Wages, Workers and Vacancy Durations: Evidence from Linked Data

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- These data allow use to study in more detail than previously possible the determinants of vacancy filling/duration.
- We relate the findings to predictions of search-theoretic models of the labor market.

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  2. characteristics of the worker matched to the vacancy
  3. labor market history of the worker matched to the vacancy
  4. wage data (including the starting wage)

Vacancy data in the U.S. and the related literature

- Job Openings and Labor Turnover Survey (JOLTS) collected by the BLS: a monthly survey of 16,000 establishments in the U.S. since 2000 (see Davis, Faberman and Haltiwanger, 2013)
- The Conference Board's Help Wanted OnLine (HWOL) database: aims at collecting the universe of online job advertisements since 2005 (see Sahin, Song, Topa and Violante, 2014)
- The Employment Opportunities Pilot Projects (EOPP) data from 1982: sample of 1,512 vacancies with information on vacancy duration and starting wages (see Faberman and Menzio, 2017)
- Various recent papers use online job board data (e.g., Marinescu and Wolthoff (2018), Banfi and Villena-Roldan (2017), Hershbein and Kahn (2018), ...)
- Earlier studies: Abraham (1983, 1987), van Ours and Ridder (1991, 1992), ...

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  - Our data is well suited to test for this relationship, because we not only observe starting wages and vacancy duration, but also worker-level characteristics including labor market histories.

Agenda

1. Introduction
2. The Data
3. The Concept of a Vacancy and Vacancy Duration in the Data
4. Replication of Davis, Faberman and Haltiwanger (DFH)
5. Vacancy Durations and Wages in New Jobs
6. Theoretical Framework
7. Conclusion

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The Data

Combine two datasets: Austrian Social Security Database (ASSD) and register data on individual vacancies.

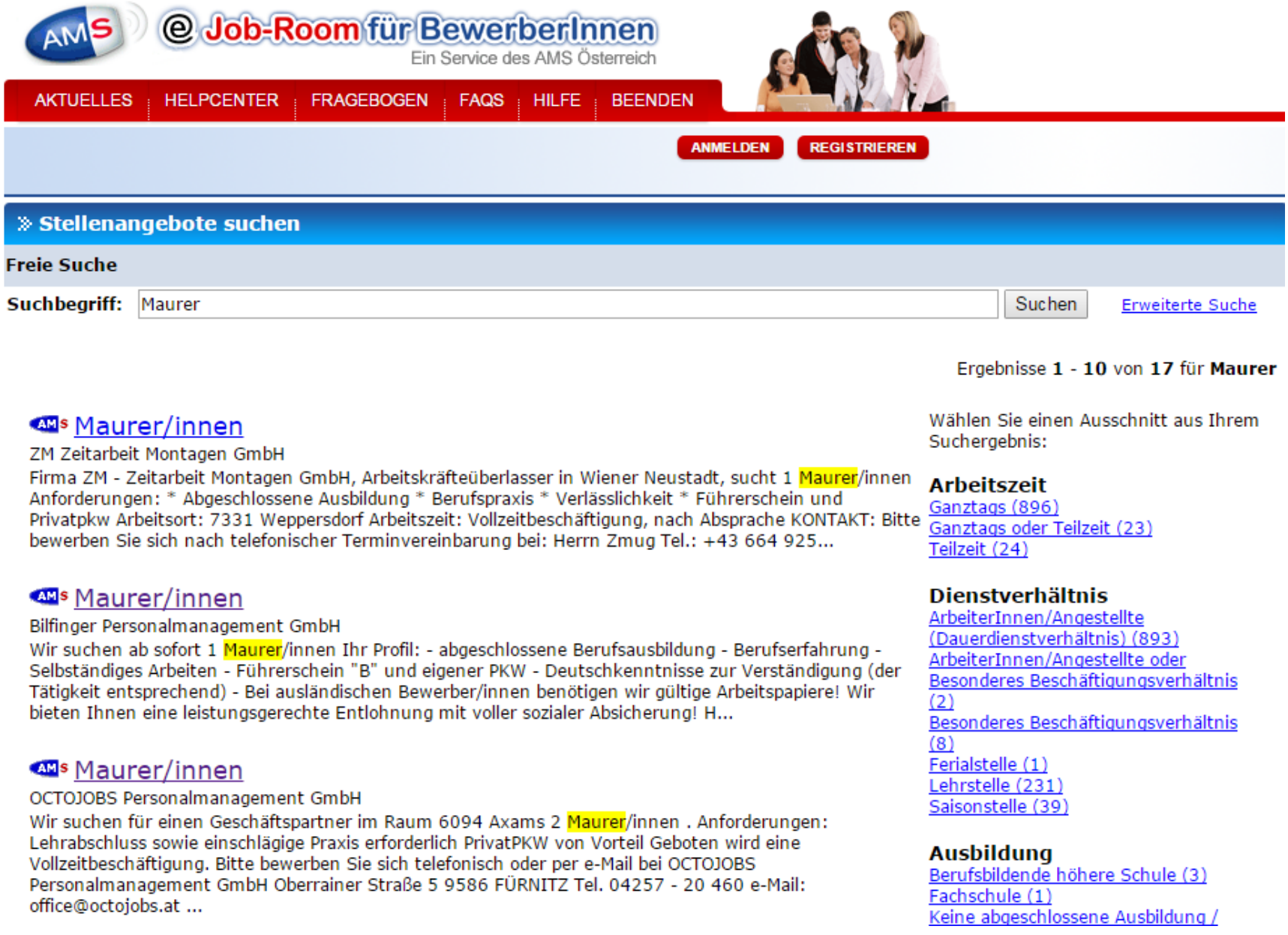
ASSD:

- Covers the universe of private sector workers ($\sim$ 80% of total workforce)
- Records, among other things, each employment and unemployment spell, as well as worker and employer characteristics and wages
- Has been used extensively: E.g., Card, Chetty & Weber (2007), Lalive, Landais and Zweimüller (2015), Alvarez, Borovickova and Shimer (2016).

