Vacancies, Employment Outcomes and Firm Growth: Evidence from Denmark*

Jesper Bagger†
Royal Holloway; Aarhus University
Francois Fontaine‡
Paris School of Economics, Université Paris 1–Panthéon Sorbonne
Manolis Galenianos§
Royal Holloway
Ija Trapeznikova¶
Royal Holloway

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Abstract

We use comprehensive data from Denmark that merge online job advertisements with a matched employer-employee dataset and a firm-level dataset with information on revenues and value added to study the relationship between vacancy-posting and various firm outcomes. Vacancy-posting is associated with a 4.4 percentage point increase in a firm's hiring rate and 85% of the additional hiring occurs within two months. The response of hiring from employment is twice as large as the response of hiring from non-employment. Firms that are smaller, low-wage and fast-growing are associated with larger hiring responses and that response materializes faster at larger firms, low-wage firms and fast-growing firms. We also find that separations are associated with subsequent vacancy-posting and this effect is stronger for separations to employment, consistent with replacement hiring and the presence of vacancy chains. Growth in revenue and value added strongly predict vacancy-posting, with negative shocks having a stronger effect than positive shocks and larger shocks having less-than-proportional responses.

Keywords: Vacancies, hiring, separations, employment growth, firm growth, value added, revenue
JEL Classification: J23, J63

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†Department of Economics, Royal Holloway, University of London, Egham, Surrey, TW20 0EX, United Kingdom
‡IZA and Paris School of Economics 48 Boulevard Jourdan, 75014 Paris, France
§Department of Economics, Royal Holloway, University of London, Egham, Surrey, TW20 0EX, United Kingdom
¶Department of Economics, Royal Holloway, University of London, Egham, Surrey, TW20 0EX, United Kingdom

1 Introduction

The starting point of the search-and-matching approach to labor market analysis is that it takes time and effort for workers to find desirable employers and for firms to find suitable employees. This approach can rationalize the coexistence of unemployed workers and vacancies, a key feature of labor markets, and it provides a coherent framework with which to study the process of matching in labor markets. While the empirical literature has documented a large set of facts about workers' job-search process, including the speed of job finding and its dependence on workers' observable characteristics and labor market conditions, the firm side of the market has been studied much less, largely due to a lack of appropriate data. A deeper understanding of when and how firms recruit, however, is essential for attaining a complete picture of the workings of labor markets both at the micro and at the macro level.

This paper uses uniquely detailed data from Denmark to document a novel set of empirical facts about firms' search process. We find that firms' vacancy-posting is associated with a significant increase in the hiring rate over several months and that the magnitude and timing of this increase is heterogeneous across firms of different sizes, growth rates, productivity and industry. Furthermore, we find that vacancy-posting increases following a rise in a firm's separation rate, consistent with replacement hiring, and following growth in firm output, measured by revenue or value added.

We merge a large dataset of online job advertisements from 2003-2009 with a matched employer-employee dataset, with detailed information about individual labor market spells and transitions, and a firm-level VAT-account dataset, which provides information on firm revenues, purchases and value added. We measure firm recruiting effort at the extensive margin (whether the firm posts any advertisements in a given month or quarter) and the intensive margin (the firm's vacancy rate in a given month or quarter) and call this effort "vacancy-posting".

The first part of our analysis examines the association between vacancy-posting and hiring outcomes at the firm level. At the extensive margin, we find that vacancy-posting is associated with an increase of 4.4 percentage points in a firm's monthly hiring rate, a rise of more than 70% over the baseline no-vacancy hiring rate. We find that 85% of this effect occurs in the month of vacancy-posting and the subsequent month. The hiring rate when no vacancies are posted is quantitatively large, consistent with the findings in the literature (e.g. Davis, Faberman, and Haltiwanger, 2013). At the intensive margin, we find a relatively weak linear association between the vacancy rate and the hiring rate. Bagger and Galenianos (2021) use a more flexible specification that allows for a nonlinear association on the same data and find a quantitatively and statistically significant relationship. Our findings suggest that online advertisements play an important, though not exclusive, role in firms' recruiting process and that this process can be quite lengthy and diverse across firms.

We decompose the vacancy-posting and hiring rate relationship into hiring from employment and non-employment, based on newly-hired workers' labor market status in the previous month. Vacancy-posting is associated with a doubling of the hiring rate from employment and a 50% increase in the hiring rate from non-employment, and that the former materialize at a slower pace than the latter.

In our firm heterogeneity analysis we find that, following vacancy-posting, firms with lower employment, lower wages, lower labor productivity and higher employment growth rates experience a larger increase in their hiring rates. Furthermore, the response materializes faster at larger firms, low wage (low productivity) firms, and fast-growing firms. Additionally the magnitude and timing of the

hiring response to vacancy-posting varies considerably across industries. Overall, we find evidence for substantial heterogeneity in terms of the hiring response of different types of firms where, interestingly, the magnitude and the speed of the response do not necessarily co-move across firm types.

Turning to the determinants of vacancy-posting, we explore the effect of separations on the probability of posting a vacancy. We find that a one standard deviation increase in the separation rate is associated with an increase in the vacancy rate by 1 percentage point, a 100% increase over the no-separation baseline. The full effect takes 3-4 months to materialize. Furthermore, separations to employment have more than three times the effect on vacancy-posting than separations to non-employment. These findings are consistent with replacement hiring at the firm level, which generates vacancy chains and propagates labor market shocks (see, for example, Elsby, Michaels, and Ratner, 2019 and Mercan and Schoefer, 2020).

Finally, we explore the relationship between revenue and value added growth and vacancy-posting. A one standard deviation change in revenue growth is associated with a 9-11 percentage point change in the quarterly probability of vacancy-posting. Negative revenue growth is associated with larger (in absolute value) vacancy-posting responses than positive revenue growth, and we find evidence of concavity in these responses. Value added growth generates similar responses, though slightly smaller in magnitude. Bagger, Fontaine, Galenianos, and Trapeznikova (2021) explore this further by separately estimating the effects of permanent and transitory output shocks on the vacancy-posting probability.

These empirical findings have implications for theoretical modeling of the labor market. First, theoretical models should account for the large heterogeneity in the hiring response to vacancy-posting across firms of different size, productivity and growth rates. Second, they should account for the finding that separations predict vacancy-posting. Third, they should account for the asymmetric and non-linear relationship between output growth and vacancy-posting. We discuss these in some more detail in section 6.

Our paper contributes to the empirical literature that studies the effect of vacancies on hiring outcomes, early contributions to which include van Ours and Ridder (1992) and Burdett and Cunningham (1998). Davis, Faberman, and Haltiwanger (2013) is probably the most prominent work in this literature and uses the US firm survey JOLTS to document several interesting features, particularly about the heterogeneous hiring outcomes of vacancy-posting across different establishment types and the large share of hires that occur without reporting an available vacancy. Carrillo-Tudela, Gartner, and Kaas (2021) and Mueller, Osterwalder, Zweimüller, and Kettemann (2020) combine vacancy information with matched employer-employee datasets in Germany and Austria, respectively, and study the determinants of vacancy duration and vacancy yield. Our paper is also related to empirical work on vacancies using online job board data such as Marinescu and Wolthoff (2020), Davis and Samaniego de la Parra (2017), Modestino, Shoag, and Ballance (2019), Hershbein and Kahn (2018) and Banfi and Villena-Roldan (2019) among others.

The rest of the paper is organized as follows: Section 2 describes the data that we use in our analysis. Section 3 examines the effect of vacancy-posting on hiring rates, including a detailed firm-heterogeneity analysis. Section 4 examines the effect of separations on vacancy-posting, and section 5 examines the effect of output growth on vacancy-posting. Section 6 briefly discusses some the implications of our findings for theoretical models of the labor market and for future empirical work.

2 Data

2.1 Data sources

Our data originates from Denmark. We combine information from three distinct sources: a matched employer-employee dataset, a firm panel with information about revenues and purchases, and a dataset with real-time online job advertisements. We describe each data source in turn.

Labor market spells dataset. The labor market spells dataset is a matched employer-employee dataset containing detailed information on employment spells for all legal residents in Denmark aged 15-70 starting on January 1st, 1985. It is constructed at Aarhus University using income tax reports obtained from the administrative registers Registerbaseret Arbejdsstyrke Statistik (CONS/RAS, covering 1985-2007) and Beskæftigelse For Lønmodtagere (BFL, covering 2008 onwards), and data on employer contributions to the employee pension fund Arbejdsmarkedets Tillægs Pension, which covers the universe of workers.[1] These administrative registers are provided by Statistics Denmark.

The unit of observation in the labor market spells dataset is a worker-spell-year. An observation contains the worker's social security number (CPR-number),[2] the firm's registration number in the Danish Central Business Registry (CVR-number), start- and end-dates of the job spell and annual worker earnings pertaining to the job. In addition, it contains an estimate of each worker's annual number of hours in the job (see Lund and Vejlin, 2016) from which we compute a worker's average hourly wage rate, and the industry classification of the firm where the worker is employed (see Appendix A.1). We define a job spell as a period of continuous primary employment at a given firm.[3] Periods when no job spells are recorded for a worker are non-employment spells; we do not observe whether the worker is unemployed or out of the labor force during a non-employment spell. We have access to the data between January 1st, 1985 ad December 31st, 2013.

VAT accounts dataset. Firms that operate in Denmark and whose expected annual revenues exceed a very low threshold are legally required to obtain a Value Added Tax (VAT) account with the tax authorities and to settle their VAT accounts on a monthly, quarterly or semi-annual frequency, depending on the level of revenues.[4] The VAT accounts dataset is a firm panel which starts in January, 2001 and contains monthly information on revenues and purchases at the firm level, where firms are

[1] Henning Bunzel at Aarhus University has been instrumental in constructing the labor market spells dataset. Hejlesen (2016) provides a technical description of the construction of the dataset from the raw administrative records. Our access to the labor market spells dataset is provided by the Dale T. Mortensen Centre at Aarhus University.

[2] The CPR-number is issued to every legal resident of Denmark, is unique to the individual and time-invariant.

[3] A worker's firm of primary employment for a particular month is defined to be the firm where the worker has the greatest number of hours worked for that month and the next two calendar months. A worker's firm of primary employment is determined separately for every calendar month.

[4] As of 2021, firms with expected annual revenues exceeding DKK 50,000 (approximately USD 8,000) must have a VAT account. Firms with expected annual revenues of more than DKK 50 mill. (approximately USD 8 mill.) must settle VAT at a monthly frequency, firms with expected revenues in the range DKK 5 mill. (approximately USD 800,000) to DKK 50 mill. must settle at least at a quarterly frequency, while firms that expect annual revenues below DKK 5 mill. must settle at least at a semi-annual frequency. Firms may apply to settle at a higher frequency than required by their expected revenues, and the tax authorities may on a case-by-case basis require a firm to settle at a higher frequency than revenues would stipulate. Firms in their first year of existence must settle VAT accounts at least quarterly for at least six quarters, independently of expected annual revenues.

identified by their CVR-number. Statistics Denmark imputes monthly information for the firms that settle VAT accounts at a quarterly or semi-annual frequency and an indicator is included with the frequency at which each firm settles their VAT accounts. We have access to the data between January, 2001 and December, 2012.

Vacancy dataset. The data source is Jobindex A/S, a major private online job board in Denmark. Jobindex features job advertisements that are either posted directly on its job board or are originally posted elsewhere on the internet. Jobindex scrapes daily job advertisements from the Danish part of the World Wide Web (e.g. from individual firms' web pages, other job boards, public job centers, etc.), operates an algorithm to detect identical advertisements posted at multiple online outlets, and re-posts all unique job advertisements on its job-board to attract traffic from job-seekers.[5] It covers up to 90% of the job advertisements posted online in Denmark during the relevant period.[6] The unit of observation is a job advertisement which contains the date of posting, the job's occupation (recorded according to the job board's own detailed occupation classification) and, for approximately two-thirds of the observations, the advertising firm's CVR-number.[7] We have access to job advertisement data from June 1st, 2002 to August 31st, 2009 and use the period starting on Jan 1st, 2003.[8] The vacancy dataset contains 1,918,966 online job advertisements.

