached workers as a share of employment in month t. We apply a 13-month centered moving average and detrend the time series using an HP-filter. HP smoothing parameter is 900,000.

Figure C.6
The Reposting Probability and Poached Separations by Firm Quality:
AKM Establishment FE

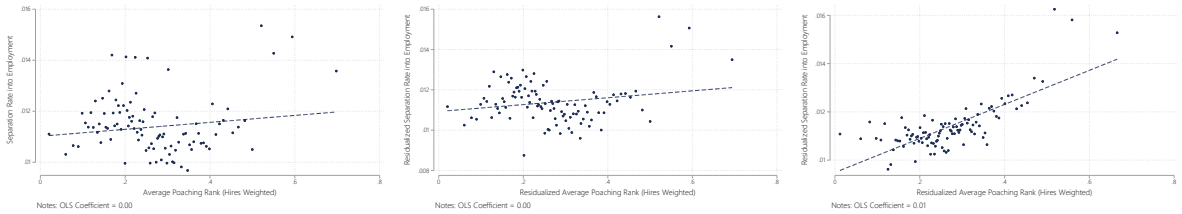


Notes: This figure shows binned scatter plots of different firm quality measures for establishments with more than 5 employed workers in the matched firm universe for the time period 1995 – 2019. LHS panels show raw data plots, middle panels show residualized measures controlling for a fourth-order polynomial of average employment, while RHS panels additionally control for the 4-digit NACE industry of the establishment. Poached separations are defined as separations into employment.

Figure C.7
The Reposting Probability and Poached Separations by Firm Quality: Poaching Rank

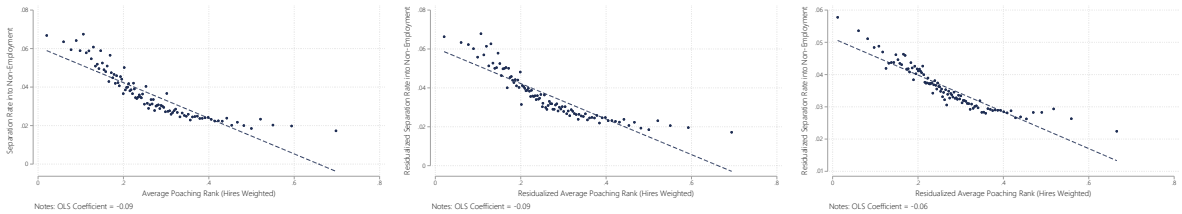
Separations into Employment

(a) Without Controls **(b) Within Firm Size** **(c) Within Size and Industry**



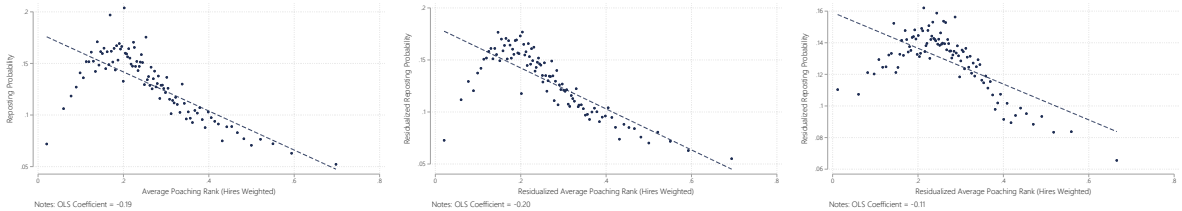
Separations into Non-Employment

(d) Without Controls **(e) Within Firm Size** **(f) Within Size and Industry**



Reposting Probability

(g) Without Controls **(h) Within Firm Size** **(i) Within Size and Industry**



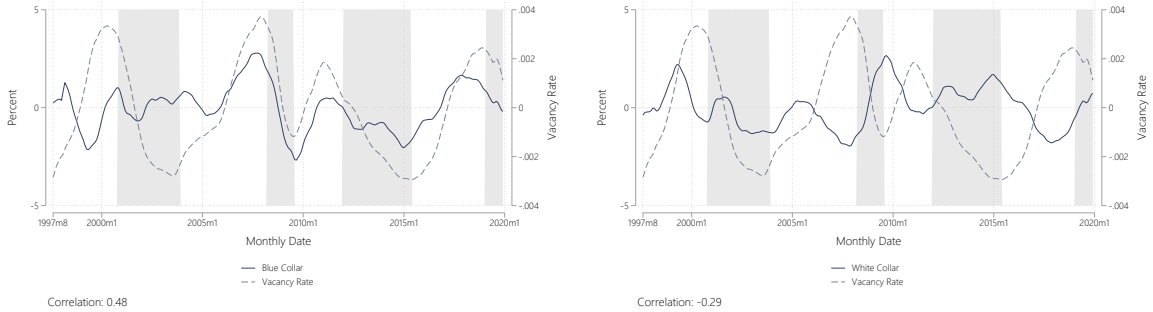
Notes: This figure shows binned scatter plots of different firm quality measures for establishments with more than 5 employed workers in the matched firm universe for the time period 1995 – 2019. LHS panels show raw data plots, middle panels show residualized measures controlling for a fourth-order polynomial of average employment, while RHS panels additionally control for the 4-digit NACE industry of the establishment. Poached separations are defined as separations into employment.

D Vacancy Composition and Vacancy Outflows

D.1 Vacancy Characteristics over the Business Cycle

Figure D.1
Composition over the Business Cycle – Blue/White Collar

(a) Blue Collar **(b) White Collar**



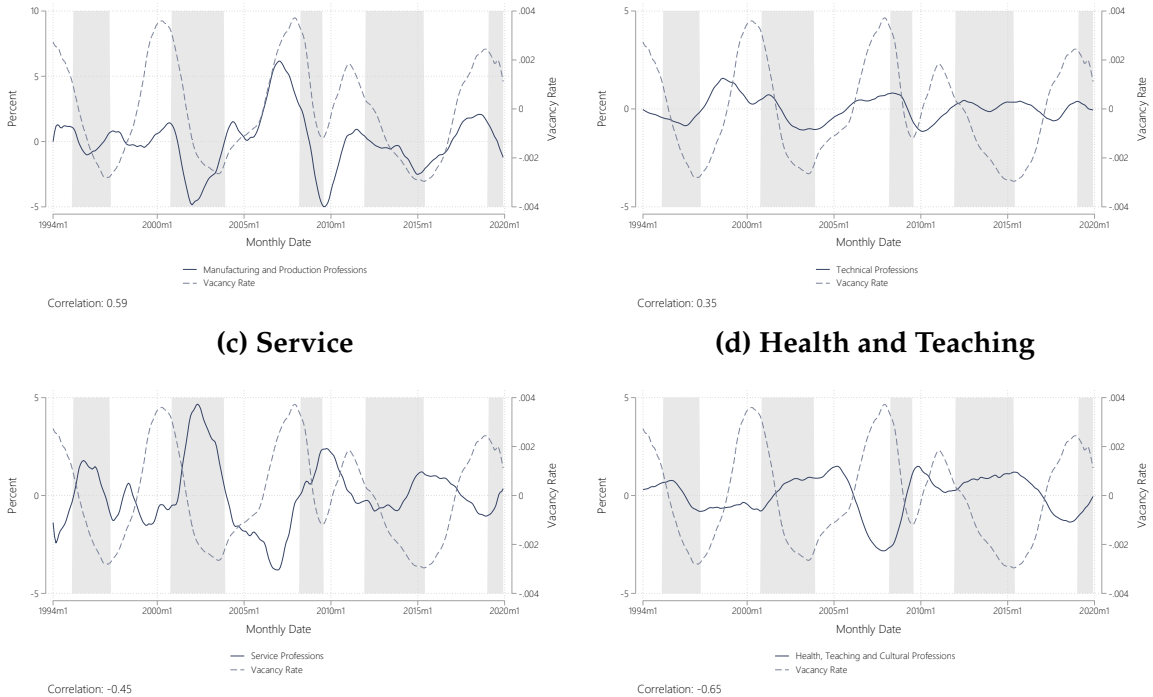
Correlation: 0.48 Correlation: -0.29

Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

Figure D.2
Composition over the Business Cycle – Occupation

(a) Production/Manual **(b) Technical**

(c) Service **(d) Health and Teaching**



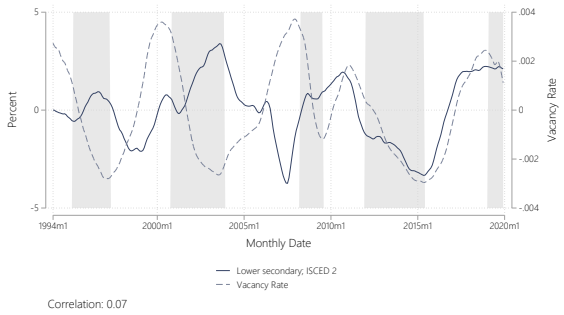
Correlation: 0.59 Correlation: 0.35

Correlation: -0.45 Correlation: -0.65

Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

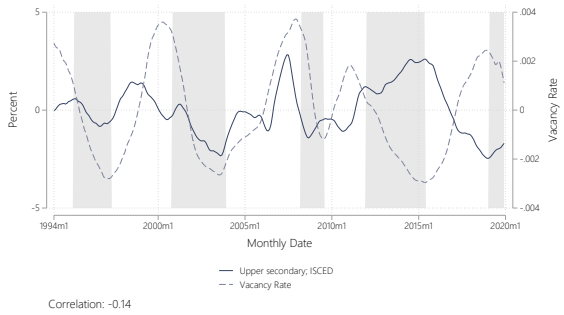
Figure D.3
Composition over the Business Cycle – Education

(a) Lower secondary



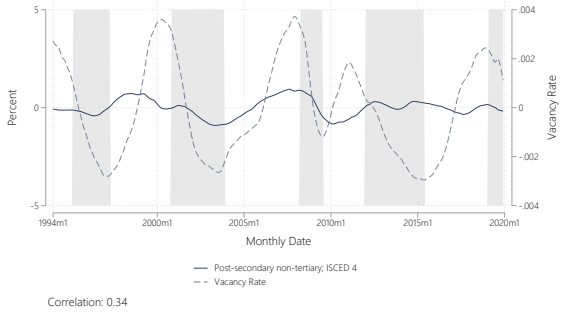
Correlation: 0.07

(b) Upper Secondary



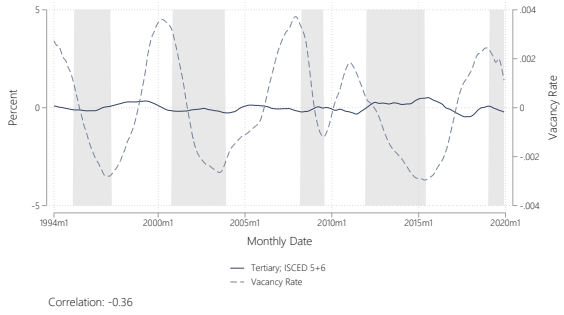
Correlation: -0.14

(c) Post Secondary (Non-Tertiary)