Vacancy Data

- Information on all vacancies posted in the Austrian Public Employment Service (AMS)
- Records, among other things, the completed duration of a vacancy, job characteristics and requirements
- Covers years 1987 - 2014, but some variables only show up after some time. Most of the analysis is restricted to years 1997-2014

The AMS website



The AMS website, continued

Treffer 1 von 17 nächster Treffer >>

Suchkriterien des Unternehmens

Unternehmen:	ZM Zeitarbeit Montagen GmbH
Dienstverhältnis:	ArbeiterInnen/Angestellte (Dauerdienstverhältnis)
Berufsgruppe:	MaurerIn
Arbeitsort:	7331 Weppersdorf
Arbeitszeit:	Ganztags
Ausbildung:	Lehre

Stellenbeschreibung

Firma ZM - Zeitarbeit Montagen GmbH, Arbeitskräfteüberlasser in Wiener Neustadt, sucht
1 Maurer/in

Anforderungen:
* Abgeschlossene Ausbildung
* Berufspraxis
* Verlässlichkeit
* Führerschein und Privatpkw

Arbeitsort: 7331 Weppersdorf

Arbeitszeit: Vollzeitbeschäftigung, nach Absprache

ANGABEN DES UNTERNEHMENS GEMÄß GLEICHBEHANDLUNGSGESETZ:

Das Mindestentgelt für die Stelle als Maurer/in beträgt 2.150,96 EUR brutto pro Monat auf Basis Vollzeitbeschäftigung. Bereitschaft zur Überzahlung.

Difference to Other Datasets

Main advantages compared to other datasets:

- Can be matched to worker- or firm-level data.
- Flow sampling: All vacancies are recorded irrespective of their length.
- Direct measure of vacancy duration/filling rate: Many previous studies infer vacancy duration/filling rate from repeated stocks of vacancies.
- Administrative data: lower measurement error.

Matching Vacancies to Firms and Workers

- Matching the AMS vacancy data to firms in the ASSD data:
  - The firm identifier in the AMS vacancy data is different from the firm identifier in the ASSD data.
  - The AMS provided a mapping of firm identifies in both data sets, but the mapping exists only in 55% of all cases (in our baseline sample).
  - Different firm/establishment logic at the AMS and at the agency responsible for the ASSD data.
  - ASSD does not include public sector employees/employers, whereas the AMS data include public-sector vacancies.
- Matching the AMS vacancy data to workers in the ASSD data:
  - Vacancy can result in hire through AMS (12%), hire elsewhere (44%), or vacancy could be withdrawn (44%).
  - We know the worker identifier in the first case.

Sample restrictions

Of the 9.6 million vacancies in our data we drop:

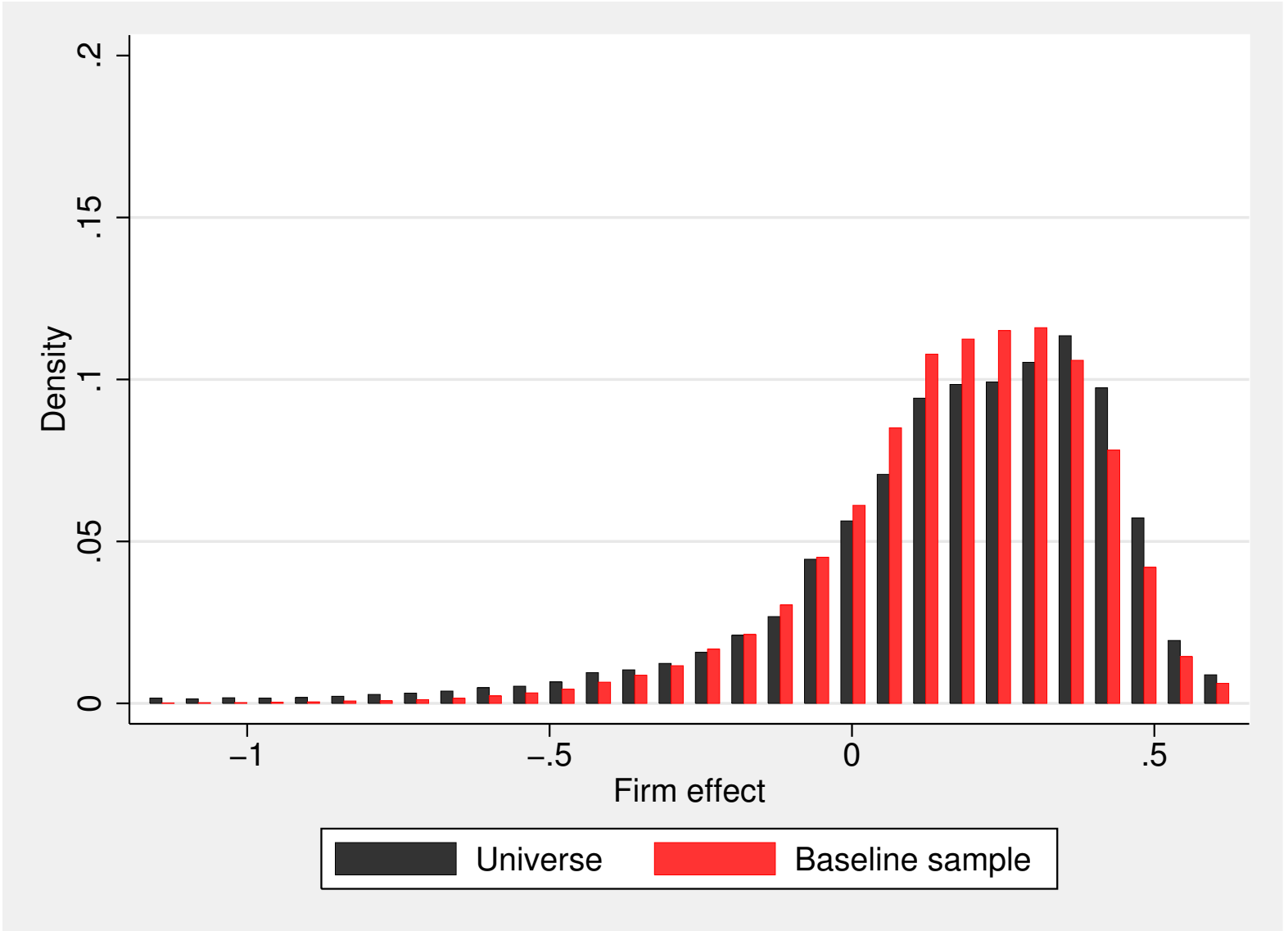
1. vacancies that lapsed (46% of obs)
2. vacancies that were not filled through AMS (72% of obs)
3. vacancies for apprentices and part-time jobs as well as recalls (27% of obs)
4. vacancies where the firm identifier cannot be mapped to an identifier in the ASSD data (45% of obs)