In the empirical analysis our interpretation will be that a firm has a vacant position when it posts an online job advertisement, and we will use the terms "vacancy" and "advertisement" interchangeably. There are two caveats to this interpretation. First, it is possible for a firm to have a vacant position without posting an online job advertisement, for example because the firm uses different search channels to recruit. Our empirical analysis allows for "no-vacancy hiring" to take this into account.[9] Second, a given advertisement might refer to multiple available positions. To the extent that this is widespread, it will lead to a higher estimated effect of vacancy-posting on hiring.

2.2 Data merging and variable construction

Data merging and cleaning. We merge the three datasets using the firm ID (CVR number). We discard 681,633 advertisements (approximately one-third of the total) that we cannot merge with the other datasets because they do not include the posting firm's CVR number. We match 83% of the CVR numbers in the vacancy dataset with those in the labor market spells dataset, which we view as a high success rate given that the source of the vacancy data is not an administrative register.

We discard firms that belong to the non-business sector,[10] and firms that settle VAT at a semi-

[5] Brodersen, Dimova, and Rosholm (2016) report the sources of job advertisements posted on Jobindex in July 2014 as: 35% direct posting on Jobindex, 35% other job databases, 25% public job centers and 5% firm websites.

[6] Source: Personal communication with the director of Jobindex.

[7] The CVR-number is a firm's main administrative identifier vis-a-vis its stakeholders and routinely appears on invoices and company websites. The CVR number is either directly provided to JobIndex or is included in the job advertisement.

[8] Jobindex began scraping data in June, 2002 and the data is considered reliable since the beginning of 2003.

[9] "No-vacancy hiring" is a robust feature in datasets that include a more complete measure vacancies: in JOLTS on average 42% of hires during a month occur at establishments that report no vacancies on the last day of the previous month. This is striking because JOLTS is a firm survey and its measure of vacancies does not depend on the usage of a particular search channel by the firm; see Davis, Faberman, and Haltiwanger (2013).

[10] According to NACE 2.0 the non-business sector consists of the following industries: Agriculture, forestry and fishing; Public administration and Defence and compulsory social security; Education; Human health and social work activi-

annual frequency (these firms have negligible employment). We delete observations on the entry- and exit-periods for entering and exiting firms and, for firms with multiple entry and exit events during the observation period, we only use data until the first exit event. To facilitate the estimation of dynamic regressions we discard firms with fewer than seven consecutive monthly observations. Nominal variables are deflated using the Danish consumer price index and expressed in 2009 Danish Kroner (DKK).

We discard firms that are never observed to post online job advertisements over the 78 months of the observation period 2003M1-2009M6. These firms are unlikely to have refrained from active recruiting over these 6.5 years; indeed, they account for roughly one-third of all hires in the labor market spells dataset over that period. Rather, these firms probably advertise without an observable CVR-number and, therefore, are mostly a source of mismeasurement. We note that, though numerous, the firms we discard tend to be much smaller than the firms that we use in our analysis and account for less than 30% of total employment and only a quarter of total revenue or value added. Therefore, the firms that we keep account for most of the economic activity, employment, hires and job creation in the Danish business sector. We present a more detailed comparison between the firms with and without measured vacancies in Appendix A.2.

Monthly employment and wage variables. We measure a firm's employment on the first day of every month and denote it by N_{jt}, where j is the firm and t is the month.[11] A worker who is not on firm-j's payroll on the first day of month t and is on firm-j's payroll on the first day of month $t+1$ is counted as a hire by firm j in month t; we denote the number of hires of firm j in month t by H_{jt}. We split the total hires of firm j in month t into hires from employment (denoted H_{jt}^{EE}) and hires from non-employment (denoted H_{jt}^{NE}) depending on the newly-hired employees' employment status on the first day of month t; by construction $H_{jt} = H_{jt}^{EE} + H_{jt}^{NE}$. To define the relevant rates we normalize these variables by firm employment, averaged over two months. Specifically, the hiring rate of firm j in month t is $h_{jt} = H_{jt}/((N_{jt} + N_{jt+1})/2)$ and similarly for the EE- and NE-hiring rates (which we denote h_{jt}^{EE} and h_{jt}^{NE}, respectively).

A worker who is on firm-j's payroll on the first day of month t and is not on firm-j's payroll on the first day of month $t+1$ is counted as a separator from firm j in month t; we denote the number of separations from firm j in month t by S_{jt}. We split the total separations from firm j in month t into separations to employment and separations to non-employment (denoted S_{jt}^{EE} and S_{jt}^{EN}, respectively) depending on the separating employees' employment status on the first day of month $t+1$; by construction $S_{jt} = S_{jt}^{EE} + S_{jt}^{EN}$. We define the separation rate (denoted s_{jt}) and the EE- and EN-separation rates (denoted s_{jt}^{EE} and s_{jt}^{EN}, respectively) analogously to the hiring rates.

The law of motion for the employment of firm j is $N_{jt+1} = N_{jt} + H_{jt} - S_{jt}$. A firm that enters in month t has $N_{jt} = 0$, $N_{jt+1} = H_{jt}$ and $S_{jt} = 0$. A firm that exits in month t has $S_{jt} = N_{jt}$, $H_{jt} = 0$ and $N_{jt+1} = 0$. We compute the average hourly wage rate among all workers employed by firm j in month t and denote it by $\overline{w}_{jt}$.[12]

ties; Arts, entertainment and recreation; Other service activities; Activities of households as employers; Activities of extraterritorial organizations and bodies. See Table 6 for a list of the business sector industries.

[11] By construction, job spells that start and end within the same calendar month are counted neither in firm employment nor in hires and separations, as described below.

[12] By construction, a worker's measured hourly wage rate at a particular job is constant during the calendar year. This does not restrict our analysis because we do not examine within-year wage growth.

Quarterly output variables. We aggregate the monthly VAT account information to a quarterly frequency. We denote revenues and value added of firm j in quarter s by R_{js} and Y_{js}, respectively. These variables are not contaminated by imputation since we discard firms that settle their VAT-accounts semi-annually.

Vacancy variables. We aggregate the daily vacancy data to create monthly and quarterly variables for vacancy-posting. We first create a variable a_{jt} which measures the number of online advertisements posted by firm j in month t. We create a monthly vacancy indicator variable I_{jt}^{M} which takes the value 1 if firm j posts one or more online advertisements in month t and 0 otherwise, and a quarterly vacancy indicator variable I_{js}^{Q} which takes the value 1 if firm j posts one or more online advertisements in quarter s and 0 otherwise. We create a monthly vacancy rate variable by dividing the number of advertisements posted by firm j in month t by the average employment of months t and $t+1$: $v_{jt}^{M} = a_{jt}/((N_{jt} + N_{jt+1})/2)$. We create a quarterly vacancy rate variable by dividing the number of advertisements posted by firm j in quarter s by the average employment of quarters s and $s+1$. Denoting the months of quarter s by t, $t+1$ and $t+2$ and of quarter $s+1$ by $t+3$, $t+4$ and $t+5$, and noting that a quarter's employment is measured on the first month of the quarter we have: $v_{js}^{Q} = (a_{jt} + a_{jt+1} + a_{jt+2})/((N_{jt} + N_{jt+3})/2)$.

Firms without measured vacancies. We discard firms that are never observed to post online job advertisements over the 78 months of the observation period 2003M1-2009M6. These firms are unlikely to have refrained from active recruiting over these 6.5 years; indeed, they account for roughly one-third of all hires in the labor market spells dataset over that period. Rather, these firms either do not use online advertisements as their recruitment channel or advertise without an observable CVR-number and, therefore, are mostly a source of mismeasurement. We note that, though numerous, the firms we discard tend to be much smaller than the firms that we use in our analysis and account for less than 30% of total employment and less than a quarter of total revenue or value added. Therefore, the firms that we keep account for most of the economic activity, employment, hires and job creation in the Danish business sector. We present a more detailed comparison between the firms with and without measured vacancies in Appendix A.2.

Summary. We create a monthly vacancy-employment firm panel on the 2003M1-2009M6 observation period and a quarterly vacancy-output firm panel on the 2003Q1-2009Q2 observation period. The monthly and the quarterly panels consist of the same 20,511 firms. The monthly firm panel contains 1,298,615 firm-months between 2003M1 and 2009M6 with information about vacancies, employment, hires, separations and wages. The quarterly firm panel contains 432,961 firm-quarters between 2003Q1 and 2009Q2 with information about vacancies, revenues and value added.

2.3 Descriptive statistics

Table 1 presents some descriptive statistics of the data that we use in our analysis. Panel A in Table 1 present various rates that relate to employment transitions. Monthly employment growth is 0.3 percent on average and very volatile, with most firm-months featuring some change in employment. Worker flows are also very volatile and the average firm hires 6.9 percent of its workforce and separates from

Table 1: Summary Statistics

	Avg.	SD	Share = 0
Panel A: Employment			
Monthly employment growth rate	0.003	0.207	0.429
Monthly hiring rate	0.069	0.155	0.510
Monthly EE-hiring rate	0.025	0.068	0.698
Monthly NE-hiring rate	0.044	0.130	0.628
Monthly separation rate	0.066	0.150	0.511
Monthly EE-separation rate	0.023	0.065	0.700
Monthly NE-separation rate	0.043	0.128	0.632
Panel B: Output			
Quarterly revenue growth rate	0.018	0.528	
Quarterly value added growth rate	0.018	0.950	
Panel C: Vacancies			
Monthly vacancy indicator	0.116		
Quarterly vacancy indicator	0.239		
Monthly vacancy rate	0.014	0.152	0.884
Quarterly vacancy rate	0.041	0.405	0.761

Notes: The monthly statistics are computed on 1,298,615 observations on 20,511 firms. The quarterly statistics are computed on 432,961 observations on the same 20,511 firms.

a further 6.6 percent every month. Approximately two thirds of monthly hires and separations involve transitions from and to non-employment.

Panel B presents output data. Revenues and value added increase at almost 2% on average per quarter, which is quite high and might be related to our sample selection of, generally, larger, more productive and faster-growing firms. The volatility of these series is, also, very large.

Panel C presents the vacancy data. We see that firms in our dataset post vacancies in 12 percent of the months and 24 percent of quarters. The average vacancy rate is 1.4 percent at a monthly frequency and 4.1 percent at a quarterly frequency.

3 Vacancies and hiring outcomes

In this section we investigate the empirical relationship between vacancy-posting and hiring outcomes. To that end, we document the *correlation* between the variables of interest and note that the estimated parameters do not warrant a causal interpretation.

3.1 The hiring rate

We investigate the relationship between the hiring rate and vacancy-posting. We estimate several variations of the distributed lag panel data regression

$$h_{jt} = \beta + \sum_{k=0}^{6} \pi_k z_{jt-k} + \mathbf{x}'_{jt}\boldsymbol{\delta} + \rho_j + \epsilon_{jt}, \tag{1}$$

where h_{jt} is the hiring rate of firm j in month t, β is a constant, z_{jt} is the vacancy-posting variable

which measures firms' recruiting effort and is specified below, $\mathbf{x}_{jt}$ is a vector of industry-dummies, month-dummies and month-dummies interacted with industry-dummies, ρ_j is a firm fixed effect, and ϵ_{jt} is the error term.

The vacancy-posting variable z_{jt} is included with a truncated lag distribution, where the lag-k weight is π_k. We allow for 6 lags; we have found that longer lags are statistically and quantitatively insignificant and they do not affect the estimates of other parameters. The constant term β is the predicted average hiring rate for firms that post no vacancies over a six months period, which we will refer to as the *no-vacancy baseline hiring rate*. β and π_k for $k = 0, 1, ..., 6$ are estimated by OLS.

We use two different vacancy-posting variables to measure firms' recruiting effort. First, a monthly vacancy indicator variable ($z_{jt} = I_{jt}^M$) which takes value 1 if any online advertisement is posted in that month and 0 otherwise and, hence, focuses on the *extensive margin* of firm recruiting effort. Second, the monthly vacancy rate ($z_{jt} = v_{jt}^M$) which normalizes the number of online advertisements by firm employment and, hence, also takes into account the *intensive margin* of firm recruiting effort.

We define the *cumulative response* of the hiring rate to vacancy-posting as

$$\Pi = \sum_{k=0}^{6} \pi_k.$$

Π measures the full response over time of hiring to vacancy-posting.

We denote the share of the cumulative response that occurs in the contemporaneous vacancy-posting month (lag 0) and subsequent month (lag 1) by

$$\Lambda = \frac{\pi_0 + \pi_1}{\Pi}.$$

Λ is a summary measure of the speed with which the cumulative response materializes.