Correlation: 0.34

(d) Tertiary

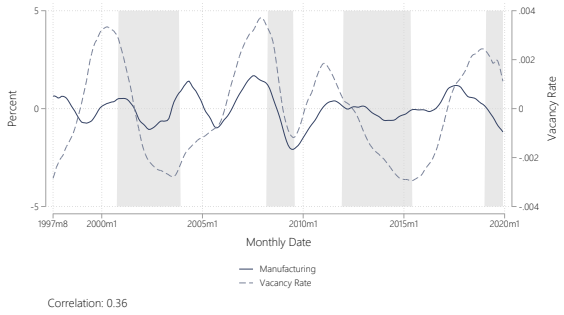


Correlation: -0.36

Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

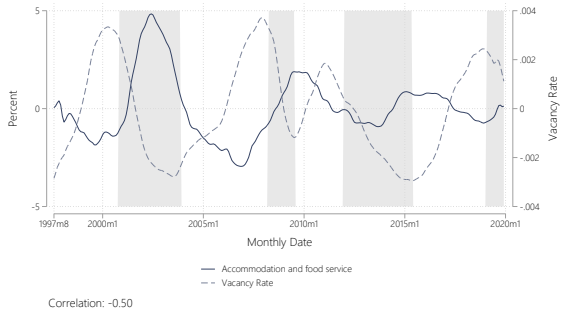
Figure D.4
Composition over the Business Cycle – Industry

(a) Manufacturing



Correlation: 0.36

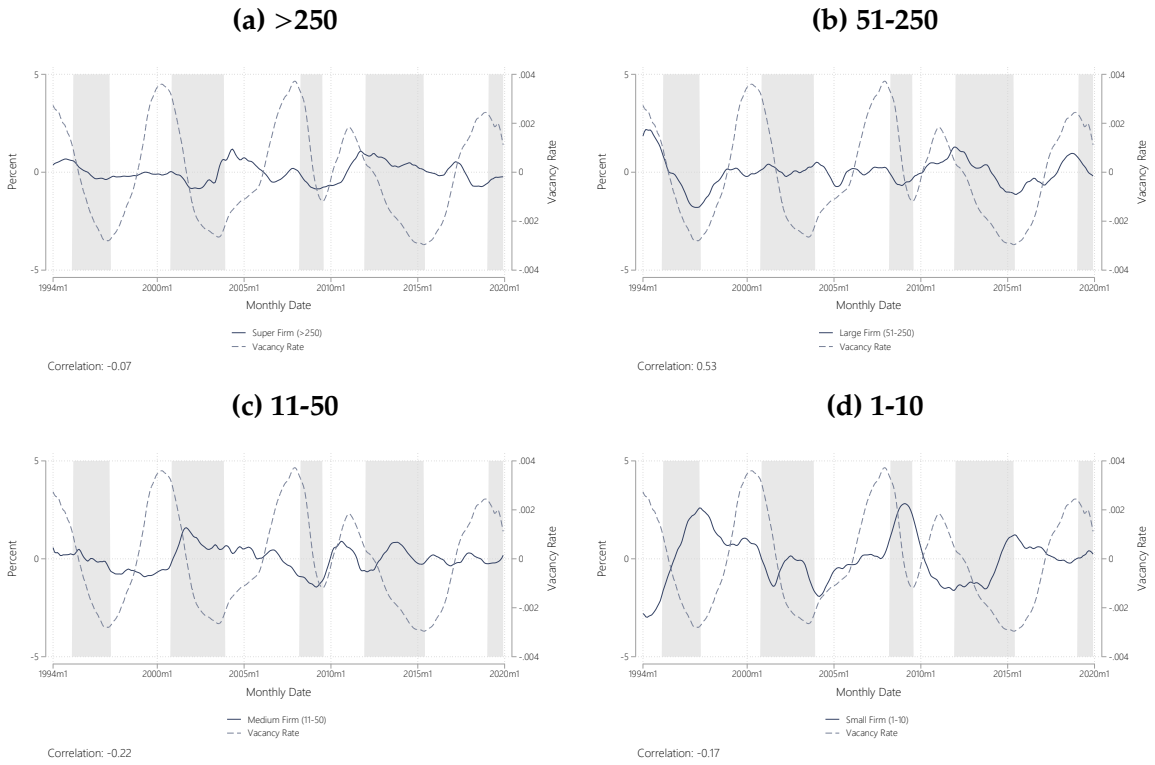
(b) Accomodation and Food



Correlation: -0.50

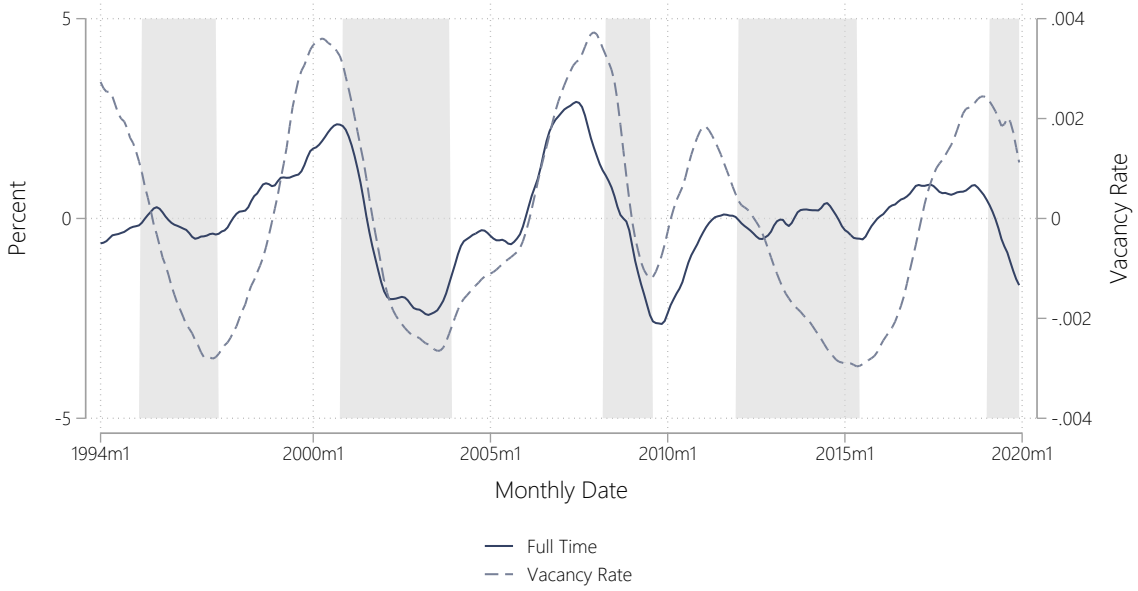
Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

Figure D.5
Composition over the Business Cycle – Firm Size



Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

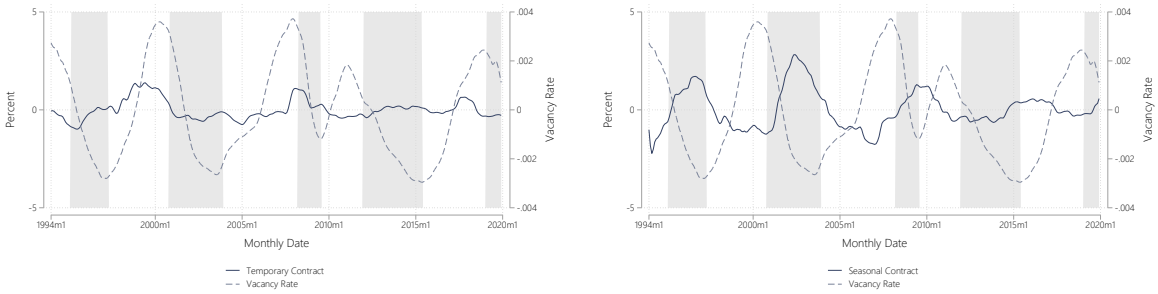
Figure D.6
Composition over the Business Cycle – Full/Part Time



Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

Figure D.7
Composition over the Business Cycle – Contract Type

(a) Temporary **(b) Seasonal**



Notes: 13-month centered moving average applied. HP smoothing parameter is 900,000.

D.2 Vacancy Characteristics of Replacement Hires

We estimate the following equation

$$y_{ijt} = \beta * R_{ijt} + \gamma_j + \alpha_t + X_i + \Omega_{jt} + \varepsilon_{ijt}, \tag{D.1}$$

where y_{ijt} is the log vacancy duration or filling probability of vacancy i at firm j posted in month t. R_{ijt} is an indicator equal to 1 if the vacancy is identified as a replacement vacancy. We control for firm fixes effects γ_j, time fixed effects α_t, vacancy characteristics X_i (job duration, education, employment extent, occupation) and firm characteristics Ω_{jt} (1-digit industry, employment growth and firm size).