Summary statistics by sample restriction

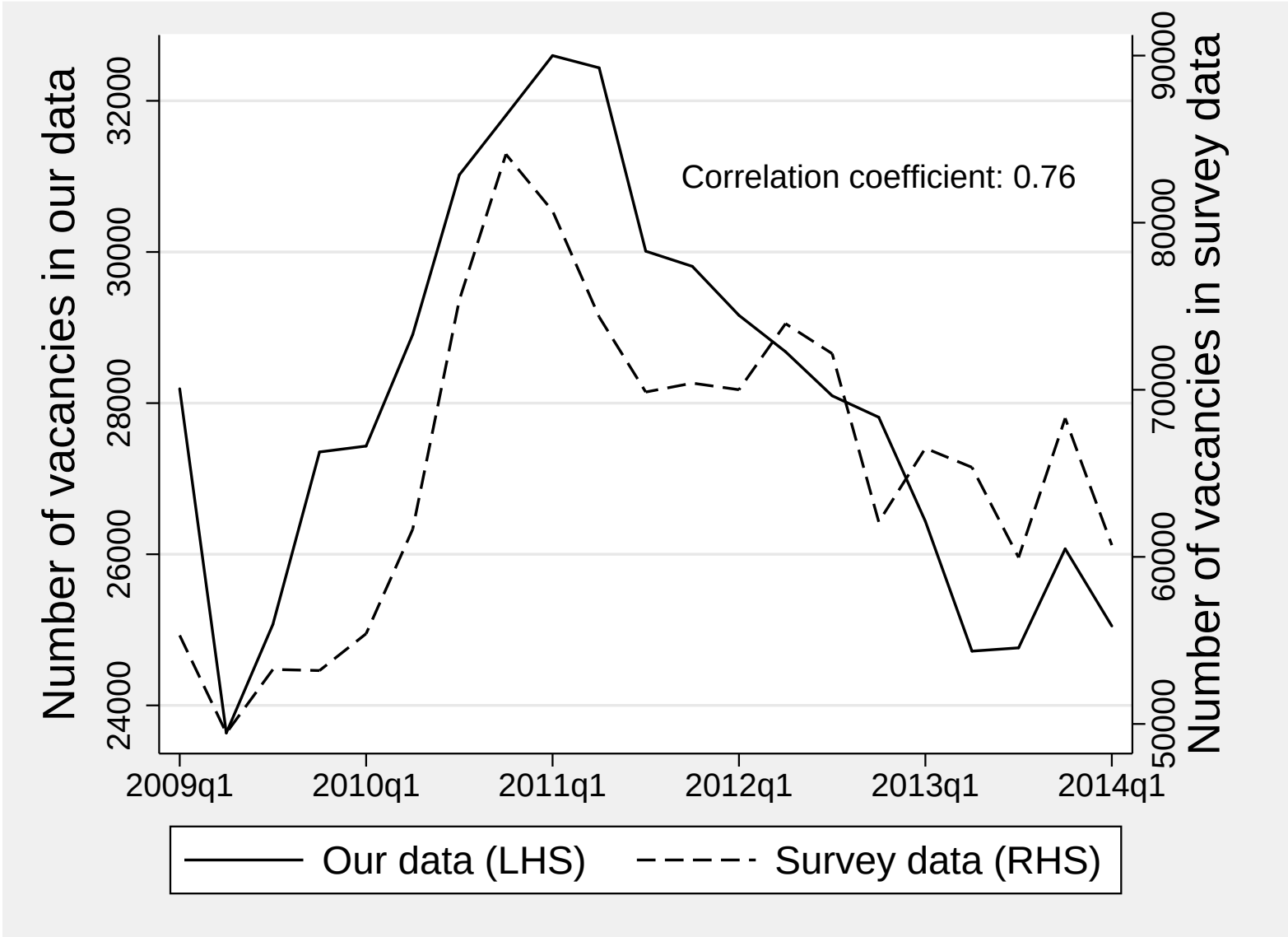
	All	Step 1	Step 2	Step 3	Step 4
At least apprenticeship (%)	48.21	43.97	43.33	46.18	47.65
Manufacturing (%)	34.92	41.09	38.65	37.14	44.15
Permanent contract (%)	79.97	77.85	82.36	81.63	79.90
Hired through system (%)	14.58	26.32	100.00	100.00	100.00
Fixed working time (%)	22.81	23.19	26.23	27.45	28.32
Small firm (%)	45.14	45.14	43.84	41.92	42.58
Vienna (%)	16.23	16.18	10.49	10.45	8.74
Full time (%)	80.55	76.20	79.23	100.00	100.00
Start of observation period	1997	1997	1997	1997	1997
Observations	9.60e+06	5.32e+06	1.11e+06	807482	441769

Table: Summary statistics by subsample

How does our sample compare to the universe of firms in ASSD?



Vacancies in our data vs. in representative survey data



Source: Statistik Austria, Survey of Job Openings.

▸ Additional descriptive statistics

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The concept of a vacancy

The Bureau of Labor Statistic defines a vacancy as:

Positions that are open (not filled) on the last business day of the month. A job is "open" only if it meets all three of the following conditions:

1. *A specific position exists and there is work available for that position*
2. *The job could start within 30 days*
3. *There is active recruiting for workers from outside the establishment location that has the opening*