Finally, for the specifications where the vacancy-posting variable is the vacancy rate, we denote the response of the hiring rate to a one-standard deviation change in the vacancy rate by

$$\Omega(\sigma_v) = \Pi\sigma_v,$$

where σ_v is the standard deviation of v_{jt}^M.

Table 2 presents the estimates of the first set of specifications where z_{jt} is the vacancy indicator variable I_{jt}^M. Column (1) reports the results of a regression without firm fixed effects (i.e. $\rho_j \equiv 0$) and without dynamic responses to vacancy-posting (i.e. where $\pi_k \equiv 0$ for $k \geq 1$). The no-vacancy baseline hiring rate is statistically significant and quantitatively large, corresponding to a no-vacancy hiring rate of 6.4% for the average firm. The contemporaneous effect of vacancy-posting is to increase the hiring rate by 2.1 percentage points, i.e by one-third of the no-vacancy baseline.

The large magnitude of the estimate for the constant, which is a robust feature across different empirical specifications, suggests that a significant amount of hiring occurs without measured recruiting effort, at least through the online advertisement channel. The restriction of our data to one recruiting channel is unlikely to fully explain this finding, as it is observed in other datasets without that restriction. For example, Davis, Faberman, and Haltiwanger (2013) document in JOLTS that 42% of hires in the average month occur at establishments that report no vacancies at the end of the previous

Table 2: Regressing the hiring rate on the vacancy-posting indicator

Dependent variable: h_{jt}	(1)	(2)	(3)
No-vacancy deadline β	0.064***	0.063***	0.061***
	(0.000)	(0.000)	(0.000)
Lag-0 weight π_0	0.021***	0.015***	0.016***
	(0.001)	(0.001)	(0.001)
Lag-1 weight π_1		0.020***	0.021***
		(0.001)	(0.001)
Lag-2 weight π_2		0.007***	0.009***
		(0.001)	(0.001)
Lag-3 weight π_3		−0.000	0.002***
		(0.001)	(0.000)
Lag-4 weight π_4		−0.002***	−0.000
		(0.001)	(0.000)
Lag-5 weight π_5		−0.003***	−0.001***
		(0.001)	(0.000)
Lag-6 weight π_6		−0.004***	−0.002***
		(0.001)	(0.000)
Cumulative response Π	0.021***	0.033***	0.044***
	(0.001)	(0.002)	(0.001)
Cumul. resp. relative to no-vacancy baseline Π/β	0.329***	0.532***	0.726***
	(0.012)	(0.029)	(0.023)
Share of Π realized within 2 months Λ		1.048***	0.846***
		(0.042)	(0.021)
Dynamic effects	No	Yes	Yes
Firm fixed effects	No	No	Yes
Number of firms	20,511	20,511	20,511
Number of observations	1,175,549	1,175,549	1,175,549

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

month.[13] Since JOLTS is a survey where each establishment reports its own vacant positions, the vacancy measure does not depend on the use of a particular recruiting channel.

The specification in column (2) in Table 2 estimates the dynamic response to a vacancy-posting event by allowing for $\pi_k \neq 0$ for $k = 0, 1, ..., 6$. The contemporaneous effect of vacancy-posting on the hiring rate is reduced to 1.5 percentage points but remains highly statistically significant. The effect in the subsequent months is highly statistically significant and quantitatively large. Specifically, the hiring rate increases by 2 percentage points one month after vacancy-posting, and by 0.7 percentage points two months later. The cumulative response of a vacancy-posting event (also taking into account the quantitatively smaller effects of subsequent months) is to increase the hiring rate by 3.3 percentage points, a 52% increase over the no-vacancy baseline and double the response from the specification in column (1). The cumulative effects materialize within the first two months after a vacancy-posting.

Finally, the specification in column (3) in Table 2 introduces firm fixed effects, i.e. allows for $\rho_j \neq 0$ for all j. The estimates are qualitatively similar in terms of timing and quantitatively larger to those in column (2), yielding a cumulative increase in the hiring rate of 4.4 percentage points, which corresponds to a 72% increase over the baseline hiring rate. Approximately 85% of that response occur in the month when the vacancy is posted and the next month.

Comparing specifications (1) and (2) in Table 2 demonstrates the importance of taking the dynamic response into account as it significantly increases the estimated effects and it shows that it takes up to

[13] Time aggregation might account for part of these hires but the majority is left unexplained (Davis, Faberman, and Haltiwanger (2013)).

Table 3: Regressing the hiring rate on the vacancy rate

Dependent variable: h_{jt}	(1)	(2)	(3)
No-vacancy baseline β	0.066^{***}	0.066^{***}	0.066^{***}
	(0.000)	(0.000)	(0.000)
Lag-0 weight π_0	0.022^{***}	0.005	0.010^{**}
	(0.008)	(0.004)	(0.005)
Lag-1 weight π_1		0.057^{***}	0.061^{***}
		(0.012)	(0.013)
Lag-2 weight π_2		0.008^{***}	0.010^{***}
		(0.003)	(0.004)
Lag-3 weight π_3		-0.008^{***}	-0.006^{**}
		(0.002)	(0.003)
Lag-4 weight π_4		-0.014^{***}	-0.012^{***}
		(0.003)	(0.003)
Lag-5 weight π_5		-0.013^{***}	-0.010^{***}
		(0.003)	(0.002)
Lag-6 weight π_6		-0.010^{***}	-0.007^{***}
		(0.003)	(0.002)
Cumulative response Π	0.022^{***}	0.025^{**}	0.046^{***}
	(0.008)	(0.011)	(0.018)
Cumul. resp. relative to no-vacancy baseline Π/β	0.339^{***}	0.377^{**}	0.705^{***}
	(0.126)	(0.167)	(0.269)
Share of Π realized within 2 months Λ		2.515^{***}	1.523^{***}
		(0.547)	(0.232)
Cumulative response to 1SD change in v_{jt}^M $\Omega(\sigma)$	0.003^{***}	0.004^{**}	0.007^{***}
	(0.001)	(0.002)	(0.003)
Dynamic effects	No	Yes	Yes
Firm fixed effects	No	No	Yes
Number of firms	20,511	20,511	20,511
Number of observations	1,175,549	1,175,549	1,175,549

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

three months for the bulk of the effect to materialize. Further comparison to specification (3) shows that the significant dynamic responses are sustained and magnified quantitatively by the inclusion of firm fixed effects in the regression.

Comparing specifications (2) and (3) in Table 2 demonstrates that controlling for firm fixed effects yields similar qualitative results and further increases the magnitude of the predicted hiring response to vacancy-posting, by approximately one-third when cumulated over time. This difference arises because the estimated parameters in specification (2), without firm fixed effects, reflect both within- and between-firm variation in the hiring rate and vacancy-posting, whereas the parameter estimates in specification (3) reflect within-firm variation only. Evidently, firms' vacancy-posting behavior is systematically related to firm-specific hiring rate heterogeneity. Specifically, the larger estimated response in specification (3) suggests that firms with above average-hiring rates (so, positive firm fixed effects ρ_j) post vacancies less frequently. We prefer specification (3) in Table 2 because it yields the marginal effect of posting a vacancy conditional on time-invariant firm-specific hiring rate heterogeneity.

Table 3 presents the estimates of the second set of specifications where the vacancy-posting variable z_{jt} is the monthly vacancy rate v_{jt}^M. As before, column (1) reports the estimates for the specification without firm fixed effects and without dynamic responses, column (2) adds dynamic responses and column (3) further adds firm fixed effects. The estimates for the no-vacancy baseline rate β are very similar to Table 2. While the estimates of the cumulative response are quite similar to those of Table 2, the quantitative implications are very different: a cumulative response of 0.046 (specification (3) in Table 3) means that a 10 percentage point increase in the vacancy rate increases the hiring rate by 0.46 percentage points or 7% over the no-vacancy baseline. Furthermore a one-standard deviation increase in the vacancy rate is associated with a 0.7 percentage point increase in the hiring rate, which corresponds to an 11% increase over the no-vacancy baseline. This is a very small response and, taken at face value, implies that the vacancy rate does not correlate strongly with hiring.

There appears to be some tension between the estimation results from the two different ways of measuring firms' recruiting intensity. Using the extensive margin of vacancy-posting (the vacancy indicator) to measure firms' recruiting effort we find that the effects of vacancy-posting on hiring outcomes are quantitatively very significant. Using the intensive margin of firms' recruiting effort (the vacancy rate) we find very small effects of vacancy-posting on hiring outcomes. The extensive and intensive margins, therefore, seem to lead to different qualitative conclusions. To understand these results, notice that we assume a very restrictive linear relationship between the vacancy rate and the hiring rate in Table 3. If the actual response of the hiring rate is in fact non-linear (specifically, concave) in the vacancy rate this would tend to reduce the estimates of the linear regression. This hypothesis, though certainly interesting, is beyond the scope of the present paper. Bagger and Galenianos (2021) regress the hiring rate on a more flexible specification of the vacancy rate and find quantitatively significant effects for the intensive margin of recruiting effort. In the remainder of this section, we focus on our first specification where z_{jt} is the vacancy indicator variable.

3.2 Hiring from employment and non-employment

We next examine the effect of vacancy-posting on hiring from employment (EE-hiring) and non-employment (NE-hiring). We re-estimate equation (1) using as dependent variables the hiring rate

Table 4: Regressing the EE- and NE-hiring rates on a vacancy-posting indicator

Dependent variable:	h_{jt}	h_{jt}^{EE}	h_{jt}^{NE}
No-vacancy baseline β	0.061***	0.021***	0.040***
	(0.000)	(0.000)	(0.000)
Lag-0 weight π_0	0.016***	0.007***	0.009***
	(0.001)	(0.000)	(0.000)
Lag-1 weight π_1	0.021***	0.010***	0.011***
	(0.001)	(0.000)	(0.000)
Lag-2 weight π_2	0.009***	0.005***	0.003***
	(0.001)	(0.000)	(0.000)
Lag-3 weight π_3	0.002***	0.001***	0.000
	(0.000)	(0.000)	(0.000)
Lag-4 weight π_4	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Lag-5 weight π_5	−0.001***	−0.001***	−0.001*
	(0.000)	(0.000)	(0.000)
Lag-6 weight π_6	−0.002***	−0.001***	−0.001**
	(0.000)	(0.000)	(0.000)
Cumulative response Π	0.044***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)
Cumul. resp. relative to no-vacancy baseline Π/β	0.726***	1.050***	0.558***
	(0.023)	(0.028)	(0.028)
Share of Π realized within 2 months Λ	0.846***	0.792***	0.899***
	(0.021)	(0.016)	(0.036)
Dynamic effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
Number of firms	20,511	20,511	20,511
Number of observations	1,175,549	1,175,549	1,175,549

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

from employment of firm j in month t (h_{jt}^{EE}) and, separately, from non-employment (h_{jt}^{NE}). Table 4 reports the results. Column (1) in Table 4 reproduces the estimates reported in column (3) in Table 2 for ease of comparison, column (2) reports the estimates for the EE-hiring rate and column (3) reports the estimates for the NE-hiring rate. The two hiring channels exactly decompose total hiring and, therefore, the estimates for the two channels sum up to the aggregate regression's estimates.

A few remarks are in order. First, the estimate of the no-vacancy baseline hiring rates, which corresponds to hires that occur without vacancy-posting, is almost twice as large for NE-hiring than for EE-hiring, consistent with the unconditional hiring rates documented in Table 1. Second, each channel yields half of the overall hiring response to vacancy-posting. Third, and related, the response of hiring to vacancy-posting is proportionally twice as large for EE hires than for NE hires: the hiring rate from employment more than doubles in response to vacancy-posting, while the hiring rate from non-employment increases by little more than 50%. Finally, hiring from employment materialize slower than hiring from non-employment: 90% of the response for hiring from non-employment materialize within two months of vacancy-posting while the share for poaching from other firms is 80%.

These findings suggest that vacancy-posting affects not just the quantity of hires but also their source (employment vs non-employment) and, potentially, other worker characteristics. One interpretation of these results is that a large proportion of the hires from non-employment are recall hires, which occur independently from vacancy-posting as they are based on pre-existing relationships between firms and workers. Bagger and Galenianos (2021) explore this route in more detail and find that the effect of vacancy-posting on non-recall hires from employment and non-employment is quite similar.