Table D.1
Log-Vacancy Duration of Replacement Inflows

	Log Vacancy Duration $\log d_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Aggregate Effect						
Replacement Inflow (1/0)	-0.0442***	-0.0508***	-0.0541***	-0.0554***	-0.0643***	-0.0645***
	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Observations	5159796	5159796	5132797	5128639	5128639	5128639
R^2	0.000	0.014	0.165	0.193	0.203	0.203
B. Firm Size Category						
Small	-0.0711***	-0.0722***	-0.0292***	-0.0331***	-0.0724***	-0.0752***
	(0.0037)	(0.0036)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
Medium	-0.0618***	-0.0651***	-0.0457***	-0.0447***	-0.0765***	-0.0784***
	(0.0027)	(0.0026)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Large	-0.0434***	-0.0482***	-0.0450***	-0.0456***	-0.0588***	-0.0597***
	(0.0025)	(0.0025)	(0.0024)	(0.0023)	(0.0024)	(0.0024)
Super	0.0172***	0.0194***	-0.0390***	-0.0438***	-0.0465***	-0.0458***
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
C. Time Period						
1994-2006	-0.0546***	-0.0577***	-0.0578***	-0.0653***	-0.0815***	-0.124***
	(0.0019)	(0.0019)	(0.0022)	(0.0021)	(0.0021)	(0.0019)
2007-2019	-0.0399***	-0.0476***	-0.0567***	-0.0563***	-0.0644***	-0.0468***
	(0.0014)	(0.0014)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
D. Recession / Expansion						
Recession	-0.0515***	-0.0574***	-0.0549***	-0.0566***	-0.0651***	-0.0638***
	(0.0017)	(0.0017)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Expansion	-0.0395***	-0.0464***	-0.0534***	-0.0543***	-0.0636***	-0.0651***
	(0.0014)	(0.0014)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
E. Blue / White Collar						
White Collar	-0.0148***	-0.0285***	-0.0509***	-0.0471***	-0.0493***	-0.0527***
	(0.0016)	(0.0016)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Blue Collar	-0.0872***	-0.0925***	-0.0573***	-0.0608***	-0.0739***	-0.0717***
	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Time FE		X	X	X	X	X
Firm FE			X	X	X	X
Job Characteristics				X	X	X
Firm Characteristics					X	X
Close Availability Dummy						X

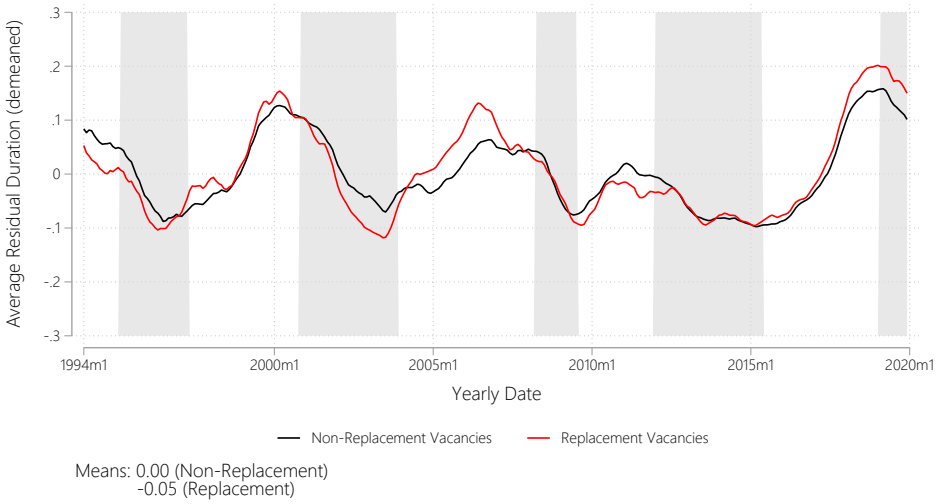
Notes: The table shows estimates of β from equation (D.1). The Close Availability Dummy indicates if the availability date is at most 7 days around the posting date. Specific industries are discarded. We use the matched firm universe sample. We use a time frame of -32 to +14 days to identify replacement vacancies. The overall mean duration is $\approx$ 48 days.

Table D.2
Vacancy Filling Probability of Replacement Inflows

	Vacancy Filling Probability					
	(1)	(2)	(3)	(4)	(5)	(6)
A. Aggregate Effect						
Replacement Inflow (1/0)	0.00995***	0.0103***	0.0168***	0.0157***	0.0169***	0.0175***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Observations	6158515	6158515	6132876	6125025	6125025	6125025
R^2	0.000	0.018	0.157	0.161	0.162	0.162
B. Firm Size						
Small	0.0209***	0.0223***	0.00472***	0.00410***	0.00552***	0.00662***
	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Medium	0.0270***	0.0273***	0.00943***	0.00871***	0.0105***	0.0114***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Large	0.0434***	0.0408***	0.0230***	0.0220***	0.0234***	0.0238***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Super	0.00186***	-0.000447	0.0186***	0.0165***	0.0163***	0.0165***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
C. Time Period						
1994-2006	0.00687***	0.00686***	0.0219***	0.0193***	0.0214***	0.0226***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
2007-2019	0.0119***	0.0119***	0.0150***	0.0141***	0.0148***	0.0152***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
D. Recession / Expansion						
Recession	0.0139***	0.0142***	0.0155***	0.0143***	0.0147***	0.0149***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Expansion	0.00757***	0.00778***	0.0169***	0.0159***	0.0175***	0.0184***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
E. Blue / White Collar						
White Collar	0.0149***	0.00977***	0.0135***	0.0123***	0.0129***	0.0133***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Blue Collar	0.00855***	0.0103***	0.0148***	0.0145***	0.0159***	0.0164***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Time FE		X	X	X	X	X
Firm FE			X	X	X	X
Job Characteristics				X	X	X
Firm Characteristics					X	X
Close Availability Dummy						X

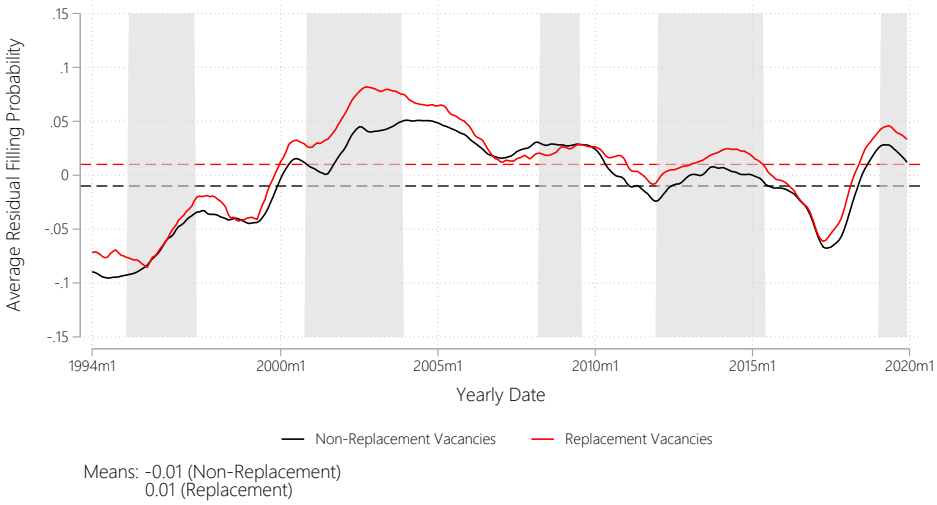
Notes: This table shows estimates of β from equation (D.1). The Close Availability Dummy indicates if the availability date is at most 7 days around the posting date. Specific industries are discarded. We use the matched firm universe sample. We use a time window of -32 to +14 days to identify replacement vacancies. The overall mean of the filling dummy is $\approx .87$.

Figure D.8
Residual Vacancy Duration over Time



Notes: This figure shows the residual (non-log) vacancy duration, controlling for all covariates from table D.1, except for the time fixed effects and the replacement dummy, by time for identified replacement and non-replacement vacancies. We use a time window of -32 to +14 days to identify replacement vacancies. The overall mean duration is ≈ 48 days.

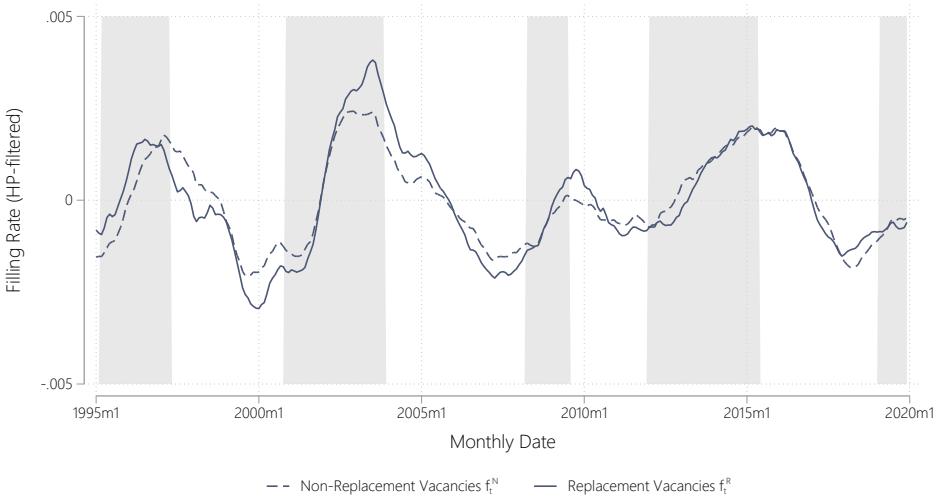
Figure D.9
Residual Filling Probability over Time



Notes: This figure shows the residual vacancy filling probability, controlling for all covariates from table D.2, except for the time fixed effects and the replacement dummy, by time for identified replacement and non-replacement vacancies. We use a time window of -32 to +14 days to identify replacement vacancies. The overall mean of the filling dummy is ≈ .87.

Figure D.10
Vacancy Filling Rate of Replacement Hires

(a) Vacancy Filling Rate (Detrended)



(b) Share of Replacement Vacancies



Notes: This figure shows the vacancy filling rate for vacancies identified as replacement inflows and non-replacement inflows in the AMS data 1994 – 2019, where we apply a 13-month centered moving average.

D.3 Non-Importance of Compositional Changes for Filling Rate

Regression Model. The daily firm-specific filling rate is defined as

$$f_{i,t,d} = \frac{H_{i,t,d}}{V_{i,t,d-1}}, \tag{D.2}$$

where $H_{i,t,d}$ are the number of vacancy fillings in firm i at day d of month t and $V_{i,t,d-1}$ the number of open vacancies. Based on daily filling rates $f_{i,t,d}$, we compute a firm-level monthly filling rate $f_{i,t}$ according to equation

$$f_{i,t} = \sum_d \omega_d^{i,t} f_{i,t,d} \tag{D.3}$$

where the weight $\omega_d^{i,t}$ is defined as

$$\omega_d^{i,t} = \frac{V_{i,t,d-1}}{\sum_d V_{i,t,d-1}} \equiv \frac{V_{i,t,d-1}}{V_{i,t}} \tag{D.4}$$

Then we estimate the fixed-effects model

$$f_{i,t} = \psi_i + \delta_t + \Gamma' X_{i,t} + \varepsilon_{i,t} \tag{D.5}$$

where Γ is a vector of coefficients and $X_{i,t}$ is a vector of control variables controlling for firm size, firm location (NUTS3) and industry. Additionally, we control for the share of vacancies with different education levels, employment extents (full time, ...), job durations (unlimited, seasonal, ...), and types of jobs (production, administration, trade, ...), as well as firm-specific monthly DFH employment growth and an indicator whether the vacancy was identified as a replacement vacancy.