Measuring Vacancy Duration

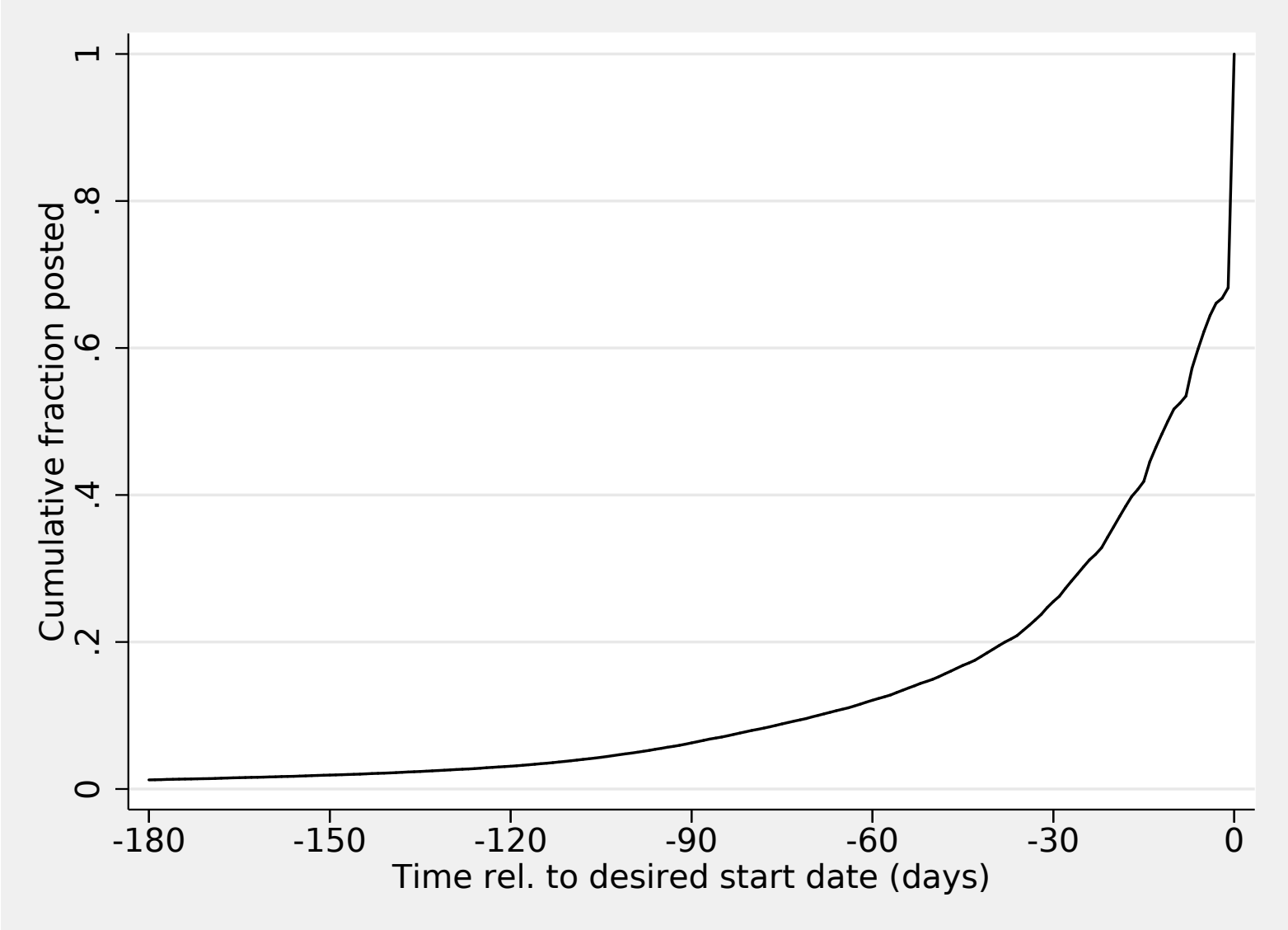
- The AMS data contains a measure of vacancy duration, defined as the difference (in days) between the date of the match and the desired start date of the job.
  - Consistent with the concept of vacancy in JOLTS, except that job must be immediately available instead of in next 30 days.
- We compute two alternative measures of vacancy duration:
  - JOLTS vacancy duration: measured as days since date of posting, but at most 30 days prior to desired start date.
  - Vacancy duration measured as days since date of posting.
- Date of posting is recorded in data only since 2007, but month of posting is known for entire sample. For the period before 2007, we impute day of posting as the 15th of the month.

Summary Statistics of Vacancy Durations

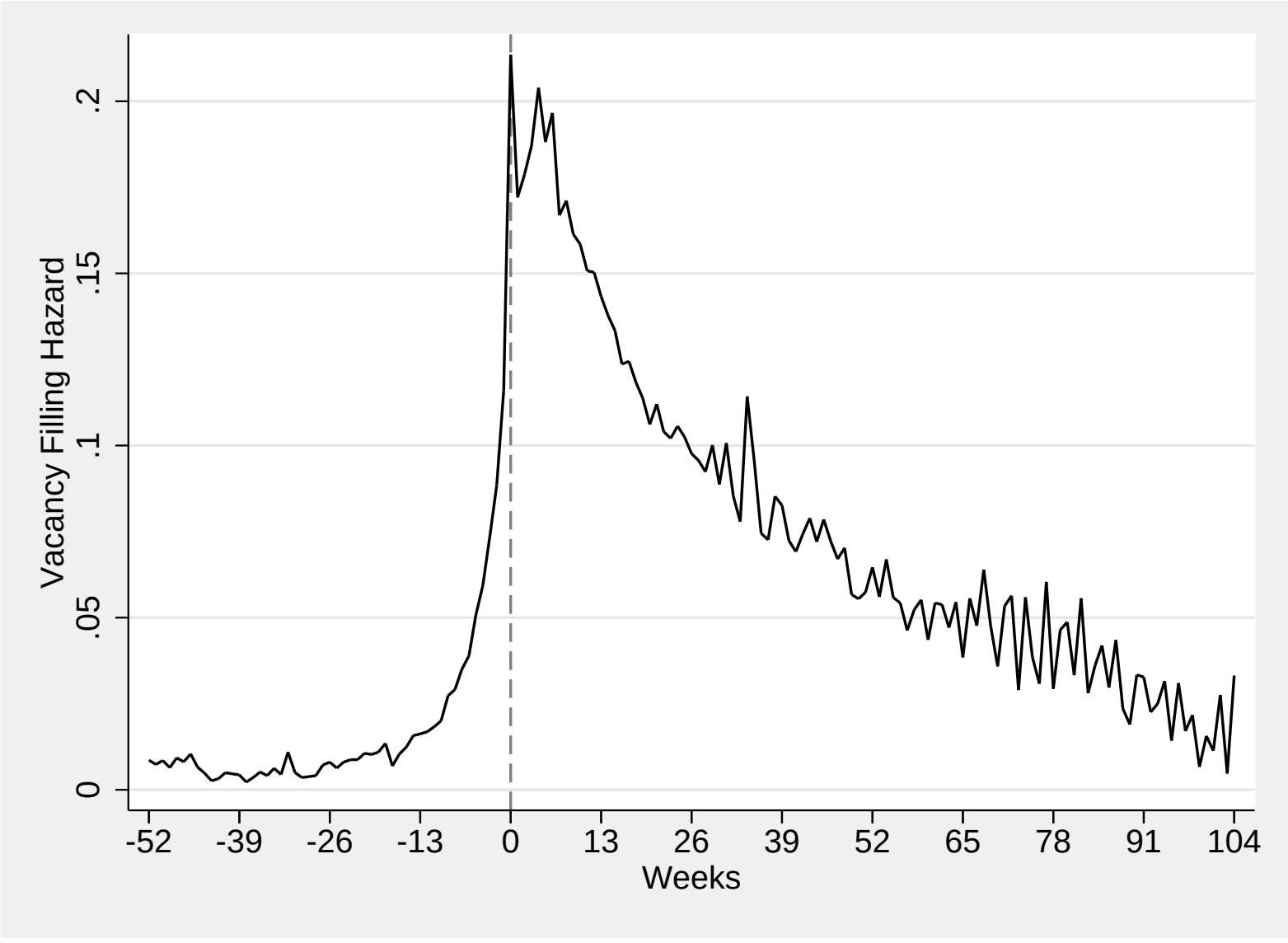
Table: Median and Average Vacancy Duration, in Days