3.3 Firm heterogeneity

To conduct our heterogeneity analysis we split our firm sample in groups according to size, productivity, firm growth and industry and replicate our earlier analysis separately for each group.

Our measures of a firm's size are employment and quarterly value added averaged over the observation period. Our measures of a firm's productivity are the average hourly wage and the average quarterly value added per worker over the whole observation period. We measure firm growth as average monthly employment growth and average quarterly value added growth for each calendar year; since our sample spans seven calendar years, each firm has up to seven different growth rates. Finally, we measure a firm's industry by the NACE 2.0 sector classification.

Letting $b(t)$ denote the calendar year of month t, we assign each firm j to group $\ell = \ell(j, b(t))$. A firm's assigned group ℓ depends only on firm identity j when we split the sample by size, productivity, and industry and it depends on both firm identity j and calendar year $b(t)$ when we split the sample by growth. We estimate the following distributed lag panel data model, which is the same as equation (1) except that the parameters are now indexed by firms' groups:

$$h_{jt} = \beta_\ell + \sum_{k=0}^{6} \pi_{k,\ell} I^M_{jt-k} + \mathbf{x}'_{jt}\boldsymbol{\delta}_\ell + \rho_{j,\ell} + \epsilon_{jt}, \tag{2}$$

where $\ell \equiv \ell(j, b(t))$ as outlined above, and where, as before, h_{jt} is the hiring rate of firm j in month t, I^M_{jt} is the vacancy-posting indicator, $\mathbf{x}_{jt}$ is a vector of industry-dummies, month-dummies and their interactions (industry dummies and interactions excluded when splitting the sample by industry), $\rho_{j,\ell}$ is a firm-group fixed effect, and ϵ_{jt} is the error term. We estimate the parameters β_ℓ and $\pi_{k,\ell}$, $k = 0, 1, \ldots, 6$ by OLS separately for each group.

Table 5 reports the parameter estimates for employment size, average hourly wage and employment growth and Table 6 reports the estimates of the hiring regression separately by industry. The estimates for value added size, value added per worker and value added growth turn out to be qualitatively very similar to the employment- and wage-based groups in Table 5 and, so, we report them in Appendix B. To keep the tables manageable, we do not report estimated lag distribution weights ($\pi_{k,l}$) and, instead, use the share of the hiring response that materializes within two months of vacancy-posting (i.e. Λ) to summarize the response dynamics.

Panel A of Table 5 splits firms in four size groups according to employment: 1-10 workers (micro firms), 10-50 (small firms), 50-250 (medium-sized firms), 250+ (large firms). The proportion of months when vacancies are posted increases monotonically in firm size from 6% for micro firms to 57% for large firms. The estimates for the no-vacancy baseline hiring rate (β_l) are quite similar across size groups. The size-specific estimates of the cumulative hiring response to a vacancy-posting (Π_ℓ) are generally decreasing in size,[14] which means that the effect of vacancy-posting on the hiring rate relative to the no-vacancy baseline (Π_ℓ/β_ℓ) is also decreasing in firm size. This decline in the hiring response with size is consistent with the findings in Davis, Faberman, and Haltiwanger (2013), though the magnitude might be an artifact of the particular dependent variables we are using: hiring one worker corresponds to a 20% hiring rate in a 5-person firm and a 2% hiring rate in a 50-person firm.

The speed with which the hiring response materializes, as measured by Λ_ℓ is, generally, increasing in firm size: in the two months after vacancy-posting micro firms complete less than 80% of their hiring,

[14] The estimates for the two largest groups are statistically indistinguishable.

Table 5: Firm heterogeneity

		Panel A: Firm size			
Dependent variable: h_{jt}	All	1-10	10-50	50-250	250+
No-vacancy baseline β	0.061***	0.064***	0.060***	0.063***	0.060***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)
Cumulative response Π	0.044***	0.104***	0.039***	0.011***	0.015***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.005)
Π relative to no-vacancy baseline Π/β	0.726***	1.634***	0.653***	0.180***	0.242**
	(0.023)	(0.053)	(0.031)	(0.043)	(0.100)
Share of Π realized within 2 months Λ	0.846***	0.782***	0.865***	0.903***	0.212
	(0.021)	(0.019)	(0.033)	(0.177)	(0.235)
Share of months w/ vacancies	0.120	0.059	0.106	0.259	0.573
Average number of workers	49.424	5.877	22.271	102.038	871.809
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	9,133	8,751	2,144	483
Number of observations	1,175,549	451,310	548,832	142,505	32,902
		Panel B: Hourly wage			
Dependent variable: h_{jt}	All	1st quartile	2nd quartile	3rd quartile	4th quartile
No-vacancy baseline β	0.061***	0.089***	0.061***	0.052***	0.046***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cumulative response Π	0.044***	0.061***	0.052***	0.037***	0.035***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)
Π relative to no-vacancy baseline Π/β	0.726***	0.691***	0.842***	0.715***	0.757***
	(0.023)	(0.043)	(0.045)	(0.046)	(0.058)
Share of Π realized within 2 months Λ	0.846***	0.973***	0.900***	0.802***	0.653***
	(0.021)	(0.045)	(0.036)	(0.042)	(0.040)
Share of months w/ vacancies	0.120	0.104	0.106	0.133	0.135
Average hourly wage	213.417	140.291	182.062	216.789	308.448
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	5,128	5,128	5,128	5,127
Number of observations	1,175,549	267,428	302,335	311,297	294,489
		Panel C: Employment growth rate			
Dependent variable: h_{jt}	All	1st quartile	2nd quartile	3rd quartile	4th quartile
No-vacancy baseline β	0.061***	0.054***	0.042***	0.056***	0.097***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cumulative response Π	0.044***	0.056***	0.043***	0.029***	0.052***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)
Π relative to no-vacancy baseline Π/β	0.726***	1.033***	1.039***	0.520***	0.541***
	(0.023)	(0.061)	(0.064)	(0.035)	(0.039)
Share of Π realized within 2 months Λ	0.846***	0.760***	0.788***	0.856***	0.965***
	(0.021)	(0.033)	(0.035)	(0.045)	(0.054)
Share of months w/ vacancies	0.120	0.092	0.105	0.163	0.120
Average monthly growthrate	0.000	−0.039	−0.003	0.007	0.039
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	16,021	15,392	12,703	15,542
Number of observations	1,175,549	287,996	322,165	287,728	277,411

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

which increases to about 85% for small firms and to more than 90% for medium-size firms. For large firms the point estimate of Λ is less than 25% and statistically insignificant. This is likely due to fact that these firms post vacancies very frequently which hinders the identification of the lag distribution weights; therefore, we think this estimate does not necessarily suggest that large firms hire very slowly.

Panel B splits firms in the four quartiles of the distribution of average hourly wages. The proportion of months with vacancies increases monotonically, but modestly, with the average wage, from little more than 10% in the lowest-wage quartile almost 14% in the highest-wage quartile. The estimate for the baseline no-vacancy hiring rate β_ℓ is strongly decreasing in the average wage from 9% in the lowest-wage quartile to less than 5% in the highest-wage quartile. The hiring response to vacancy-posting is also decreasing in the average wage and the proportional increase of the hiring rate over the no-vacancy baseline is relatively similar across the average wage groups, at approximately 70-80%. Finally, the speed of the response (as measured by the share that materializes within two months) decreases significantly in the average wage, from more than 95% in the lowest-wage quartile to 65% in the highest-wage quartile. This is interesting because several prominent models of labor search predict that high-wage firms hire faster in the context of homogeneous workers (e.g. models with on-the-job search or directed search). Therefore, to rationalize the timing of the hiring response to vacancy-posting across different wage groups, a model with worker or match heterogeneity might be necessary.[15]

Panel C splits *firm-years* in the four quartiles of the distribution of average monthly employment growth across firm-years. The proportion of months with vacancies is increasing in firm growth, though somewhat modestly from 9% in the lowest-growth quartile to 12% in the highest-growth quartile. The baseline no-vacancy hiring rate is U-shaped in firm growth, at approximately 4-6% for the lowest three quartiles and considerably higher at 9.7% for firms in the fastest-growing quartile. The response of hiring to vacancy-posting as a proportion over the no-vacancy baseline is generally decreasing in firm growth and the share of the response that occurs within two months is increasing in firm growth. Overall, it appears that high employment growth is not achieved through more vacancy-posting or a greater hiring response to vacancy postings but, rather, through no-vacancy hiring.

It seems reasonable that high-growth firms exert greater recruiting effort overall and that vacancy-posting is only one aspect of that effort. To the extent that recruiting effort (and its outcomes) is imperfectly correlated with vacancy-posting, it is likely to be partially absorbed by the baseline no-vacancy hiring rate and the firm fixed effects.[16] Note, however, that the average effect of recruiting effort on filling posted vacancies is captured by our estimated response to vacancy-posting. Davis, Faberman, and Haltiwanger (2013) find that the vacancy yield (hires per vacancy) increases sharply in establishments' employment growth (when growth is positive) which can be interpreted as high-growth firms exerting more recruiting effort per vacancy.[17] Under this interpretation, therefore, high baseline hiring rates in our framework correspond to high vacancy yields in Davis, Faberman, and Haltiwanger

[15] Faberman and Menzio (2018) and Mueller, Osterwalder, Zweimüller, and Kettemann (2020) document similar findings and introduce firm and worker heterogeneity in directed search models to rationalize them.

[16] For example, see Galenianos (2013) for a model where some firms specialize in recruiting through informal channels while others specialize in more formal recruiting. That feature would result in the undermeasurement of recruiting effort for the former type of firms in an online advertisement dataset like the one we use.

[17] Carrillo-Tudela, Gartner, and Kaas (2021) and Bagger and Galenianos (2021) report similar findings using the Job Vacancy Survey from Germany and the JobIndex data from Denmark, respectively, using the same methodology as Davis, Faberman, and Haltiwanger (2013).

(2013). Clearly, more work is required to explore whether this interpretation is accurate.

Table 6 splits firms by industry. We observe some heterogeneity in the response of hiring to vacancy-posting: In industries such as Construction and Accommodation the hiring rate increases by 5.5 and 6.7 percentage points, respectively, while in Administrative Services and the combined Financial and Insurance Activities/Real Estate Activities, it rises by only 1.9 and 2.3 percentage points. Furthermore, vacancy-posting almost doubles the hiring rate in comparison to the no-vacancy baseline in Construction and Wholesale Trade and increases it by less than a fifth in Administrative Services. Finally, the response of the hiring rate is fastest in Administrative Services, Construction, and Accommodation. Further work to determine the extent to which this heterogeneity is due to firm composition or to industry-specific characteristics is certainly desirable, but beyond the scope of the present paper.

4 Vacancies and separations

This section explores the extent to which separations predict vacancy-posting at the firm level, i.e. whether separations are followed by increased recruitment effort by the firm to replace the departing worker(s). The goal is to provide direct descriptive evidence regarding the empirical relevance of "vacancy chains", the process where a separation event leads to a sequence of vacancy-posting, worker-poaching, and yet more vacancy-posting, thereby contributing to the volatility of labor markets.[18]

We estimate how a firm's vacancy rate responds to the firm's separation rate using a number of different specifications. Appendix C presents the estimates of the effect of the separation rate on the vacancy-posting indicator variable, which yield qualitatively similar results.

The starting point for this part of our empirical analysis is the following distributed lag model for the monthly vacancy rate v_{jt}^M of firm j in month t,

$$v_{jt}^M = \beta + \sum_{k=0}^{6} \pi_k s_{jt-k} + \mathbf{x}_{jt}'\boldsymbol{\delta} + \rho_j + \epsilon_{jt}, \tag{3}$$

where s_{jt} is the separation rate of firm j in month t, β is a constant measuring the no-separation baseline vacancy rate, $\mathbf{x}_{jt}$ is a vector of month-dummies, industry-dummies and their interactions, ρ_j is a firm fixed effect and ϵ_{jt} is the error term. The separation rate s_{jt} is included with a truncated lag distribution with up to 6 months lag, and the lag-k weight is π_k.

We define the cumulative response of the vacancy rate to a marginal change in the separation rate as $\Pi = \sum_{k=0}^{6} \pi_k$, and the share of this marginal response that materializes within two months by $\Lambda = (\pi_0 + \pi_1)/\Pi$. We report the vacancy rate response to a one standard deviation separation rate change, which we denote by $\Omega(\sigma_s)$, where σ_s is the standard deviation of the separation rate.