Variance Decomposition. In the regression model (D.5), we have

$$f_{i,t} = \psi_i + \delta_t + \Gamma' X_{i,t} + \varepsilon_{i,t}$$

using our weights from above,

$$\begin{aligned}\sum_i \omega_i^t f_{i,t} &= \sum_i \omega_i^t \left(\psi_i + \delta_t + \Gamma' X_{i,t} + \varepsilon_{i,t}\right) \\ &= \sum_i \omega_i^t \psi_i + \delta_t \underbrace{\sum_i \omega_i^t}_{=1} + \sum_i \omega_i^t \chi_{i,t} + \sum_i \omega_i^t \varepsilon_{i,t}\end{aligned}$$

where $\chi_{i,t} \equiv \Gamma' X_{i,t}$. Hence,

$$f_t = \overline{\psi}_t + \delta_t + \overline{\chi}_t + \overline{\varepsilon}_t$$

where we define

$$\overline{z}_t \equiv \sum_i \omega_i^t z_{i,t}$$

for $z_{it} = \{\psi_i, \chi_{i,t}, \varepsilon_{i,t}\}$ with $\overline{\varepsilon}_t = 0$. Hence, in order to assess the composition over the business cycle, we decompose the monthly filling rate f_t using a weighted average with weights

$$\omega_i^t = \frac{\sum_d V_{i,t,d-1}}{\sum_d \sum_i V_{i,t,d-1}} \tag{D.6}$$

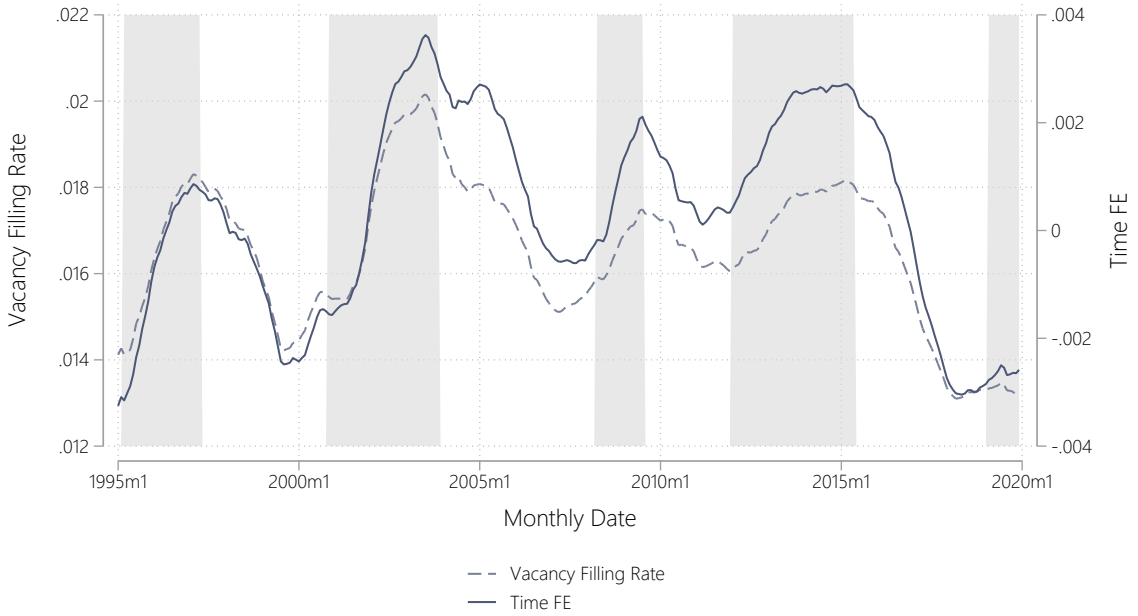
of the estimated firm fixed effects $\hat{\psi}_i$, the firm-specific partial prediction of the monthly filling rate $f_{i,t}$ based on the covariates $\hat{\chi}_{i,t} = \hat{\Gamma}' X_{i,t}$, and the estimated time fixed effects $\hat{\delta}_t$. As a consequence, the observed monthly filling rate f_t can be decomposed according to

$$f_t \approx \overline{\hat{\psi}}_t + \hat{\delta}_t + \overline{\hat{\chi}}_t \tag{D.7}$$

Hence, we report results for the following variance decomposition

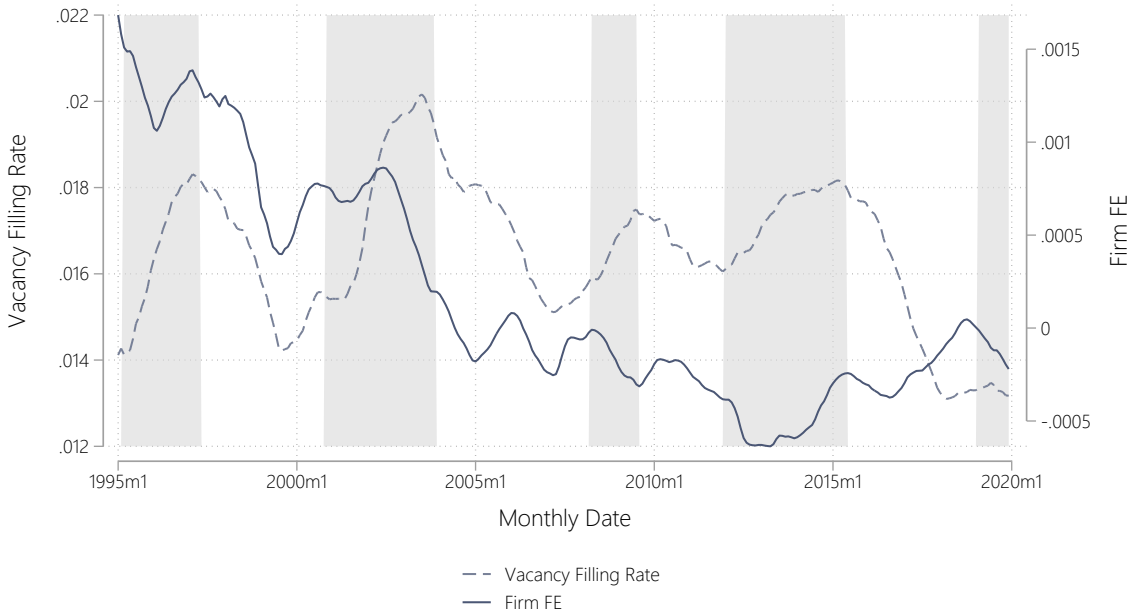
$$\underbrace{\frac{cov(f_t, f_t)}{var(f_t)}}_{=1} = \frac{cov(f_t, \overline{\hat{\psi}}_t)}{var(f_t)} + \frac{cov(f_t, \hat{\delta}_t)}{var(f_t)} + \frac{cov(f_t, \overline{\hat{\chi}}_t)}{var(f_t)} \tag{D.8}$$

Figure D.11
Decomposition of Filling Rate - Time Fixed Effects



Notes: This figure shows the estimated time fixed effects from equation (D.5) using AMS data for the time period 1994 – 2019, where we apply 13-month centered moving average.

Figure D.12
Decomposition of Filling Rate - Firm Fixed Effects



Notes: This figure shows the estimated firm fixed effects from equation (D.5) using AMS data for the time period 1994 – 2019, where we apply 13-month centered moving average.

Table D.3
Variance Decomposition of Filling Rate
using Different Filtering Methods

	Filling Rate f_t					
	$\overline{\hat{\psi}}_t$	$\overline{\hat{\chi}}_t^{\text{vac}}$	$\overline{\hat{\chi}}_t^{\text{firm}}$	$\overline{\hat{\chi}}_t^{\text{emplgrowth}}$	$\overline{\hat{\chi}}_t^{\text{replacement}}$	$\hat{\delta}_t$
A. Matched Firm Sample 1995 – 2019						
Christiano-Fitzgerald	0.0654***	0.0881***	-0.139***	0.0359***	-0.00166	0.965***
	(0.0201)	(0.0102)	(0.0121)	(0.0063)	(0.0014)	(0.0252)
Hamilton	-0.0320	-0.0304	-0.0936***	0.0464***	0.00492***	1.058***
	(0.0214)	(0.0236)	(0.0165)	(0.0102)	(0.0016)	(0.0463)
Hodrick-Prescott	0.0257	0.0358***	-0.0930***	0.0331***	-0.0002	1.010***
	(0.0188)	(0.0137)	(0.0098)	(0.0059)	(0.0013)	(0.0198)
Baxter-King	0.0719***	0.0527***	-0.138***	0.0283***	0.000464	0.995***
	(0.0263)	(0.0141)	(0.0149)	(0.0060)	(0.0015)	(0.0293)
B. Matched Restrictive Sample 1995 – 2019						
Christiano-Fitzgerald	-0.00182	0.131***	-0.124***	0.0372***	-0.0123***	1.000***
	(0.0120)	(0.0128)	(0.0141)	(0.0067)	(0.0014)	(0.0298)
Hamilton	-0.0914***	0.00664	-0.0863***	0.0395***	-0.00529***	1.137***
	(0.0192)	(0.0257)	(0.0136)	(0.0098)	(0.0017)	(0.0456)
Hodrick-Prescott	-0.0138	0.0699***	-0.0802***	0.0320***	-0.00734***	1.046***
	(0.0154)	(0.0162)	(0.0094)	(0.0063)	(0.0010)	(0.0266)
Baxter-King	0.00975	0.0909***	-0.113***	0.0267***	-0.0127***	1.027***
	(0.0157)	(0.0167)	(0.0178)	(0.0065)	(0.0017)	(0.0382)

Notes: This table shows a variance decomposition of the observed monthly vacancy filling rate according to equation (D.8). The matched firm sample covers the time period 1995 – 2019. HP smoothing parameter is 900,000.