	Median	Mean
AMS Vacancy Duration	14	27.5
JOLTS Vacancy Duration	21	30.4
Vacancy Duration Since Posting	22	38.3

Cumulative fraction posted, by time to desired start date



Vacancy filling rate, before and after the desired start date



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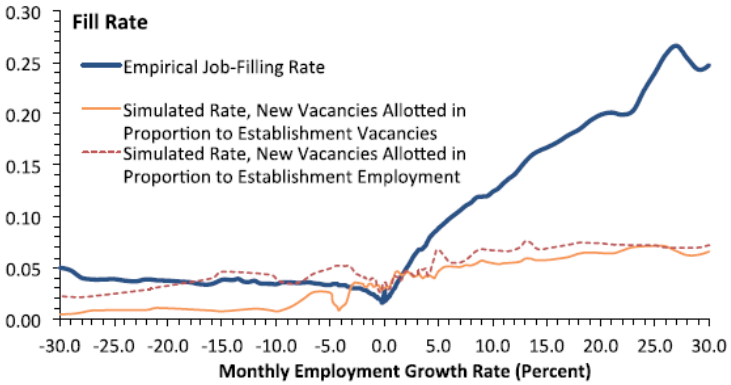
Hiring Intensity and Establishment Growth

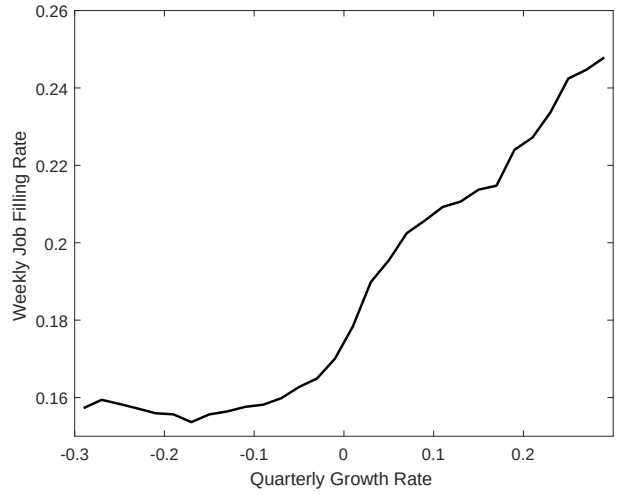
- Davis, Faberman and Haltiwanger (2013) document that growing firms increase their hiring intensity: not only higher vacancy rate, but also more hires per posted vacancy. Results are based on survey data.

- Using administrative data, we can confirm their findings. We can also show that the vacancy filling rate increases for growing firms.

Hiring Intensity and Establishment Growth



(a) Vacancy-filling rate in DFH (Figure 8)



(b) Vacancy-filling rate in Austrian data

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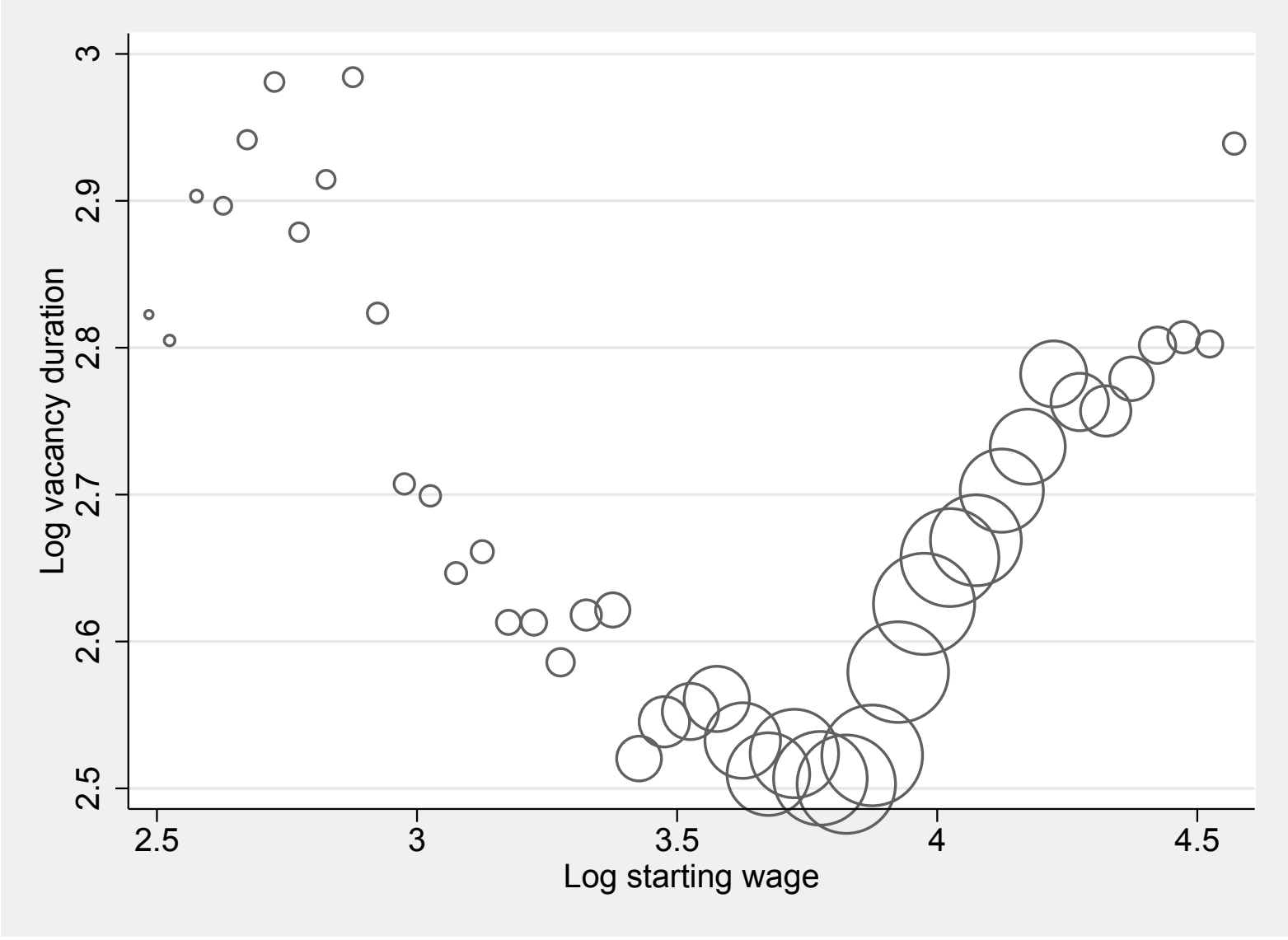
Vacancy Durations and Wages in New Jobs