Table 7 presents the results. Column (1) reports the estimates of a static specification that only includes the contemporaneous separation rate, i.e. where $\pi_k \equiv 0$ for $k \geq 1$, and firm fixed effects. The baseline monthly vacancy rate when there are no contemporaneous separations is 1.3%, and the vacancy rate response to a 10 percentage point increase in the contemporaneous separation rate is an

[18] See Elsby, Michaels, and Ratner (2019) and Mercan and Schoefer (2020) for a detailed description of vacancy chains and the evidence about replacement hiring. These studies infer the presence of replacement hiring by observing that firms facing quits often report stable employment, i.e. they also report that hires exactly offset their earlier separations. Faberman and Nagypal (2008) find that the monthly vacancy rate more than doubles at establishments reporting worker quit(s) in comparison to those without quits.

Table 6: By industry

Dependent variable: h_{jt}	All	Manu	Cons	Whol	Tran	Acco	Info	Prof	Admi	Fina	Mini
No-vacancy baseline β	0.061***	0.052***	0.063***	0.052***	0.063***	0.133***	0.054***	0.057***	0.117***	0.057***	0.052***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)
Cumulative response Π	0.044***	0.042***	0.055***	0.050***	0.045***	0.067***	0.038***	0.035***	0.019***	0.023**	0.046***
	(0.001)	(0.003)	(0.003)	(0.002)	(0.006)	(0.008)	(0.005)	(0.004)	(0.006)	(0.011)	(0.011)
Π relative to no-vacancy baseline Π/β	0.726***	0.798***	0.876***	0.946***	0.703***	0.501***	0.700***	0.622***	0.160***	0.397**	0.883***
	(0.023)	(0.058)	(0.057)	(0.046)	(0.097)	(0.061)	(0.106)	(0.071)	(0.054)	(0.199)	(0.232)
Share of Π realized within 2 months Λ	0.846***	0.747***	1.037***	0.743***	0.881***	0.913***	0.584***	0.825***	2.366***	0.888***	0.510***
	(0.021)	(0.042)	(0.051)	(0.026)	(0.087)	(0.089)	(0.085)	(0.078)	(0.702)	(0.330)	(0.116)
Share of months w/ vacancies	0.120	0.136	0.077	0.109	0.125	0.140	0.151	0.128	0.222	0.155	0.088
Dynamic effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	3,897	3,532	6,411	1,031	1,141	1,044	1,854	832	500	269
Number of observations	1,175,549	246,919	205,542	370,325	60,057	53,291	54,952	100,044	41,657	25,977	16,785

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month effects. Industries are NACE 2.0 sectors: Manufacturing (Manu), Construction (Cons), Wholesale and Retail Trade, Repair of Motor Vehicles and Motor Cycles, Transport and Storage (Tran), Accommodation and Food Service Activities (Acco), Information and Communication (Info), Professional, Scientific, and Technical Services (Prof), and Administrative and Support Service Activities (Admi). Finally, the Fina-label covers the two NACE 2.0 sectors Financial and Insurance Activities and Real Estate Activities, and the Mini-label covers the three NACE 2.0 sectors Mining and Quarrying, and Electricity, Gas, Steam and Airconditioning, and Water Supply and Sewerage Contractors.

Table 7: Separations and vacancies

Dependent variable v_{jt}	(1)	(2)	(3)	
			EE	*EN*
No-separation baseline β	0.013***	0.010***	0.009***	
	(0.000)	(0.000)	(0.000)	
Lag-0 weight π_0^1	0.015***	0.015***	0.044***	0.007***
	(0.001)	(0.001)	(0.003)	(0.001)
Lag-1 weight π_1^1		0.022***	0.041***	0.016***
		(0.002)	(0.007)	(0.002)
Lag-2 weight π_2^1		0.010***	0.019***	0.008***
		(0.002)	(0.004)	(0.002)
Lag-3 weight π_3^1		0.006***	0.013***	0.004***
		(0.001)	(0.004)	(0.001)
Lag-4 weight π_4^1		0.004***	0.010***	0.002**
		(0.001)	(0.003)	(0.001)
Lag-5 weight π_5^1		0.005***	0.009**	0.003**
		(0.001)	(0.004)	(0.001)
Lag-6 weight π_6^1		0.003***	0.003	0.003***
		(0.001)	(0.002)	(0.001)
Cumulative response Π	0.015***	0.065***	0.139***	0.043***
	(0.001)	(0.006)	(0.019)	(0.005)
Share of Π realized within 2 months Λ		0.570***	0.612***	0.530***
		(0.029)	(0.046)	(0.049)
Cumulative response to 1SD s-shock $\Omega(\sigma_s)$	0.002***	0.010***	0.009***	0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
Dynamic effects	No	Yes	Yes	
Firm fixed effects	Yes	Yes	Yes	
Number of firms	20,511	20,511	20,511	
Number of observations	1,175,549	1,175,549	1,175,549	

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions. σ_s is the standard deviation of the overall separation rate in columns (1) and (2), of the separation rate to employment in column (3-EE) and of the separation rate to non-employment in column (3-EN).

increase of 0.15 percentage points. Furthermore, a one-standard-deviation increase of the separation rate is associated with an increases in the vacancy rate by 0.2 percentage points, a 15% increase over the baseline no-separation vacancy rate.

Column (2) in Table 7 reports the estimates of the full specification which allows for the dynamic effects of separations, i.e. for $\pi_k \neq 0$ for $k = 0, 1..., 6$. The baseline no-separation vacancy rate is reduced slightly to 1%. The cumulative response to a separation event is more than four times greater than in the static specification, highlighting the importance of accounting for dynamic responses. Indeed, only 57% of the total vacancy-posting response occurs within the month of the separation and the subsequent month. A typical one standard deviation separation event is associated with an increase in the vacancy rate of 1 percentage point, a 100% increase compared to the baseline vacancy rate.

Next, we extend our analysis to examine the heterogeneous effect of separations to employment and separations to non-employment on vacancy-posting. This is potentially interesting since separations to employment might be due to poaching, leading to more replacement and the propagation of a vacancy chain, while separations to non-employment might include downsizing by firms and, therefore, be associated with less replacement hiring.

To this end, we amend equation (3) in a straightforward way to distinguish between the separation

rates into employment (denoted s_{jt}^{EE}) and non-employment (denoted s_{jt}^{EN}):

$$v_{jt}^{M} = \sum_{k=0}^{K} \pi_{k}^{EE} s_{jt-k}^{EE} + \sum_{k=0}^{K} \pi_{k}^{EN} s_{jt-k}^{EN} + \mathbf{x}_{jt}'\boldsymbol{\delta} + \rho_j + \epsilon_{jt}, \tag{4}$$

The remaining right-hand side variables in (4) are defined analogously to equation (3). Note that equation (4) does not decompose equation (3).

Column (3) in Table 7 reports the estimates. We do, indeed, find that separations to employment generate a much stronger vacancy-posting response than separations to non-employment: the cumulative response Π to EE-separation events is more than three times as large as the cumulative response to EN-separation events. The timing of the responses is quite similar, with approximately half of the overall effect occurring within the separation month and subsequent month. The effect of a one standard deviation separation-to-employment event increases the baseline vacancy-posting rate by 0.9 percentage points, or 100% over baseline; a one-standard-deviation separation-to-nonemployment event increases the baseline vacancy-posting rate by 0.5 percentage points, or 56% over baseline. For these computations we use the empirical standard deviation of EE- and EN-separations, $\sigma_{s^{EE}}$ and $\sigma_{s^{EN}}$, rather than the standard deviation of the overall separation rate, σ_s.

These results are consistent with replacement hiring and vacancy chains: separations are associated with an increase in recruitment effort by firms, presumably to replace the separator(s). This effect is much stronger for separations into employment, which provides direct evidence of shock propagation through vacancy chains. A notable feature is that vacancy-posting takes some time to materialize and the static model of column (1) captures less than a quarter of the overall effect. Furthermore, our estimates suggest that one would need to examine time periods that last at least two quarters to evaluate whether replacement hiring is taking place: our estimated lag distributions imply that it takes approximately 4 months to reach three-quarters of the vacancy-posting response and then another 2 months to reach a similar proportion of the hiring response of vacancy-posting.

5 Output growth and vacancies

In this final part of the paper, we examine the extent to which output growth predicts vacancy-posting. We measure output using firm revenue and value added and, since these variables are primarily available at a quarterly frequency, our analysis of output growth and vacancy-posting is conducted using the quarterly firm-panel (see our data description in section 2 for further details). This section presents the estimated vacancy-posting responses to revenue growth. Appendix D reports responses to value added growth, which turn out to be qualitatively similar.

We document the empirical relationship between vacancy-posting, measured by the *quarterly* vacancy-posting indicator variable I_{jt}^{Q} and the *quarterly* vacancy rate v_{jt}^{Q}, and growth in log quarterly revenue $r_{jt} \equiv \log(R_{jt})$ using a set of distributed lag regressions, in line with the preceding sections.

Specifically, we estimate several variations of the following equation:

$$\begin{aligned} z_{js} = \beta + \sum_{k=0}^{6} \pi_{S,k}^{+} \mathbb{1}(\Delta r_{js-k} \in (0, \sigma_{\Delta r}]) \quad &+ \quad \sum_{k=0}^{6} \pi_{L,k}^{+} \mathbb{1}(\Delta r_{js-k} \in (\sigma_{\Delta r}, \infty)) + \sum_{k=0}^{6} \pi_{S,k}^{-} \mathbb{1}(\Delta r_{js-k} \in [-\sigma_{\Delta r}, 0)) \\ &+ \quad \sum_{k=0}^{6} \pi_{L,k}^{-} \mathbb{1}(\Delta r_{js-k} \in (-\infty, -\sigma_{\Delta r})) + \mathbf{x}_{js}'\boldsymbol{\delta} + \rho_j + \epsilon_{js}, \end{aligned} \tag{5}$$

where z_{js} is either the quarterly vacancy-posting indicator variable I^Q_{js}, in which case this is a linear probability model, or the quarterly vacancy rate v^Q_{js}. $\mathbb{1}(\cdot)$ is the indicator function, Δr_{js} denotes revenue growth between quarters $s-1$ and s, $\sigma_{\Delta r}$ is the cross-sectional standard deviation of Δr_{js}, $\mathbf{x}_{js}$ is a vector of quarter-dummies, industry dummies, and quarter-dummies interacted with industry-dummies, ρ_j is a firm fixed effect and ϵ_{js} is the error term.

Equation (5) allows flexible vacancy-posting responses to revenue growth. As before, we allow for contemporaneous and lagged growth events to impact vacancy-posting by including lag distributions, truncated at six quarters. We allow for asymmetric responses to positive and negative growth events, which we indicate by superscripting the lag weights by "+" and "−", respectively. Furthermore, we allow for separate nonlinear responses to small and large revent growth, which we indicate by subscripting the lag weights by S and L respectively, using a linear spline specification with a single knot at the cross-sectional standard deviation of revenue growth, $\sigma_{\Delta r}$.[19]

The cumulative response to a small increase in revenue growth is $\Pi^+_S = \sum_{k=0}^{6} \pi^+_{S,k}$ for $\Delta r \in (0, \sigma_{\Delta r}]$, to large increase in revenue growth is $\Pi^+_L = \sum_{k=0}^{6} \pi^+_{L,k}$ for $\Delta r \in (\sigma_{\Delta r}, \infty)$, and similarly for small and large declines in revenue growth: $\Pi^-_S = \sum_{k=0}^{6} \pi^-_{S,k}$ for $\Delta r \in [-\sigma_{\Delta r}, 0)$, and $\Pi^-_L = \sum_{k=0}^{6} \pi^-_{L,k}$ for $\Delta r \in (-\infty, -\sigma_{\Delta r})$. Notice that positive values for Π^-_S or Π^-_L imply a *negative* response of vacancy-posting to negative revenue shock ($\Delta r < 0$).