Table D.4
Variance Decomposition of Log Vacancy Duration
using Different Filtering Methods

	Vacancy Duration d_t					
	$\overline{\hat{\psi}}_t$	$\overline{\hat{\chi}}_t^{\text{vac}}$	$\overline{\hat{\chi}}_t^{\text{firm}}$	$\overline{\hat{\chi}}_t^{\text{emplgrowth}}$	$\overline{\hat{\chi}}_t^{\text{replacement}}$	$\hat{\delta}_t$
A. Matched Firm Sample 1995 – 2019						
Christiano-Fitzgerald	-0.0103	0.00416	-0.0742***	0.0198***	-0.00801***	1.073***
	(0.0143)	(0.0071)	(0.0117)	(0.0040)	(0.0015)	(0.0226)
Hamilton	0.00652	-0.0467***	-0.0429***	0.0166***	-0.00656***	0.988***
	(0.0189)	(0.0106)	(0.0134)	(0.0061)	(0.0009)	(0.0512)
Hodrick-Prescott	0.00649	-0.0170*	-0.0450***	0.0182***	-0.00766***	1.099***
	(0.0194)	(0.0092)	(0.0097)	(0.0045)	(0.0010)	(0.0195)
Baxter-King	-0.00584	-0.0142	-0.0937***	0.0157***	-0.0125***	1.110***
	(0.0230)	(0.0113)	(0.0140)	(0.0045)	(0.0019)	(0.0331)
B. Matched Restrictive Sample 1995 – 2019						
Christiano-Fitzgerald	-0.0000524	0.00746	-0.0567***	0.0200***	-0.00714***	1.022***
	(0.0178)	(0.0079)	(0.0066)	(0.0037)	(0.0010)	(0.0226)
Hamilton	0.00885	-0.0380***	-0.0247***	0.0178***	-0.00604***	0.899***
	(0.0310)	(0.0101)	(0.0090)	(0.0050)	(0.0007)	(0.0504)
Hodrick-Prescott	0.0320	-0.00808	-0.0266***	0.0196***	-0.00602***	0.952***
	(0.0376)	(0.0097)	(0.0067)	(0.0054)	(0.0006)	(0.0351)
Baxter-King	-0.0103	-0.0122	-0.0514***	0.0158***	-0.00944***	1.042***
	(0.0275)	(0.0107)	(0.0098)	(0.0039)	(0.0012)	(0.0329)

Notes: This table shows a variance decomposition of the observed monthly vacancy filling rate according to equation (D.8). The matched firm sample covers the time period 1995 – 2019. HP smoothing parameter is 900,000.

E Vacancy Flows and Replacement Hires in a Search Model

This section proposes a simple extension of the standard DMP model, allowing for (1) fixed costs in vacancy creation, (2) endogenous recruiting effort and (3) on-the-job search and replacement hires. We start with the stationary version of the model and then extend it to the case of non-stationary productivity.

E.1 Model Set-Up

Model Features

- DMP model with random matching with matching function $M = M(S, aV)$, where $S = u + \sigma(1-u)$ is aggregate search effort and σ is the employed workers' search effectiveness (relative to unemployed). a is a measure of recruiting effort. We assume a CRS matching function such that the matching rate per unit of search effort is $\frac{M}{S} = M(1, \theta) = \lambda(\theta)$ and where $\theta = \frac{aV}{S}$ is labor market tightness. The implied job-finding rate for unemployed is $\lambda(\theta)$ and for the employed it is $\sigma\lambda(\theta)$. We normalize the matching function such that $\lambda(1) = 1$.
- Firms exert recruiting effort a at cost $k(s)$, where $k(0) \geq 0$, $k'(a) > 0$ and $k''(a) > 0$, and are matched to workers at rate $aq(\theta)$, where $\lambda(\theta) = \theta q(\theta)$.
- Firms face a fixed vacancy creation cost x, which is i.i.d. and drawn from distribution $F(.)$.
- Wages are determined by Nash Bargaining (NB) with worker bargaining share α.
- Vacancies are determined endogenously by the condition that there are zero profits from vacancy creation: $n = F(V)$.

Value of Unemployment

The value of unemployment is:

$$U = b + \beta[(1 - \lambda(\theta))U + \lambda(\theta)W], \tag{E.1}$$

Value of Employment

The value of employment for the worker is:

$$W = w + \beta[(1-\rho)(1-\delta)W + (1 - (1-\rho)(1-\delta))U]. \tag{E.2}$$

Note that the value of employed is not affected by on-the-job search, since all values of employment are the same in this simple model. (Eventually, we need to expand the model in this dimension, since there is not any incentive for employed jobseekers to look for a new job in this model.)

Value of Unfilled Vacancy

The value of an unfilled vacancy and a filled job are:

$$V = \max_{a} \left(-k(a) + \beta(1-\rho)\left[(1-aq(\theta))V + aq(\theta)J\right]\right), \tag{E.3}$$

with FOC:

$$k'(a) = \beta(1-\rho)q(\theta)(J-V). \tag{E.4}$$

Value of Filled Vacancy

The value of a filled vacancy is:

$$J = p - w + \beta(1-\rho)[(1-\delta)(1-\sigma\lambda(\theta))J + \gamma(1-(1-\delta)(1-\sigma\lambda(\theta)))V]. \tag{E.5}$$

Nash-Bargaining

Wages are negotiated in each period according to the Nash-Bargaining Solution:

$$\omega = \arg\max_{w} = (W-U)^{\alpha}(J-V)^{1-\alpha}, \tag{E.6}$$

where α is the worker's bargaining share. Wages are the solution to the Nash Bargaining problem

$$\omega = \arg\max_{w} \quad (W-U)^{\alpha}\ (J-V)^{1-\alpha}$$

with FOC

$$\alpha(W-U)^{\alpha-1}\frac{\partial(W-U)}{\partial w}(J-V)^{1-\alpha} + (W-U)^{\alpha}(1-\alpha)(J-V)^{-\alpha}\frac{\partial(J-V)}{\partial w} = 0$$
$$\alpha(W-U)^{\alpha-1}(J-V)^{1-\alpha} = (W-U)^{\alpha}(1-\alpha)(J-V)^{-\alpha}$$
$$\alpha(J-V) = (1-\alpha)(W-U)$$

using the value functions, we get that

$$\begin{aligned}\omega &= \alpha(p + k(a)) + (1-\alpha)b + (1-\alpha)\lambda(\theta)\beta(W-U) - \alpha(1-\rho)aq(\theta)\beta(J-V) \\ &= \alpha(p + k(a)) + (1-\alpha)b + \alpha\big(\theta(1-\sigma(1-\delta)(1-\rho)) - (1-\rho)a\big)q(\theta)\beta(J-V)\end{aligned}$$

In the standard DMP model, we have $a = 1, \rho = 0, \sigma = 0$ as well as $k(a) = \kappa$ and $V = 0$ in equilibrium. Therefore, $\kappa = \beta q(\theta) J$ and the wage is

$$\omega = \alpha p + (1-\alpha)b + \alpha\theta q(\theta)\beta J - \alpha q(\theta)\beta J + \alpha\kappa = \alpha p + (1-\alpha)b + \alpha\theta\kappa$$

Vacancy Creation

Firms post vacancies subject to i.i.d. vacancy creation costs such that new vacancies satisfy:

$$n = F(V). \tag{E.7}$$

Vacancy Lapses

There is an exogenous vacancy lapse rate, related to the rate of obsolence, ρ. It is also possible that firms shut down open vacancies if

$$k(0) > \beta(1-\rho)V. \tag{E.8}$$

Law of Motions

Vacancies follow the law of motion:

$$v_{t+1} = (1 - aq(\theta))(1-\rho)v_t + \gamma(1-\rho)(\delta + (1-\delta)\sigma\lambda(\theta))(1-u_t) + n_t. \tag{E.9}$$

Unemployment follows the law of motion:

$$u_{t+1} = (1-\lambda(\theta))u_t + (1-(1-\delta)(1-\rho))(1-u_t). \tag{E.10}$$

Functional Forms

As in Leduc and Liu (2020), we assume that

$$k(a) = \kappa_0 + \kappa_1(a - \bar{a}) + \frac{\kappa_2}{2}(a - \bar{a})^2 \tag{E.11}$$

$$c(s) = \zeta_0 + \zeta_1(s - \bar{s}) + \frac{\zeta_2}{2}(s - \bar{s})^2 \tag{E.12}$$

$$F(V) = \eta(V)^{\xi} \tag{E.13}$$

$$M(S, sv) = \mu(S)^{\phi}(av)^{1-\phi} \tag{E.14}$$

with $\bar{a} = \bar{s} = 1$.[7]

E.2 Model Equilibrium

Steady-State Definition

A steady-state is defined as a set $(u, v, \theta, n, a, V, J, W, U, w)$ satisfying

(1) Unemployment u

$$u = \frac{(1 - (1 - \delta)(1 - \rho))}{\lambda(\theta) + (1 - (1 - \delta)(1 - \rho))} \tag{E.16}$$

(2) Vacancy Stocks v

$$v = \frac{\gamma(1 - \rho)(\delta + (1 - \delta)\sigma\lambda(\theta))(1 - u) + n}{1 - (1 - aq(\theta))(1 - \rho)} \tag{E.17}$$

(3) Labor Market Tightness θ

$$\theta = \frac{av}{u + \sigma(1 - u)} \tag{E.18}$$

(4) Vacancy Inflows n

$$n = F(V) \tag{E.19}$$

[7] Note that the assumption on the matching function $M(\cdot)$ implies that $\lambda(\theta) = \mu\theta^{1-\phi}$ and $q(\theta) = \mu\theta^{-\phi}$. In contrast to the *vacancy* creation costs in Leduc and Liu (2020), Mercan and Schoefer (2020) use *job* creation costs with

$$V = k(n) \quad \Rightarrow \quad k(n) = k_1 + k_2\frac{n - \bar{n}}{\bar{n}} \tag{E.15}$$

and the model does not feature search effort of workers, i.e., $c(s) = 0$.