- A central assumption in many search-theoretic models of the labor market is that firms post wages. In these models, a higher posted wage is associated with a higher job filling rate, because more workers apply to the job (directed search) or more workers accept the job (random search).

- Faberman and Menzio (2017) test relationship between vacancy duration and starting wage with data from 1980-82 from the Employment Opportunity Pilot Project (EOPP).
  - They find a *positive* relationship between vacancy duration and the starting wage.

Vacancy Durations and Wages in New Jobs



Regressions w/ log vacancy duration as dependent variable

	Log AMS vacancy duration
Log starting wage	0.164***
	(0.013)
On-job wage growth	
Log job duration	
Lagged firm growth (yearly)	
Firm age	
Log firm size	
Quarter FE	Yes
Early Posting FE	No
Controls	No
Region FE	No
Industry FE	No
Observations	273960

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log vacancy duration as dependent variable

	Log AMS vacancy duration	
Log starting wage	0.164***	0.040***
	(0.013)	(0.009)
On-job wage growth		
Log job duration		
Lagged firm growth (yearly)		
Firm age		
Log firm size		
Quarter FE	Yes	Yes
Early Posting FE	No	Yes
Controls	No	Yes
Region FE	No	Yes
Industry FE	No	Yes
Observations	273960	244880

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log vacancy duration as dependent variable

	Log AMS vacancy duration		
Log starting wage	0.164***	0.040***	0.059***
	(0.013)	(0.009)	(0.012)
On-job wage growth			-0.021
			(0.036)
Log job duration			0.031***
			(0.003)
Lagged firm growth			-0.054***
(yearly)			(0.007)
Firm age			-0.002***
			(0.000)
Log firm size			0.002
			(0.005)
Quarter FE	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes
Controls	No	Yes	Yes
Region FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Observations	273960	244880	153574

Standard errors clustered at firm level in parentheses

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

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Regressions w/ log vacancy duration as dependent variable

	Log AMS vacancy duration			Log JOLTS duration
Log starting wage	0.164***	0.040***	0.059***	0.050***
	(0.013)	(0.009)	(0.012)	(0.009)
On-job wage growth			-0.021	-0.029
			(0.036)	(0.028)
Log job duration			0.031***	0.030***
			(0.003)	(0.002)
Lagged firm growth			-0.054***	-0.030***
(yearly)			(0.007)	(0.005)
Firm age			-0.002***	-0.001**
			(0.000)	(0.000)
Log firm size			0.002	-0.003
			(0.005)	(0.004)
Quarter FE	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Observations	273960	244880	153574	200317

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log vacancy duration as dependent variable

	Log AMS vacancy duration			Log JOLTS duration	Log duration since posting
Log starting wage	0.164***	0.040***	0.059***	0.050***	0.052***
	(0.013)	(0.009)	(0.012)	(0.009)	(0.009)
On-job wage growth			-0.021	-0.029	-0.031
			(0.036)	(0.028)	(0.027)
Log job duration			0.031***	0.030***	0.036***
			(0.003)	(0.002)	(0.002)
Lagged firm growth			-0.054***	-0.030***	-0.024***
(yearly)			(0.007)	(0.005)	(0.005)
Firm age			-0.002***	-0.001**	-0.001**
			(0.000)	(0.000)	(0.000)
Log firm size			0.002	-0.003	-0.006*
			(0.005)	(0.004)	(0.004)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	No	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Observations	273960	244880	153574	200317	202909

Standard errors clustered at firm level in parentheses

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

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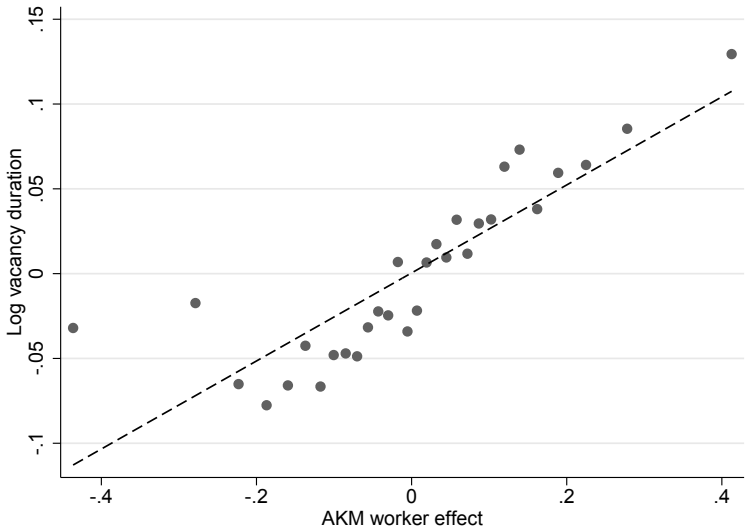
High-Wage Workers and High-Wage Firms

- Key issue: Unobserved worker-level heterogeneity.
- To approximate "types", we decompose wages into worker and firm effects as in Abowd, Kramarz and Margolis (1999),