The cumulative vacancy-posting response to a revenue growth shock of size Δr is given by

$$\Omega(\Delta r) = \begin{cases} \Pi^+_L \Delta r & \text{if } \Delta r \in (\sigma_{\Delta r}, \infty), \\ \Pi^+_S \Delta r & \text{if } \Delta r \in (0, \sigma_{\Delta r}], \\ \Pi^-_S \Delta r & \text{if } \Delta r \in [-\sigma_{\Delta r}, 0), \\ \Pi^-_L \Delta r & \text{if } \Delta r \in (-\infty, -\sigma_{\Delta r}). \end{cases} \tag{6}$$

In our results we report $\Omega(\sigma)$, $\Omega(2\sigma)$, $\Omega(-\sigma)$, and $\Omega(-2\sigma)$.

Table 8 reports the estimates for $z_{jt} = I^Q_{jt}$ for 5 different specifications based on equation (5). We do not report the estimated effect of each lag, but instead present the dynamics of the response graphically in Figure 1. Column (1) presents the estimate of the simplest specification with static, symmetric and linear effects: $\pi^+_{1,k} = \pi^-_{1,k}$ for all k and equal to zero for $k \geq 1$; $\pi^+_{2,k} = \pi^-_{2,k} = 0$ for all k. The contemporaneous effect is estimated at 1.1%, meaning that a one-standard deviation revenue shock is associated with a change in the probability of vacancy-posting of 0.5 percentage points, on a baseline quarterly vacancy-posting probability of 26.4% when there are no shocks to revenues. Column (2) introduces dynamic effects: the coefficients are allowed to differ from 0 when $k = 0, 1..., 6$ but the effects are still constrained to be linear and symmetric around 0. Under this specification, the estimated effect of a revenue shock on vacancy-posting increases more than ten-fold to 14.6% and a one-standard deviation shock is associated with a 7.2 percentage point change in the probability of vacancy-posting.

Column (3) introduces the possibility of non-linearities by allowing large revenue shocks (larger than a standard deviation in absolute value) to have a different effect on vacancy-posting than smaller shocks. The estimated effect of large shocks is quite similar to the overall effect from the linear and symmetric specification, but the effect of small shocks is approximately 15% greater than in the linear case pointing to a mildly non-linear response. Specifically, a one-standard deviation shock to revenue

[19] For robustness, we have run the regressions with the knot at 0.5 standard deviations and 2 standard deviations. The results are quantitatively very similar to those we present here so we omit them.

Table 8: Distributed Lag regressions of the vacancy indicator on revenue growth

Dependent variable I_{jt}^{Q}	(1)	(2)	(3)	(4)	(5)
Constant β	0.264^{***} (0.000)	0.263^{***} (0.000)	0.260^{***} (0.001)	0.266^{***} (0.002)	0.269^{***} (0.004)
Π^{1}	0.011^{***} (0.001)	0.146^{***} (0.013)	0.168^{***} (0.016)		
Π^{2}			0.144^{***} (0.014)		
$\Pi^{1,-}$				0.159^{***} (0.016)	0.225^{***} (0.027)
$\Pi^{2,-}$					0.096^{***} (0.024)
$\Pi^{1,+}$				0.139^{***} (0.015)	0.173^{***} (0.027)
$\Pi^{2,+}$					0.089^{***} (0.023)
Cumul. resp. to positive 1SD Δr_{js}-shock, $\Omega(\sigma_{\Delta r})$	0.005^{***} (0.001)	0.072^{***} (0.007)	0.082^{***} (0.008)	0.068^{***} (0.008)	0.085^{***} (0.013)
Cumul. resp. to positive 2SD Δr_{js}-shock, $\Omega(2\sigma_{\Delta r})$	0.010^{***} (0.001)	0.143^{***} (0.013)	0.153^{***} (0.014)	0.136^{***} (0.015)	0.129^{***} (0.016)
Cumul. resp. to negative 1SD Δr_{js}-shock, $\Omega(-\sigma_{\Delta r})$	-0.005^{***} (0.001)	-0.072^{***} (0.007)	-0.082^{***} (0.008)	-0.078^{***} (0.008)	-0.110^{***} (0.013)
Cumul. resp. to negative 2SD Δr_{js}-shock, $\Omega(-2\sigma_{\Delta r})$	-0.010^{***} (0.001)	-0.143^{***} (0.013)	-0.153^{***} (0.014)	-0.156^{***} (0.016)	-0.158^{***} (0.016)
Dynamic effects	No	Yes	Yes	Yes	Yes
Nonlinear effects	No	No	Yes	No	Yes
Asymmetric effects	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	18,155	18,155	18,155	18,155	18,155
Number of observations	288,180	288,180	288,180	288,180	288,180

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

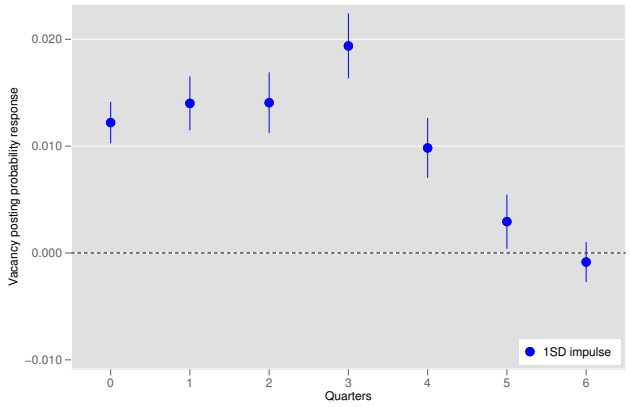
growth yields an 8.2 percentage point change in the probability of vacancy-posting while a two-standard deviations shock changes it by 15.3 percentage point. Column (4) introduces an asymmetric vacancy-posting response to positive and negative revenue shocks, with linear effects, and the effects of negative shocks are estimated to be 15% larger than those of positive shocks.

Finally, column (5) includes asymmetric and non-linear effects and is our preferred specification. The difference between the effect of positive and negative shocks is now greater than before and the non-linearities are more pronounced. Specifically, the response of vacancy-posting to negative shocks is 20-30% greater than that to positive shocks, both for one- and two-standard deviation shocks, as compared to 15% greater in the linear specification of column (4). Furthermore, a one-standard-deviation shock is associated with a change in the vacancy-posting probability of 8.5 or 11 percentage points (following a positive or negative shock, respectively) while a two-standard-deviations shock by 13 or 16 percentage points. These results suggest that asymmetries and non-linearities interact in a non-trivial way and a flexible model is required to account for the effect of revenue shocks on vacancy-posting.

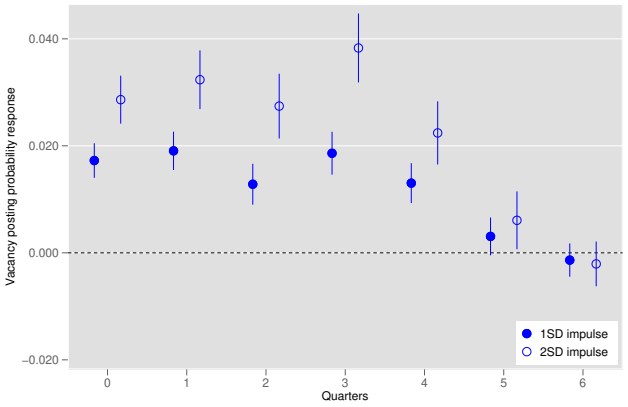
The dynamic behavior of the responses is depicted in Figure 1, which graphs the impulse response of vacancy-posting to a one- and two-standard deviation shock in the four dynamic specifications that we consider (columns 2-5 in Table 8). The qualitative features of the response are quite similar across specifications: the response is significant on impact, it generally peaks three quarters later and declines thereafter, to statistical insignificance around quarter five or six.

A noticeable feature of our results is that the estimated impulses are significant after many quarters: vacancy-posting seemingly responds to revenue shocks that occurred a full year earlier. This result, which we also find in the value-added analysis, is perhaps surprising and worthy of additional

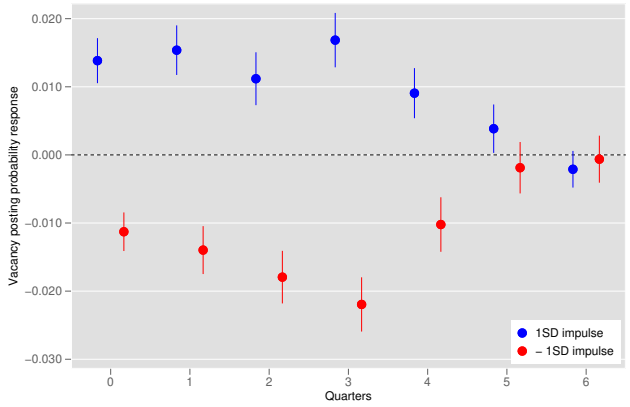
Figure 1: Distributed Lag regressions of the vacancy indicator on revenue growth



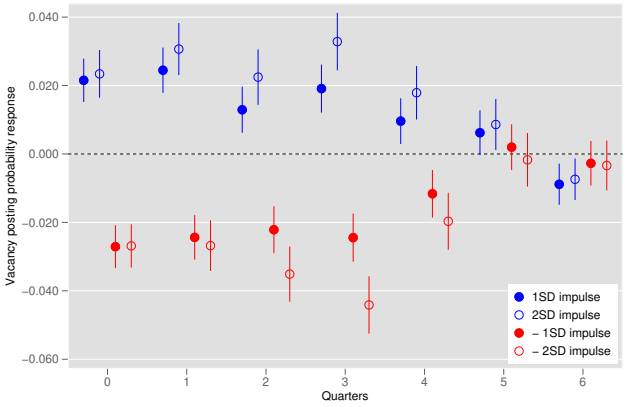
A: Estimates from Table 8, column (2)



B: Estimates from Table 8, column (3)



C: Estimates from Table 8, column (4)



D: Estimates from Table 8, column (5)

Notes: The plotted regression coefficients refer to regression specificiations tabulated in Table 8. Vertical bars represent 95% confidence intervals with clustering at the firm-level.

Table 9: Distributed Lag regressions of the vacancy rate on revenue growth

Dependent variable v_{jt}	(1)	(2)	(3)	(4)	(5)
Constant β	0.040***	0.040***	0.040***	0.041***	0.042***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.006)
Π^1	0.001	−0.005	−0.003		
	(0.001)	(0.012)	(0.013)		
Π^2			−0.005		
			(0.014)		
$\Pi^{1,-}$				−0.002	0.006
				(0.019)	(0.045)
$\Pi^{2,-}$					−0.009
					(0.012)
$\Pi^{1,+}$				−0.004	−0.009
				(0.009)	(0.018)
$\Pi^{2,+}$					−0.005
					(0.012)
Cumul. resp. to positive 1SD Δr_{js}-shock, $\Omega(\sigma_{\Delta r})$	0.000	−0.002	−0.001	−0.002	−0.004
	(0.000)	(0.006)	(0.006)	(0.005)	(0.009)
Cumul. resp. to positive 2SD Δr_{js}-shock, $\Omega(2\sigma_{\Delta r})$	0.001	−0.005	−0.004	−0.004	−0.007
	(0.001)	(0.012)	(0.012)	(0.009)	(0.008)
Cumul. resp. to negative 1SD Δr_{js}-shock, $\Omega(-\sigma_{\Delta r})$	−0.000	0.002	0.001	0.001	−0.003
	(0.000)	(0.006)	(0.006)	(0.009)	(0.022)
Cumul. resp. to negative 2SD Δr_{js}-shock, $\Omega(-2\sigma_{\Delta r})$	−0.001	0.005	0.004	0.002	0.002
	(0.001)	(0.012)	(0.012)	(0.019)	(0.023)
Dynamic effects	No	Yes	Yes	Yes	Yes
Nonlinear effects	No	No	Yes	No	Yes
Asymmetric effects	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	18,155	18,155	18,155	18,155	18,155
Number of observations	288,180	288,180	288,180	288,180	288,180

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

study. In Bagger, Fontaine, Galenianos, and Trapeznikova (2021) we estimate a process for firm output that includes permanent and transitory shocks and explore the effects of these different shocks on vacancy-posting. Interestingly, permanent shocks have a much larger effect on vacancy-posting which is consistent with the significant responses to long lags of revenue shocks that we find in Table 8.

Table 9 repeats the regressions with the quarterly vacancy rate as the dependent variable in equation (5). The only feature of note in these regressions is the lack of statistical relationship between the vacancy rate and revenue growth. As in our earlier analysis of the relationship between vacancy-posting and hiring, this is likely due to strong non-linearities in the response of vacancy-posting to revenue growth which are poorly captured in the specifications of equation (5).