(5) Recruiting Effort a

$$k'(a) = \beta(1-\rho)q(\theta)(J-V) \tag{E.20}$$

(6) Value of Unfilled Vacancy V

$$V = \frac{-k(a) + \beta(1-\rho)aq(\theta)J}{1-\beta(1-\rho)(1-aq(\theta))} \tag{E.21}$$

(7) Value of Filled Vacancy J

$$J = \frac{p-\omega+\beta\gamma(1-\rho)[\delta+(1-\delta)\sigma\lambda(\theta)]V}{1-\beta(1-\rho)(1-\delta)(1-\sigma\lambda(\theta))} \tag{E.22}$$

(8) Value of Employment W

$$W = \frac{w+\beta(1-(1-\rho)(1-\delta))U}{1-\beta(1-\rho)(1-\delta)} \tag{E.23}$$

(9) Value of Unemployment U

$$U = \frac{b+\beta\lambda(\theta)W}{1-\beta(1-\lambda(\theta))} \tag{E.24}$$

(10) Wage ω

$$\omega = \alpha(p+k(a)) + (1-\alpha)b + \alpha\big(\theta(1-\sigma(1-\delta)(1-\rho)) - (1-\rho)a\big)q(\theta)\beta(J-V) \tag{E.25}$$

Solution Algorithm

In order to calibrate the steady state equilibrium, we use the following algorithm

1. guess θ

   1.1. guess ω

      1.1.1 solve for J and V:

$$\underbrace{\begin{pmatrix} 1 & -\frac{\beta(1-\rho)aq(\theta)}{1-\beta(1-\rho)(1-aq(\theta))} \\ -\frac{\beta\gamma(1-\rho)[\delta+(1-\delta)\sigma\lambda(\theta)]}{1-\beta(1-\rho)(1-\delta)(1-\sigma\lambda(\theta))} & 1 \end{pmatrix}}_{\equiv \mathbf{A}} \begin{pmatrix} V \\ J \end{pmatrix} = \underbrace{\begin{pmatrix} -\frac{k(a)}{1-\beta(1-\rho)(1-aq(\theta))} \\ \frac{p-w}{1-\beta(1-\rho)(1-\delta)(1-\sigma\lambda(\theta))} \end{pmatrix}}_{\equiv \mathbf{b}}$$

      1.1.2 solve for U and W:

$$\underbrace{\begin{pmatrix} 1 & -\frac{\beta\lambda(\theta)}{1-\beta(1-\lambda(\theta))} \\ -\frac{\beta(1-(1-\rho)(1-\delta))}{1-\beta(1-\rho)(1-\delta)} & 1 \end{pmatrix}}_{\equiv \mathbf{A}} \begin{pmatrix} U \\ W \end{pmatrix} = \underbrace{\begin{pmatrix} \frac{b}{1-\beta(1-\lambda(\theta))} \\ \frac{\omega}{1-\beta(1-\rho)(1-\delta)} \end{pmatrix}}_{\equiv \mathbf{b}}$$

      1.1.3 update ω:

$$\omega' = \alpha(p + k(a)) + (1 - \alpha)b + \alpha\big(\theta(1 - \sigma(1 - \delta)(1 - \rho)) - (1 - \rho)a\big)q(\theta)\beta(J - V)$$

   $\Rightarrow$ iterate 1.1.1 – 1.1.3 until $|\omega' - \omega| < \varepsilon_\omega$.

   1.2 calculate n:

$$n = \eta(V)^\xi$$

   1.3 solve for u and v:

$$\underbrace{\begin{pmatrix} u & - & \frac{(1-(1-\delta)(1-\rho))}{\lambda(\theta)+(1-(1-\delta)(1-\rho))} \\ v & - & \frac{\gamma(1-\rho)(\delta+(1-\delta)\sigma\lambda(\theta))(1-u)+n}{1-(1-aq(\theta))(1-\rho)} \end{pmatrix}}_{\equiv F(\mathbf{x})} = \underbrace{\begin{pmatrix} 0 \\ 0 \end{pmatrix}}_{\equiv \mathbf{0}}$$

   1.4 update θ:

$$\theta' = \frac{av}{su}$$

$\Rightarrow$ iterate 1.1. – 1.4. until $|\theta' - \theta| < \varepsilon_\theta$.

E.3 Model Calibration

Empirical Data Moments for Austria. Let $t \in \{1, ..., 12\}$ be the month, $d \in \{0, ..., 31\}$ be the day in month t, where $d = D$ indicates the last day of month t and $d = 0, t = t_0$ is the same day as $d = D$ in month $t = t_0 - 1$. Let F_{jdt}, L_{jdt}, N_{jdt}, V_{jdt}, H_{jdt} and E_{jdt} be vacancy fillings, vacancy lapses, vacancy inflows, vacancy stocks, hires and employment of firm j on day d of month t. The empirical data moments for Austria in Table E.1 are then calculated as

$$\begin{aligned} f_t &= \frac{\sum_d \sum_j F_{jdt}}{\sum_j V_{jDt}} \\ l_t &= \frac{\sum_d \sum_j L_{jdt}}{\sum_j V_{jDt}} \\ n_t &= \frac{\sum_d \sum_j N_{jdt}}{\sum_j E_{jDt}} \\ v_t &= \frac{\sum_d \sum_j V_{jdt}}{\sum_d \sum_j V_{jdt} + E_{jdt}} \\ h_t &= \frac{\sum_d \sum_j H_{jdt}}{\sum_j E_{jDt}} \\ \theta_t &= \frac{v_t}{u_t} \end{aligned} \tag{E.26}$$

Furthermore, we calibrate $\sigma = 0.050$ in order to match $h^{R,P} = 0.41$, according to

$$(1 - \Psi) = h^{R,P} \quad \Leftrightarrow \quad \sigma = \frac{u(1 - \Psi)}{\Psi(1 - u)} \tag{E.27}$$

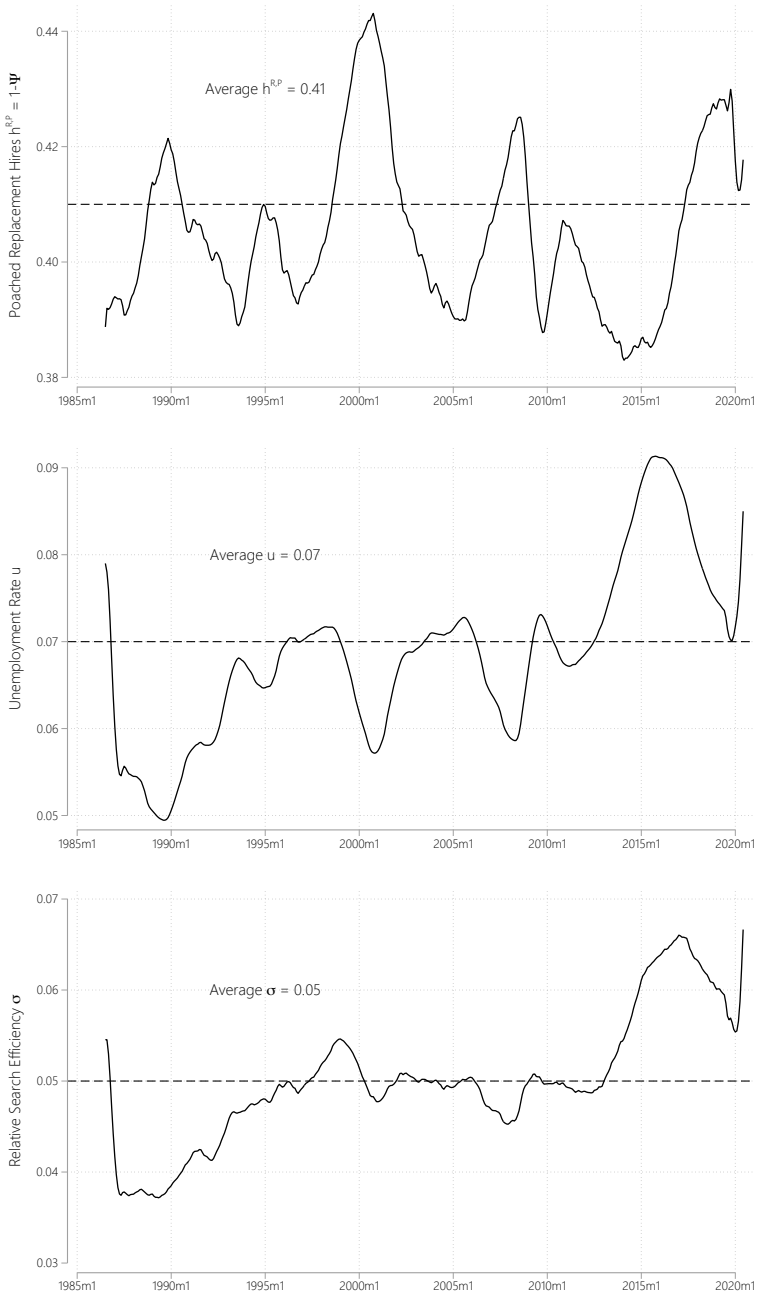
with an average $u = 0.07$ and $v = 0.018$, see Figure E.1.

Table E.1
Empirical Data Moments for Austria

	Sample			
	AMS Universe	Matched Restrictive	Matched Firm Universe	ASSD Universe
Unemployment Rate (ASSD)	0.0877	0.0877	0.0877	0.0877
Unemployment Rate (OENB)	0.0715	0.0715	0.0715	0.0715
Labor Market Tightness	0.2517	0.2893	0.2027	-
Job-Filling Probability	0.8311	0.8471	0.8451	-
Hiring Rate	-	0.0336	0.0289	0.0318
Separation Rate (E)	-	0.0080	0.0073	0.0082
Separation Rate (N)	-	0.0250	0.0213	0.0243
Vacancy Rate	0.0173	0.0201	0.0141	-
Inflow Rate	0.0095	0.0121	0.0083	-
Filling Rate	0.4967	0.5238	0.5069	-
Lapse Rate	0.0942	0.0907	0.0895	-
Vacancy Yield	-	1.7815	2.2715	-
Hires / Filled	-	3.4462	4.5130	-

Notes: Empirical data moments for Austria based on equation (E.26), where labor market tightness is calculated using the official OENB unemployment rate (see text for details). We use years 1987 – 2019 for the AMS Universe, 1994 – 2019 for both matched firm samples and 1986 – 2019 for the ASSD Universe.

Figure E.1
Relative Search Efficiency σ



Parameter Values and Targeted Model Moments. Based on the empirical data moments for Austria in Table E.1, we consider the following targets:

- (Adjusted) vacancy inflow rate $n = 0.0121 \cdot 1/0.58 = 0.0209$[8]
- Vacancy filling rate $f = 0.5238$
- (Implied) steady-state vacancy rate $\tilde{v} = 0.0370$ (or vacancy stocks $v = 0.0351$)
- Unemployment Rate $u = 0.087$
- Recruiting Effort $a = 1$

and we internally calibrate the following parameters

- Matching Efficiency μ
- Vacancy Yield/Coverage ψ
- Vacancy Creation Cost η_1
- Recruiting Cost (Intercept) κ_0
- Recruiting Cost (Slope, Linear) κ_1

Table E.2 shows the external and calibrated parameter values.