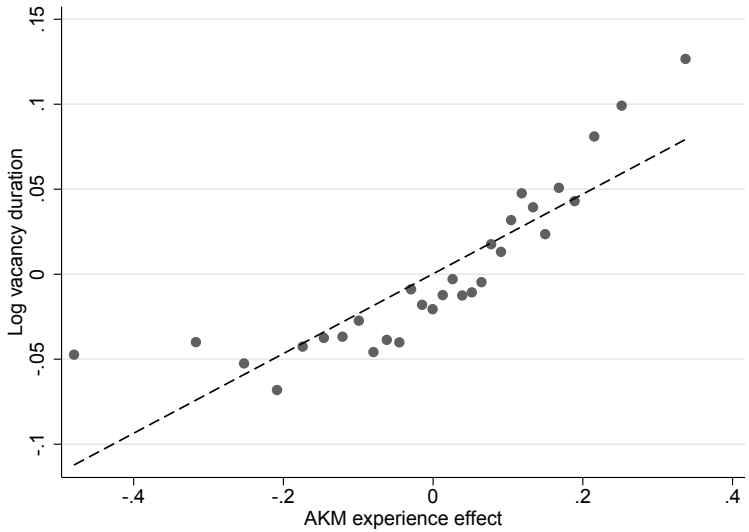
$$\log w_{it} = \theta_i + \psi_{\mathbf{J}(i,t)} + x'_{it}\beta + \varepsilon_{it},$$

  where θ_i and $\psi_{\mathbf{J}(i,t)}$ identify the fixed worker and firm effects and x_{it} are variable worker characteristics (experience).
- We estimate AKM with the universe of private sector workers (1985-2014).
- We relate the AKM effects to vacancy duration:
  - How long do different firms wait for identical workers?
  - How long do identical firms wait for different types of workers?

Vacancy Durations and Worker Effects



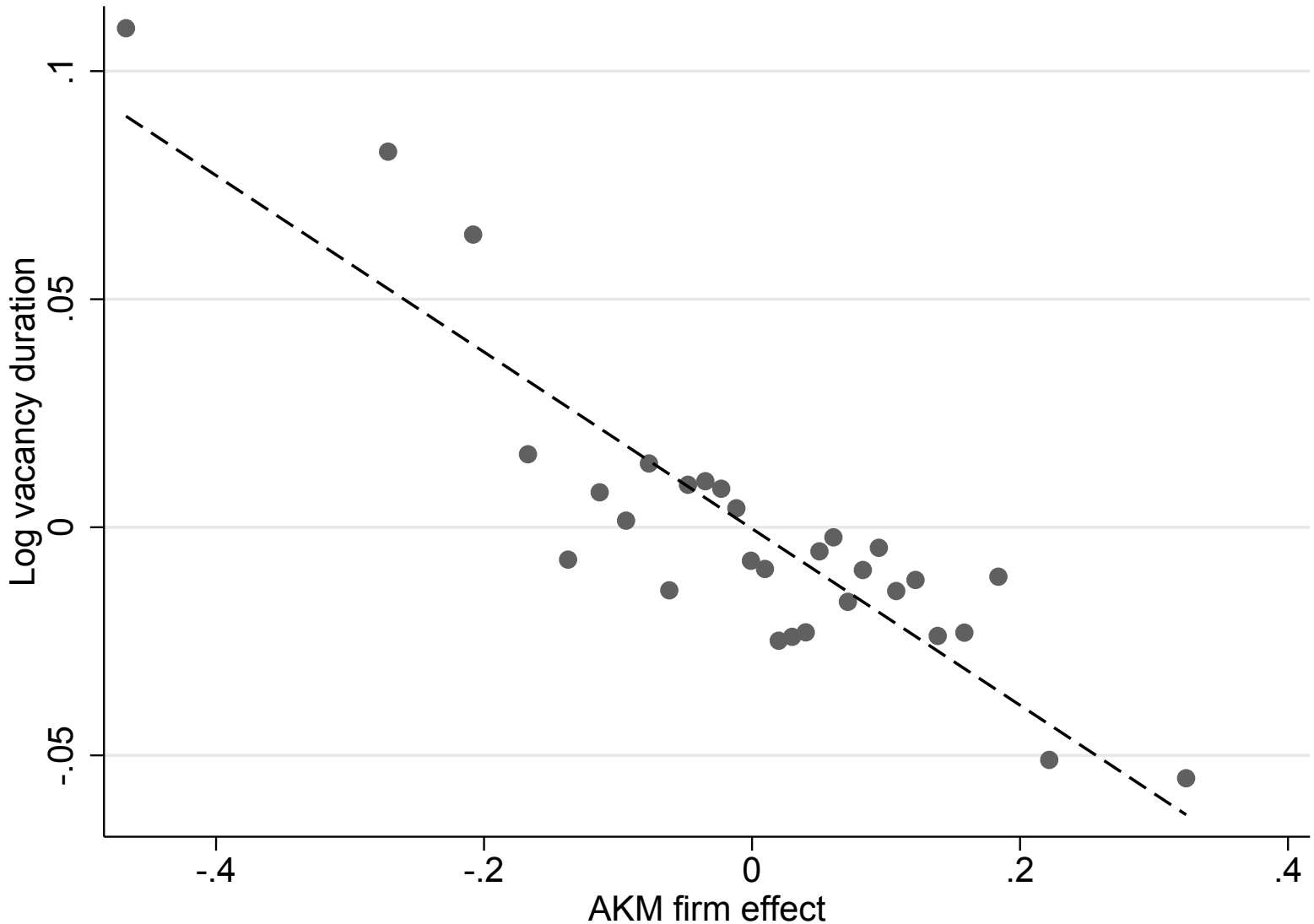
(a) AKM worker effect and log vacancy duration