6 Discussion

Our paper contributes to the empirical literature on vacancies by exploring a new comprehensive dataset on job advertisements, employment, worker flows and output. We believe our findings have important implications for future empirical and theoretical research.

On the empirical side, the presence of a significant number of hires without vacancy-posting is a puzzling feature of the data (also reported in other work, such as Davis, Faberman, and Haltiwanger, 2013). While our results suggest that online advertisements capture an important dimension of firm recruiting effort, more work is required to determine how to account for the large amount hiring without measured vacancy postings. A further point is that the estimated hiring response to vacancy-posting is

highly heterogeneous across industries which suggests that the nature of frictions varies substantially across different sectors of the economy. One possibility that could be further explored is that the length of time separating vacancy-posting from hiring might be informative about the difficulty of finding the right match/skills in a particular industry. Another implication is that changes in the sectoral composition of hires and vacancies might affect aggregate estimates of frictions.

On the theoretical side, labor market models that predict heterogenous hiring responses to vacancy-posting (e.g. competitive search models as in Kaas and Kircher, 2015) are needed to interpret our finding that the hiring response to vacancy-posting is indeed highly heterogeneous across firms of different sizes, productivities and growth rates. The evidence that separations predict vacancy-posting suggest that poaching and replacement hiring are likely to be important features of labor markets. Therefore, on-the-job search and a distinction between jobs and matches are important elements of models even when the focus is on the aggregate labor market, e.g. as in Faberman and Nagypal (2008), Elsby, Michaels, and Ratner (2019) and Mercan and Schoefer (2020).

The finding the revenue growth predicts vacancy-posting is consistent with firm-level demand growth driving labor demand. The asymmetry and non-linearity of the vacancy-posting response to output growth can be an input to the further development of models with multi-worker firms, as in Elsby and Gottfries (2021) and Bilal, Engbom, Mongey, and Violante (2021). We further contribute in this direction in two companion papers: Bagger, Fontaine, Galenianos, and Trapeznikova (2021) imposes more structure on the output growth process to estimate the separate effect of permanent and transitory output shocks on vacancy-posting; and in Bagger, Fontaine, Galenianos, and Trapeznikova (2020) we estimate the direct effect of output growth on employment outcomes using a very flexible specification that includes permanent and transitory output shocks.

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Appendices

A Data Appendix

A.1 Industry classification of firms

To assign an industry classification to firms in the labor market spells datasets we use a separate matched employer-employee panel, the Integreret Database for Arbejdsmarkedsforskning (IDA). IDA is a comprehensive matched employer-employee panel which links workers and firms via their employment relationships in the last week of November and covers the entire Danish population and all firms with economic activity. IDA is constructed, updated and maintained by Statistics Denmark using administrative records and is organized in three main components: *IDA-P* contains person-information (e.g. age, gender, education, labor market experience); *IDA-S* contains information on every establishment (physical workplace) in Denmark (e.g. location, industry classification), including a unique establishment ID (variable $LBNR$); *IDA-N* contains information on all employment relationships in the last week of November (e.g. worker ID, establishment ID, earnings and hours).

Industry information is coded according to the NACE 2.0 classification scheme. Our data period is long enough to stretch across several versions of the NACE taxonomy and we recode earlier NACE 1.0 and NACE 1.1 codes to the newer NACE 2.0 codes using their empirical correspondence, as follows. New NACE classifications appear in 2003, when NACE 1.1 replaced NACE 1.0, and in 2007, when NACE 2.0 replaced NACE 1.1. In the first year after each new NACE classification is introduced, Statistics Denmark classifies each establishment according to both the new and the old NACE-scheme which allows us to construct an empirical correspondence table between the old and new NACE classifications. We use the 2003 correspondence table to assign NACE 1.1 codes to the pre-2003 establishment-years based on the most frequently occurring 2003-correspondence. In the same way, we use the 2007 correspondence table to assign NACE 2.0 codes to the pre-2007 establishment-years.

We use workers' unique ID number (CPR number) to match, essentially, every person in the labor market spell data to an individual in the IDA data. In November of each year we observe every worker's employer both on the IDA dataset and the labor market spells dataset which allows us to create a mapping from the establishment ID $LBNR$ that we observe in IDA to the firm CVR number that we observe in the labor market spells data (noting that multiple establishments might be mapped to the same firm). This mapping matches more than 90% of the observations in the spells data with IDA information. We aggregate the establishment industry information to the firm-year level by assigning to a firm-year in the merged labor market spells/IDA data the industry affiliation of the establishment with the largest number of employed workers.[20]

A.2 Comparison of firms with and without vacancies

The firm panel that we construct from our three datasets before discarding the firms without online advertisements consists of approximately 125,000 firms. Table A.1 provides a comparison of the subset of these firms that we use in our analysis (i.e. the firms for which we observe at least one online advertisement at some point in the observation period) with the firms that we discard (i.e. the firms for which we do not observe any online job advertisements).

The top panel of Table A.1 reports that 21,048 firms are observed to post an online job advertisement at some point during 2003M1-2009M6 and 104,724 are not. The firms used in the analysis consist of 17% of the total number of firms and make up 34% of the firm-month observations. The number of firms with job advertisements and the number of observations in Table A.1 are slightly larger from those used in the empirical analysis because they include some firms with fewer than 7 consecutive monthly observations which are dropped

[20] A natural alternative merging procedure where we first aggregate IDA information to the firm-level and then merge this aggregated firm-level panel to the labor market spells data by the firm ID (CVR-number) yields significantly fewer matched firm-years.

Table A.1: Characteristics of firms in vacancy and non-vacancy panels

	w/ online job advert.	w/o online job advert.
Number of firms	21,048	104,724
Number of observations	1,301,121	2,576,180
Employment per firm-month	48.406	9.581
Revenue per firm-month (in DKK 1,000)	7,671.544	1,292.151
Value added per firm-month (in DKK 1,000)	2,346.921	395.846
Hires per firm-month	2.904	0.682
Net job creation	102,623	−39,042
Share of total employment	0.718	0.282
Share of total revenue	0.750	0.250
Share of total value added	0.750	0.250
Share of hires	0.683	0.317
Share of net job creation	1.614	−0.614

Notes: In May, 2021 the exchange rate of the Danish Krone to the US Dollar was approximately 1 USD = 6.2 DKK.

from the analysis (see section 2.2). The middle panel of the Table shows that the firms with observed online advertisements are, on average, five times larger in terms of employment and almost six times larger in terms of revenues and value added than firms without observed online advertisements. Moreover, firms with observed online job advertisements hired four times more workers per month and created more than 100,000 jobs over the observation period, whereas firms without observed online job advertisements shrank during the observation period, shedding close to 40,000 jobs in the process. Overall, firms with observed online job advertisements account for 72% of employment, 75% of revenue, 75% of value added, 68% of hires, and 160% of net job growth.

B Firm heterogeneity by value added

We replicate the analysis of section 3.3 using value added to split firms in different size, productivity and growth groups and report the results in Table B.1.

Panel A reports that the cumulative response Π to vacancy-posting is monotonically decreasing in firm size, as is the speed of the response (unlike the employment-based size measure).[21] Furthermore, the no-vacancy baseline hiring rate β is quite similar across different size groups, with the partial exception of the smallest firms.

Panel B in Table B.1 splits firms in quartiles according to value added per worker, a measure of firm productivity. The baseline no-vacancy hiring rate is decreasing in productivity and the response of the hiring rate to vacancy-posting (essentially) declines with productivity, although there is no strong pattern regarding the response's proportional change over the no-vacancy baseline. The speed of the response decreases in productivity.

Panel C in Table B.1 splits firm-years in quartiles according to each year's value added growth rate. The baseline no-vacancy hiring rate and the hiring response both have very modest U-shape in firm growth, while the response as a proportion of the baseline is modestly decreasing in firm growth. The speed of the response is increasing in firm growth.

Overall, most of these responses are qualitatively quite similar to those reported in section 3.3, using employment and wages to create similar firm groupings.

[21] Of course, the caveats regarding identification of dynamic responses among the largest firms, that post vacancies frequently and post many vacancies simultaneously, applies here as well.

Table B.1: Firm heterogeneity

		Panel A: Quarterly value added			
Dependent variable: h_{jt}	All	$< 1M$	$1M$-$5M$	$5M$-$15M$	$\geq 15M$
No-vacancy baseline β	0.061*** (0.000)	0.071*** (0.000)	0.056*** (0.000)	0.053*** (0.001)	0.055*** (0.001)
Cumulative response Π	0.044*** (0.001)	0.091*** (0.003)	0.040*** (0.002)	0.019*** (0.003)	0.012*** (0.003)
Π relative to no-vacancy baseline Π/β	0.726*** (0.023)	1.282*** (0.047)	0.712*** (0.034)	0.360*** (0.054)	0.217*** (0.066)
Share of Π realized within 2 months Λ	0.846*** (0.021)	0.836*** (0.022)	0.842*** (0.032)	0.797*** (0.091)	0.383** (0.178)
Share of months w/ vacancies	0.120	0.070	0.104	0.189	0.381
Average quarterly value added (in mill. DKK)	7.248	0.152	2.328	8.464	76.953
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	9,470	7,720	2,147	1,174
Number of observations	1,175,549	465,274	487,186	143,833	79,256
		Panel B: Value added per worker			
Dependent variable: h_{jt}	All	1st quartile	2nd quartile	3rd quartile	4th quartile
No-vacancy baseline β	0.061*** (0.000)	0.090*** (0.000)	0.061*** (0.000)	0.053*** (0.000)	0.048*** (0.000)
Cumulative response Π	0.044*** (0.001)	0.048*** (0.003)	0.049*** (0.002)	0.044*** (0.002)	0.039*** (0.002)
Π relative to no-vacancy baseline Π/β	0.726*** (0.023)	0.537*** (0.040)	0.807*** (0.044)	0.832*** (0.048)	0.821*** (0.056)
Share of Π realized within 2 months Λ	0.846*** (0.021)	0.955*** (0.053)	0.942*** (0.038)	0.840*** (0.037)	0.651*** (0.038)
Share of months w/ vacancies	0.120	0.136	0.103	0.114	0.129
Quarterly value added per worker (1000 DKK)	168.939	22.324	89.487	123.344	408.597
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	5,128	5,128	5,128	5,127
Number of observations	1,175,549	243,975	304,071	317,110	310,393
		Panel C: Quarterly value added growth rate			
Dependent variable: h_{jt}	All	1st quartile	2nd quartile	3rd quartile	4th quartile
No-vacancy baseline β	0.061*** (0.000)	0.059*** (0.000)	0.058*** (0.000)	0.060*** (0.000)	0.066*** (0.000)
Cumulative response Π	0.044*** (0.001)	0.055*** (0.003)	0.044*** (0.002)	0.045*** (0.003)	0.045*** (0.003)
Π relative to no-vacancy baseline Π/β	0.726*** (0.023)	0.929*** (0.058)	0.756*** (0.047)	0.752*** (0.048)	0.686*** (0.054)
Share of Π realized within 2 months Λ	0.846*** (0.021)	0.741*** (0.036)	0.792*** (0.037)	0.817*** (0.039)	0.928*** (0.055)
Share of months w/ vacancies	0.120	0.106	0.126	0.132	0.112
Average quarterly value added growth rate	0.003	−0.356	−0.038	0.061	0.346
Dynamic effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	20,511	15,919	13,990	14,000	15,610
Number of observations	1,175,549	261,031	303,525	302,264	255,588

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

C Separations and vacancy indicator variable

Table C.1: Separations and vacancies

Dependent variable I_{jt}^M	(1)	(2)	(3)	(4)	(5)	
					EE	*EN*
No-separation baseline β	0.104*** (0.000)	0.090*** (0.001)	0.090*** (0.001)	0.114*** (0.000)	0.087*** (0.001)	
Cumulative response (intercept) Π^0	0.031*** (0.001)	0.060*** (0.002)	0.058*** (0.003)		0.084*** (0.003)	0.021*** (0.003)
Cumulative response (magnitude) Π^1			0.013 (0.009)	0.085*** (0.007)	−0.070*** (0.021)	0.020** (0.010)
Share of Π^0 realized within 2 months Λ^0		0.735*** (0.020)	0.749*** (0.025)		0.649*** (0.020)	0.850*** (0.083)
Share of Π^1 realized within 2 months Λ^1			0.278 (0.218)	0.741*** (0.048)	−0.080 (0.155)	−0.269 (0.312)
Cumulative response to 1SD s-shock $\Omega(\sigma_s)$	0.031*** (0.001)	0.060*** (0.002)	0.060*** (0.002)	0.013*** (0.001)	0.080*** (0.003)	0.024*** (0.002)
Dynamic effects	No	Yes	Yes	Yes	Yes	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	
Number of firms	20,511	20,511	20,511	20,511	20,511	
Number of observations	1,175,549	1,175,549	1,175,549	1,175,549	1,175,549	

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions. σ_s is the standard deviation of the overall separation rate in columns (1), (2), (3), and (4), of the separation rate to employment in column (5-EE) and of the separation rate to non-employment in column (5-EN).