[8] Let $\psi \equiv M/F$, then the vacancy (job) filling probability

$$q(\theta) \equiv \frac{F}{aV} = \frac{F}{M}\frac{M}{aV} = \psi^{-1}\frac{M}{aV} = \psi^{-1}\mu\theta^{-\phi}$$

and the job-finding probability

$$\lambda(\theta) = \psi\theta q(\theta)$$

Table E.2
Parameter Values

Moment	Description	Baseline	
		$\sigma = 0.056$	$\sigma = 0.056$
A. External Parameter Values			
β	Discount Factor	0.9967	0.9967
α	Nash Bargaining Weight	0.5000	0.5000
ϕ	Elasticity of Matching Function	0.5000	0.5000
γ	Real Wage Rigidity	0.0000	0.0000
κ_2	Recruiting Cost (Slope)	5.8751	5.8751
b	Unemployment Benefits	0.8636	0.8636
ρ	Obsolence Rate	0.0196	0.0196
ξ	Elasticity of Vacancy Creation	1.0000	1.0000
B. Calibrated Parameter Values			
σ	Relative Seach Efficiency	0.0500	0.0500
η_1	Vacancy Creation Cost (Slope)	0.2690	0.2690
η_0	Vacancy Creation Cost (Intercept)	0.0000	0.0194
μ	Matching Efficiency	0.3704	1.1633
δ	Job Separation Rate	-0.0073	0.0250
κ_0	Recruiting Cost (Intercept)	0.4802	0.5605
κ_1	Recruiting Cost (Slope)	0.5579	0.6482

Notes: External and calibrated model parameters. The first column show the baseline parameters with $\sigma = 0.001$. The second column show model parameters using a value of $\sigma = 0.056$.

Model Counterfactuals. Table E.3 reports the steady-state counterfactuals in the calibrated search model with job search $\sigma = 0.05$ for a fixed counterfactual $\gamma_1 = 1$ and a counterfactual $\gamma_1 = 0.93$

Table E.3
Steady-State Counterfactuals in Calibrated Search Model

	Moment	Baseline $p = 1.00$		Counterfactual $p = 0.96$	
		$\gamma_0 = 1.00$	$\gamma_0 = 1.00$	$\gamma_1 = 1.00$	$\gamma_1 = 0.93$
a	Recruiting Effort	1.0000	1.0000	1.0000	1.0000
u	Unemployment	0.0870	0.0870	0.1045	0.1046
v	Vacancy Rate	0.0374	0.0374	0.0289	0.0288
n	Vacancy Inflow Rate	0.0203	0.0203	0.0191	0.0191
f	Vacancy Filling Rate	0.5237	0.5237	0.6412	0.6418
θ	Labor Market Tightness	0.2670	0.2670	0.1782	0.1778
$q(\theta)$	Job-Filling Probability	0.5342	0.5342	0.6540	0.6546
$\lambda(\theta)$	Job-Finding Probability	0.2612	0.2612	0.2134	0.2132
m	Hiring Rate	0.0380	0.0380	0.0356	0.0356
S	Vacancy Stocks	0.0354	0.0354	0.0266	0.0266
N	Vacancy Inflows	0.0028	0.0028	0.0035	0.0045
M	Total Hires	0.0347	0.0347	0.0319	0.0318
V	Value of Unfilled Vacancy	0.0107	0.0107	0.0136	0.0174
J	Value of Filled Vacancy	0.6396	0.6396	0.5273	0.5308
U	Value of Unemployment	291.9172	291.9172	282.1242	282.0985
W	Value of Employment	292.3003	292.3003	282.4412	282.4153
w^B	Baseline Wage Rate	0.9741	0.9741	0.9741	0.9741
w^N	Nash Wage Rate	0.9741	0.9741	0.9399	0.9398
w	Real Wage Rate	0.9741	0.9741	0.9399	0.9398

Notes: Steady-state counterfactuals in a calibrated search model with job search $\sigma = 0.05$ for a fixed counterfactual $\gamma_1 = 1$ and a counterfactual $\gamma_1 = 0.93$.

E.4 Vacancy Rate Decomposition

In flow steady state

$$\tilde{v}_t = \frac{\tilde{n}_t}{\tilde{n}_t + f_t + l_t}, \tag{E.28}$$

where

$$\begin{aligned} n_t &= \frac{(1-\rho)(\delta + (1-\delta)\sigma\lambda(\theta)) + N_t}{V_t + (1-u_t)} \\ l_t &= \rho \\ f_t &= (1-\rho)aq(\theta) \end{aligned}$$

Hence, we use

$$\tilde{v}^f = \frac{\tilde{n}_0}{\tilde{n}_0 + f_1 + l_0} \tag{E.29}$$

$$\tilde{v}^n = \frac{\tilde{n}_1}{\tilde{n}_1 + f_0 + l_0} \tag{E.30}$$

for a baseline calibration $t = 0$ and a counterfactual steady state calibration $t = 1$ following a negative productivity shock from $p = 1$ to $p = 0.96$.

E.5 Vacancy Chain Multiplier

The vacancy chain after 1 initial poached hire in $t = 0$ can be written according to[9]

$t = 1$ we start with $v_1^n = \gamma$ new vacancies (inflows). During t out of the stock $v_1 = v_1^n$

- ρ vacancies are destroyed,
- $(1-\rho)q(\theta)$ vacancies are filled (replacement hires)
  $\rightarrow$ fraction $\sigma(1-u)/s = 1-\Psi$ poached (with a probability γ to remain intact),
- $(1-\rho)(1-q(\theta))$ vacancies are not filled
  $\rightarrow$ fraction φ lapsed.

$t = 2$ we start with $v_2^n = v_1 \cdot ((1-\rho)q(\theta)(1-\Psi)\gamma)$ new and $v_2^o = v_1\,((1-\rho)(1-q(\theta))(1-\varphi))$ old vacancies. During t out of the stock $v_2 = v_2^n + v_2^o$

- ρ vacancies are destroyed,
- $(1-\rho)q(\theta)$ vacancies are filled (replacement hires)
  $\rightarrow$ fraction $\sigma(1-u)/s = 1-\Psi$ poached (with a probability γ to remain intact),

[9] In Mercan and Schoefer (2020) this happens in step 5, where jobs are hit by a σ shock. Hence, we have inherited vacancies $\tilde{v}_t = v_t^o$ and newly created vacancies $n_t = v_t^n$ and, therefore, $v_t = \tilde{v}_t + n_t = v_t^n + v_t^o$ vacancies that can be potentially filled.

– $(1-\rho)(1-q(\theta))$ vacancies are not filled
→ fraction φ lapsed.

$t = 3$ we start with $v_3^n = v_2 \cdot ((1-\rho)q(\theta)(1-\Psi)\gamma)$ new and $v_3^o = v_2\,((1-\rho)(1-q(\theta))(1-\varphi))$ old vacancies. During t out of the stock $v_3 = v_3^n + v_3^o$

– ρ vacancies are destroyed,

– $(1-\rho)q(\theta)$ vacancies are filled (replacement hires)
→ fraction $\sigma(1-u)/s = 1-\Psi$ poached (with a probability γ to remain intact),

– $(1-\rho)(1-q(\theta))$ vacancies are not filled
→ fraction φ lapsed.

...

We therefore have that

$$v_{t+1}^n = v_t \cdot \Gamma \quad , \quad v_{t+1}^f = v_{t+1} \cdot \Phi \quad , \quad v_{t+1} = v_t \cdot (\Gamma + \Delta)$$

with

$$\begin{aligned}
\Gamma &\equiv \gamma(1-\rho)q(\theta)(1-\Psi) \\
\Delta &\equiv (1-\varphi)(1-\rho)(1-q(\theta)) \\
\Phi &\equiv (1-\rho)q(\theta)
\end{aligned}$$

Vacancy Inflows. Hence, for $T \to \infty$ we have that 1 initial poached hire gives

$$\begin{aligned}
\sum_{t=0}^{T} v_{t+1}^n &= v_1 + v_1\Gamma + v_2\Gamma + v_3\Gamma + \dots \\
&= v_1 + v_1\Gamma + v_1(\Gamma+\Delta)\Gamma + v_2(\Gamma+\Delta)\Gamma + \dots \\
&= v_1 + v_1\Gamma + v_1(\Gamma+\Delta)\Gamma + v_1(\Gamma+\Delta)^2\Gamma + \dots \\
&= v_1 + \sum_{t=0}^{T} v_1\Gamma(\Gamma+\Delta)^t \\
&= \gamma + \frac{\gamma\Gamma}{1-(\Gamma+\Delta)} \\
&= \gamma\left(1 + \frac{\Gamma}{1-(\Gamma+\Delta)}\right) \\
&= \frac{\gamma(1-\Delta)}{1-(\Gamma+\Delta)}
\end{aligned}$$

because $v_1 = \gamma$. Using Γ as well as Δ from above, we get

$$\phi^n = \frac{\gamma(1-(1-\rho)(1-q(\theta))(1-\varphi))}{1-(1-\rho)\left((1-q(\theta)\Psi\gamma)-(1-\gamma)q(\theta)-\varphi(1-q(\theta))\right)} \tag{E.31}$$

additional vacancy inflows.

Vacancy Fillings. If we consider filled vacancies v^f (= replacement hires), then

$$\begin{aligned}
\sum_{t=0}^{T} v_{t+1}^f &= v_1\Phi + v_2\Phi + v_3\Phi + \dots \\
&= v_1\Phi + v_1(\Gamma+\Delta)\Phi + v_2(\Gamma+\Delta)\Phi + \dots \\
&= v_1\Phi + v_1(\Gamma+\Delta)\Phi + v_1(\Gamma+\Delta)^2\Phi + \dots \\
&= \sum_{t=0}^{T} v_1\Phi(\Gamma+\Delta)^t \\
&= \frac{\gamma\Phi}{1-(\Gamma+\Delta)}
\end{aligned}$$

Therefore,[10]

$$\phi^f = \frac{\gamma(1-\rho)q(\theta)}{1-(1-\rho)\left((1-q(\theta)\Psi\gamma)-(1-\gamma)q(\theta)-\varphi(1-q(\theta))\right)} \tag{E.32}$$

E.6 Vacancy Replacement Costs

To endogenize the reposting probability γ, we could introduce vacancy replacement costs to match $\gamma = 0.93$ in the data that depend on the value of a *filled* vacancy J (in contrast to an unfilled vacancy V for new inflows N)

$$R_t = G(J) \tag{E.33}$$

similarly to $N_t = F(V)$.

[10]Note that the difference between ϕ^f and ϕ^n is mostly the lapse rate. For the special case with $\varphi = 0$ and $\gamma = 0$ as in Mercan and Schoefer (2020), we have $\phi^n = \frac{\rho+f_t}{\rho+f_t\Psi}$, which is equal to $E(C)$ in Mercan and Schoefer (2020).

F Additional Results

F.1 Replication of Mercan & Schoefer (2020)

Mercan and Schoefer (2020) estimate the following regression using yearly establishment-level data:

$$\frac{\{\text{Hires}_{e,t}, \text{Job Openings}_{e,t}\}}{\text{Emp}_{e,t-1}} = \beta_0 + \sum_{s=-L}^{+L} \nu_s \frac{\text{Quits}_{e,t+s}}{\text{Emp}_{e,(t+s)-1}} + \alpha_e + \alpha_t + \varepsilon_{e,t}. \tag{F.1}$$

where e is the establishment and t is the year. We use quarterly data and approximate quits using separations into employment. Table F.1 and F.2 replicate the event study in the ASSD and confirm that the coefficients are close to 1, indicating that separations into employment are replaced by new hires.

Table F.1
Mercan & Schoefer (2020) Replication
in the ASSD Universe

	$\frac{\text{Hires}_{e,t}}{\text{Emp}_{e,t-1}}$			
Lead/Lag	(1)	(2)	(3)	(4)
-3				0.00760***
				(0.0028)
-2			0.0296***	0.0766***
			(0.0038)	(0.0144)
-1		0.0754***	0.153***	0.186***
		(0.0143)	(0.0409)	(0.0289)
0	0.942***	0.905***	0.886***	0.875***
	(0.0053)	(0.0053)	(0.0057)	(0.0054)
+1		0.183***	0.189***	0.200***
		(0.0040)	(0.0044)	(0.0042)
+2			0.0933***	0.100***
			(0.0039)	(0.0041)
+3				0.0429***
				(0.0102)
Establishment FE	X	X	X	X
Quarter FE	X	X	X	X
Observations	786121	746129	700242	651278

Notes: Regressions run at the establishment level. Standard errors reported in parentheses and clustered around establishments. Sample restricted to establishments with at least 40 employees, less than 10 percent absolute employment change and less than 5 percent quit rate. Certain industries are omitted.

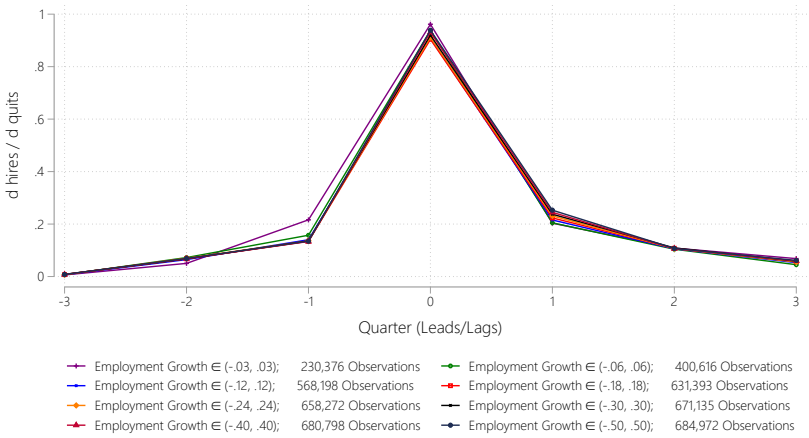
Table F.2
Mercan & Schoefer (2020) Replication
in the Matched Firm Universe

	$\frac{\text{Hires}_{e,t}}{\text{Emp}_{e,t-1}}$			
Lead/Lag	(1)	(2)	(3)	(4)
-3				0.0173***
				(0.0054)
-2			0.0215***	0.0213***
			(0.0082)	(0.0082)
-1		0.0323**	0.0315**	0.0317**
		(0.0140)	(0.0139)	(0.0148)
0	0.838***	0.812***	0.799***	0.795***
	(0.0108)	(0.0105)	(0.0105)	(0.0105)
+1		0.0996***	0.0969***	0.0976***
		(0.0051)	(0.0051)	(0.0052)
+2			0.0358***	0.0358***
			(0.0040)	(0.0040)
+3				0.0144***
				(0.0038)
Establishment FE	X	X	X	X
Quarter FE	X	X	X	X
Observations	468604	456598	445169	434401

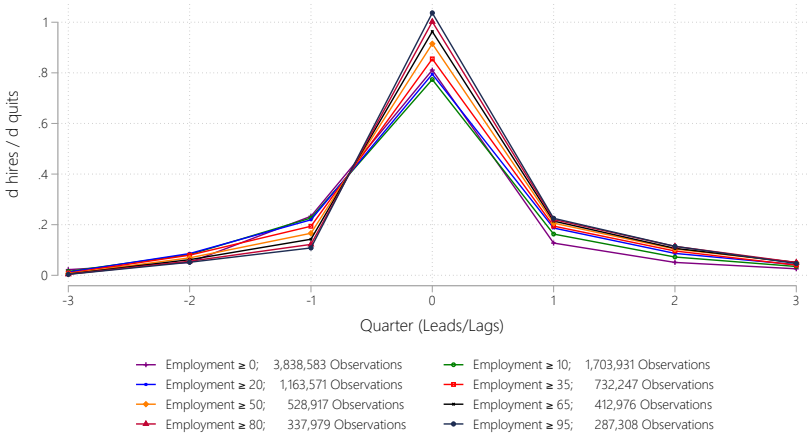
Notes: Regressions run at the establishment level. Standard errors reported in parentheses and clustered around establishments. Sample restricted to establishments with at least 40 employees, less than 10 percent absolute employment change and less than 5 percent quit rate. Certain industries are omitted.

Figure F.1
Mercan & Schoefer (2020) Replication: Sensitivity

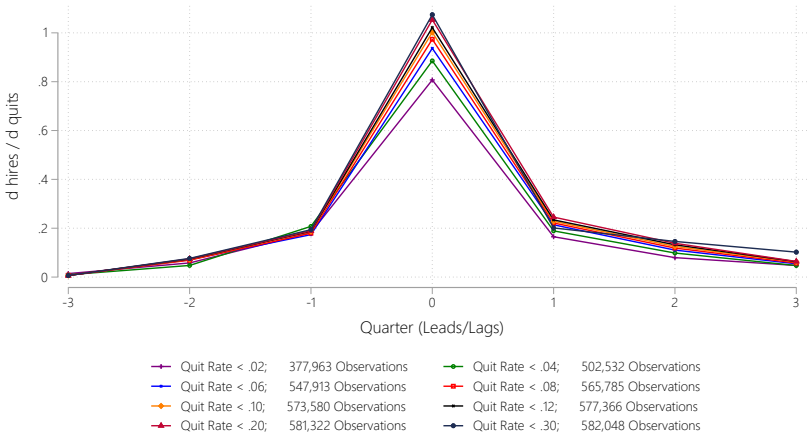
(a) Employment Growth



(b) Employment



(c) Quit Rate



Notes: Estimates obtained from F.1 using the ASSD data for the time period 1994 – 2019. We use quarterly data and approximate Quits using E-Separations.

F.2 Aggregate Recruiting Intensity over the Business Cycle

Mongey and Violante (2019) decompose the aggregate recruiting intensity

$$\begin{aligned}\Phi_t = & \underbrace{Q\left(A_t, \theta_t\right)^{-\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{\text{Slack}_t} \\ & \times \underbrace{\left(\frac{H_t}{N_t}\right)^{\frac{\gamma\alpha}{1-\gamma(1-\alpha)}}}_{\text{Growth}_t} \\ & \times \underbrace{\left[\int \phi_i^{1-\gamma}\left(\frac{h_{it}/n_{it}}{H_t/N_t}\right)^{\gamma}\frac{v_{it}}{V_t}di\right]^{\frac{\alpha}{1-\gamma(1-\alpha)}}}_{\text{Comp}_t},\end{aligned} \tag{F.2}$$

where they estimate γ $(= \beta)$ and ϕ_i $(= \xi_i)$ using the regression

$$\log\left(\frac{h_{it}}{v_{it}}\right) = \delta_t + \xi_i + \beta \log\left(\frac{h_{it}}{n_{it}}\right) + \varepsilon_{ijt}. \tag{F.3}$$

Table F.3
Recruiting Intensity Estimates

Sample	Weight		
$\hat{\beta}$	Unweighted	Employment	Vacancy Stocks
A. Employment and Non-Employment Hires			
Restrictive	0.710^{***}	0.858^{***}	0.712^{***}
	(0.0011)	(0.0011)	(0.0013)
Firm Universe	0.736^{***}	0.831^{***}	0.732^{***}
	(0.0010)	(0.0013)	(0.0011)
B. Including Recalls			
Restrictive	0.745^{***}	0.872^{***}	0.739^{***}
	(0.0010)	(0.0010)	(0.0011)
Firm Universe	0.765^{***}	0.854^{***}	0.757^{***}
	(0.0009)	(0.0012)	(0.0010)
C. Mongey & Violante			
Average		0.741	

Notes: This table shows recruitment intensity estimates based on equation (F.3) following Mongey and Violante (2019) for Austria.

Table F.4
ARI Decomposition

Sample	Component			
	Slack	Growth	Comp.	Cov.
A. Employment and Non-Employment Hires				
Restrictive	.644	.024	.056	.276
Firm Universe	.674	.056	.066	.203
B. Including Recalls				
Restrictive	.699	.032	.045	.224
Firm Universe	.727	.064	.049	.16
C. Mongey & Violante				
Average	.570	.034	.051	.350

Notes: This table shows the ARI decomposition based on equation (F.2) following Mongey and Violante (2019) for Austria. Estimates of firm fixed effects and recruiting intensity are obtained using employment weights.

Appendix References

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