We extend the analysis of section 4 by estimating the effect on the binary vacancy indicator variable of the separation rate and the heterogeneous effect of the separation rate into employment and non-employment. We estimate the following linear probability distributed lag models for the vacancy-posting indicator variable I_{jt}^M:

$$I_{jt}^M = \beta + \sum_{k=0}^{6} \pi_k^0 \mathbb{1}(s_{jt-k} > 0) + \sum_{k=0}^{6} \pi_k^1 s_{jt-k} + \mathbf{x}_{jt}'\boldsymbol{\delta} + \rho_j + \epsilon_{jt}, \tag{C1}$$

$$I_{jt}^M = \beta + \sum_{k=0}^{6} \pi_k^{0,EE} \mathbb{1}(s_{jt-k}^{EE} > 0) + \sum_{k=0}^{6} \pi_k^{0,EN} \mathbb{1}(s_{jt-k}^{EN} > 0) + \sum_{k=0}^{6} \pi_k^{1,EE} s_{jt-k}^{EE} + \sum_{k=0}^{6} \pi_k^{1,EN} s_{jt-k}^{EN} + \mathbf{x}_{jt}'\boldsymbol{\delta} + \rho_j + \epsilon_{jt}, \tag{C2}$$

where $\mathbb{1}(\cdot)$ is the indicator function, and the remaining right-hand side variables are as in section 4. The regression (C1) includes a linear effect on the magnitude of the separation event (superscript "1") and a dummy variable (superscript "0") that indicates the event that any separations took place ($\mathbb{1}(s_{jt-k} > 0)$). Similarly regression (C2) includes linear effects on the magnitude of the separation events into employment and into non-employment and dummies for any separations into employment and into non-employment. The dummy variables capture the large inaction that we observe in the data, where separations occur in roughly half of firm-months.[22]

First we estimate the effect of total separations on the vacancy indicator. Columns (1) and (2) report the estimates when the dummy variable is the only regressor ($\pi_k^1 \equiv 0$) and affects vacancy-posting statically ($\pi_k^0 \equiv 0$ for $k \geq 1$) or dynamically, respectively. Comparing columns (1) and (2) we conclude that dynamic effects are important, almost doubling the response to a 1SD separation event on the probability of posting a vacancy from 3.1 to 6.0 percentage points, which corresponds to a 66% increase over the baseline. Column (3) reports the estimates when both the dummy variable and the linear effect are regressors in a dynamic specification. The estimated coefficients on the linear effect are quantitatively and statistically insignificant and, therefore, the

[22] We did include the dummy variable in the specification of section 4, where the dependent variable is the vacancy rate. We found that the coefficient on the dummy variable is quantitatively insignificant and that the estimates of the other coefficient do not meaningfully change (we do not report the results but they are available upon request). For this reason we only include the dummy variable in the regressions where the dependent variable is the vacancy indicator.

magnitude of the separation event does not have additional predictive power. Column (4) reports the estimates when the linear effect where the linear effect is the only regressor ($\pi_k^0 \equiv 0$). In this specification, the predicted vacancy-posting probability response to a 1SD separation event is small, 1.3 percentage points compared to a baseline of 11.4 percent.

Then we turn to the heterogeneous effects of separations into employment and non-employment. Column (5) reports that a 1SD separation-to-employment event increases the probability of vacancy-posting by 8 percentage points, which is more than three times larger than the effect of a 1SD separation-to-non-employment event.[23] The probability of vacancy-posting increases by 91% over the baseline no-separation vacancy-posting probability after a 1SD separation-to-employment event, and by 28% after a 1SD separation-to-non-employment event. Overall these results are qualitatively similar to the results of section 4: separations predict vacancy-posting in a statistically and quantitatively significant way, the estimates are considerably larger when dynamics effects are included and separations to employment are associated with more vacancy-posting.

D Value added growth and vacancy-posting

Table D.1: Vacancies and value added growth

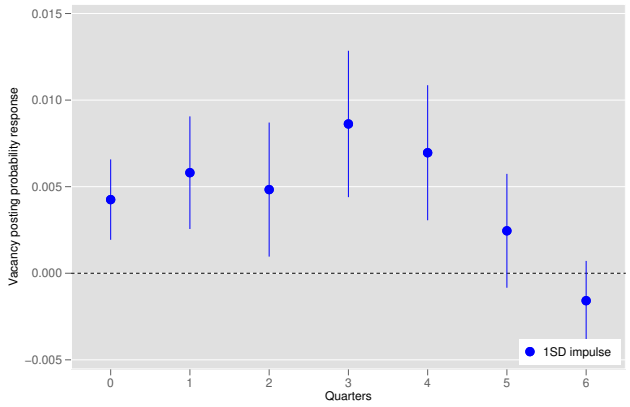
Dependent variable I_{js}^Q	(1)	(2)	(3)	(4)	(5)
Constant β	0.264*** (0.000)	0.268*** (0.000)	0.269*** (0.001)	0.270*** (0.002)	0.268*** (0.005)
Π^1	0.001 (0.001)	0.038*** (0.011)	0.065*** (0.014)		
Π^2			0.048*** (0.016)		
$\Pi^{1,-}$				0.079*** (0.015)	0.084*** (0.021)
$\Pi^{2,-}$					0.061*** (0.022)
$\Pi^{1,+}$				0.071*** (0.015)	0.087*** (0.020)
$\Pi^{2,+}$					0.050** (0.022)
Cumul. resp. to positive 1SD Δy_{js}-shock, $\Omega(\sigma_{\Delta y})$	0.001 (0.001)	0.031*** (0.009)	0.054*** (0.011)	0.059*** (0.012)	0.072*** (0.017)
Cumul. resp. to positive 2SD Δy_{js}-shock, $\Omega(2\sigma_{\Delta y})$	0.001 (0.001)	0.063*** (0.019)	0.093*** (0.023)	0.118*** (0.024)	0.113*** (0.026)
Cumul. resp. to negative 1SD Δy_{js}-shock, $\Omega(-\sigma_{\Delta y})$	−0.001 (0.001)	−0.031*** (0.009)	−0.054*** (0.011)	−0.065*** (0.012)	−0.070*** (0.017)
Cumul. resp. to negative 2SD Δy_{js}-shock, $\Omega(-2\sigma_{\Delta y})$	−0.001 (0.001)	−0.063*** (0.019)	−0.093*** (0.023)	−0.130*** (0.025)	−0.120*** (0.026)
Dynamic effects	No	Yes	Yes	Yes	Yes
Nonlinear effects	No	No	Yes	No	Yes
Asymmetric effects	No	No	No	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Number of firms	17,749	15,509	15,509	15,509	15,509
Number of observations	253,456	208,334	208,334	208,334	208,334

Notes: Standard errors (in parentheses) are clustered at the firm-level. ***, ** and * indicates statistical significance at the 1, 5, and 10 percent level, respectively. All regressions include controls for month and industry effects and their interactions.

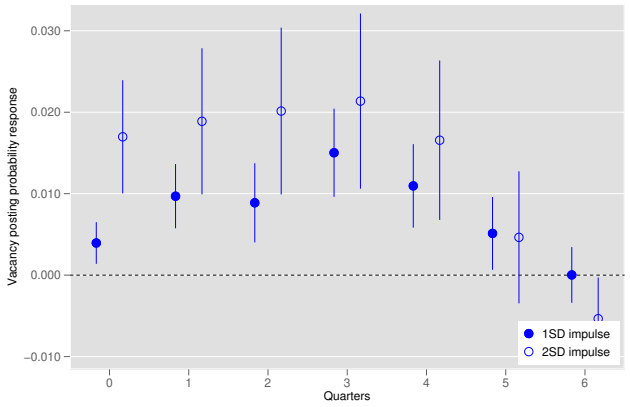
Table D.1 reports the estimates from a set of regressions similar to those in Table 8, with value-added growth on the right-hand side and the vacancy indicator variable on the left-hand side. As with revenues, having the vacancy rate as a dependent variable yields quantitatively and statistically insignificant estimates, so we do not report estimates of that specification. In Table D.1 $\sigma_{\Delta y}$ indicates 1SD in the cross sectional distribution of quarterly value-added growth. The pattern of value added growth's effect on vacancy-posting is similar to that of revenue growth, though with somewhat smaller magnitudes. Indeed, without dynamic, nonlinear and asymmetric

[23] As in the specification presented in the main text, the reported responses to 1SD separation events into employment and non-employment are computed using the empirical cross sectional standard deviations of s^{EE} and s^{EN}, respectively.

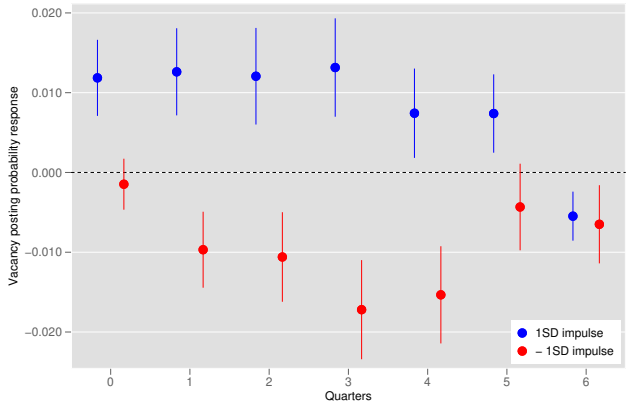
Figure D.1: Vacancies and value added growth



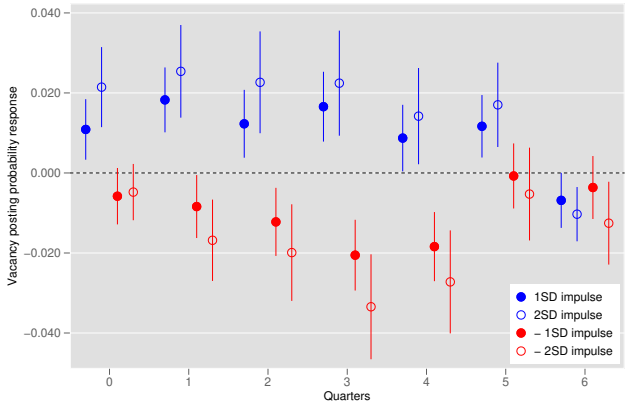
A: Estimates from Table D.1, column (2)



B: Estimates from Table D.1, column (3)



C: Estimates from Table D.1, column (4)



D: Estimates from Table D.1, column (5)

Notes: The plotted regression coefficients refer to regression specifications tabulated in Table D.1. Vertical bars represent 95% confidence intervals with clustering at the firm-level.

effects (column (1)), value added growth have very little impact on vacancy-posting. In column (2), which accounts for dynamic effects, a one-standard deviation growth shock is associated with a 3.1 percentage point change in the probability of vacancy-posting. The magnitude of the vacancy-posting response further increases when we include dynamic, non-linear effects (see column (3)). Column (4) allows dynamic linear effects that are asymmetric for positive and negative shocks, a specification that yields predicted responses largely similar to those obtained with dynamic, non-linear, but symmetric effects in column (3). Finally, the specification reported in column (5) allows for dynamic, nonlinear, and asymmetric effects. A one-standard deviation growth shock is associated with around 7 percentage point change in the probability of vacancy-posting, with no evidence of asymmetric effects. Reflecting a slight concavity in the response, a two-standard devation growth shock is associated with 11-12 percentage point change in the probability of vacancy-posting, again with no evidence of asymmetric effects.

Figure D.1 illustrates the timing of the vacancy-posting response which, as was the case with the effect of revenue growth on vacancy-posting, features statistically significant long lags.