(b) AKM worker experience effect and log vacancy duration

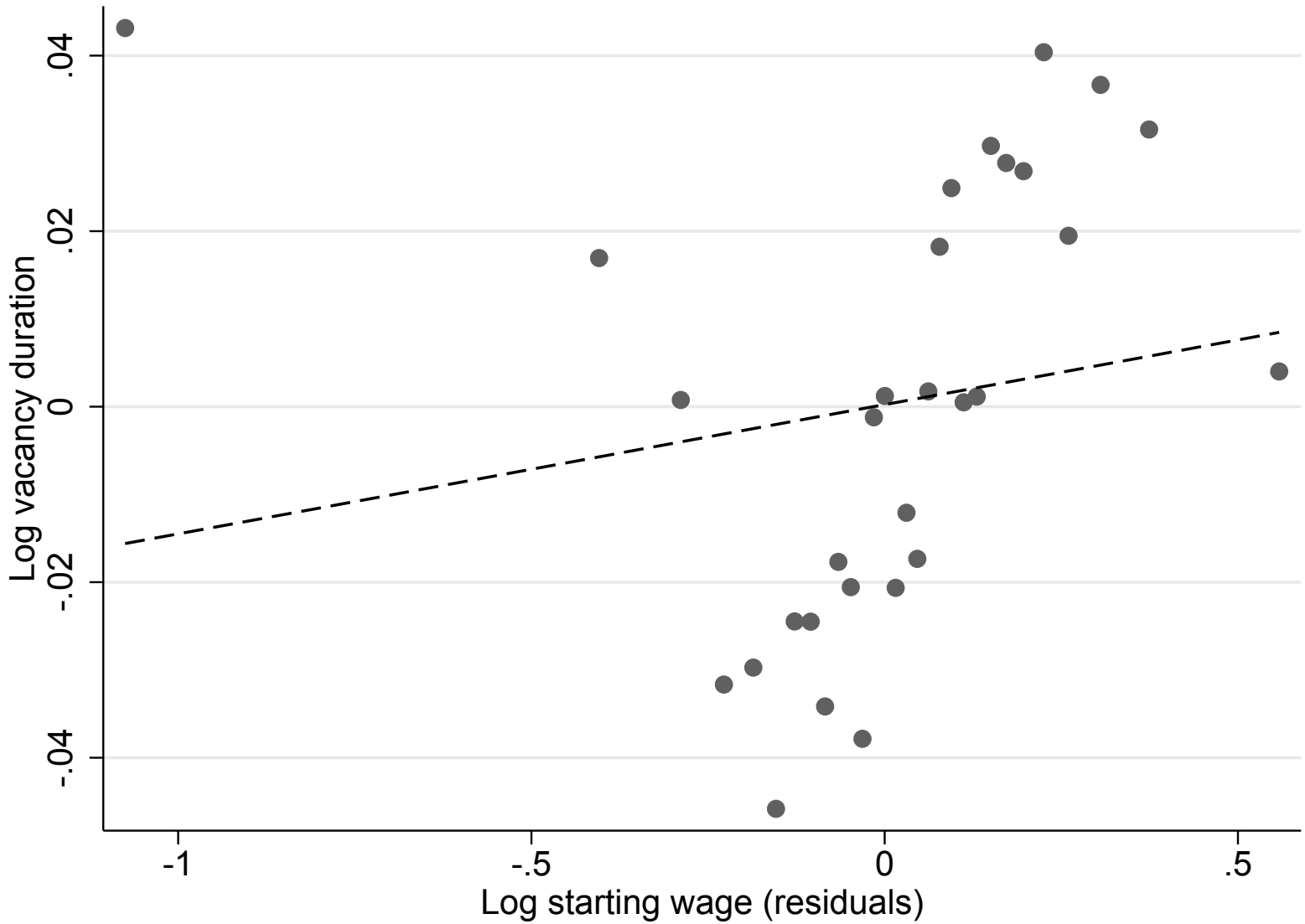
Note: The plots show partial correlations (added variable plots), controlling for AKM effects and time fixed effects.

Vacancy Durations and AKM Firm Effects



Note: The plot shows a partial correlation (added variable plot), controlling for AKM effects and time fixed effects.

Vacancy Durations and AKM Residual



Note: The plot shows a partial correlation (added variable plot), controlling for AKM effects and time fixed effects.

Regressions w/ log AMS vacancy duration as dep. variable

Log AMS vac. duration	(1)
Log starting wage	0.040***
	(0.009)
AKM person effect	
AKM worker exp. effect	
AKM establishment effect	
AKM residual	
Quarter FE	Yes
Early Posting FE	Yes
Controls	Yes
Region FE	Yes
Industry FE	Yes
Further Controls	No
Firm FE	No
Worker FE	No
Observations	244880

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log AMS vacancy duration as dep. variable

Log AMS vac. duration	(1)	(2)
Log starting wage	0.040***	
	(0.009)	
AKM person effect		0.255***
		(0.016)
AKM worker exp. effect		0.226***
		(0.016)
AKM establishment effect		-0.157***
		(0.025)
AKM residual		0.022**
		(0.009)
Quarter FE	Yes	Yes
Early Posting FE	Yes	Yes
Controls	Yes	Yes
Region FE	Yes	Yes
Industry FE	Yes	Yes
Further Controls	No	No
Firm FE	No	No
Worker FE	No	No
Observations	244880	244880

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log AMS vacancy duration as dep. variable

Log AMS vac. duration	(1)	(2)	(3)
Log starting wage	0.040***		
	(0.009)		
AKM person effect		0.255***	0.250***
		(0.016)	(0.020)
AKM worker exp. effect		0.226***	0.205***
		(0.016)	(0.020)
AKM establishment effect		-0.157***	-0.184***
		(0.025)	(0.034)
AKM residual		0.022**	0.049***
		(0.009)	(0.012)
Quarter FE	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Further Controls	No	No	Yes
Firm FE	No	No	No
Worker FE	No	No	No
Observations	244880	244880	153574

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log AMS vacancy duration as dep. variable

Log AMS vac. duration	(1)	(2)	(3)	(4)
Log starting wage	0.040***			
	(0.009)			
AKM person effect		0.255***	0.250***	0.212***
		(0.016)	(0.020)	(0.018)
AKM worker exp. effect		0.226***	0.205***	0.152***
		(0.016)	(0.020)	(0.018)
AKM establishment effect		-0.157***	-0.184***	
		(0.025)	(0.034)	
AKM residual		0.022**	0.049***	0.046***
		(0.009)	(0.012)	(0.009)
Quarter FE	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No
Industry FE	Yes	Yes	Yes	No
Further Controls	No	No	Yes	No
Firm FE	No	No	No	Yes
Worker FE	No	No	No	No
Observations	244880	244880	153574	233090

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log AMS vacancy duration as dep. variable

Log AMS vac. duration	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.040***				
	(0.009)				
AKM person effect		0.255***	0.250***	0.212***	
		(0.016)	(0.020)	(0.018)	
AKM worker exp. effect		0.226***	0.205***	0.152***	0.130
		(0.016)	(0.020)	(0.018)	(0.099)
AKM establishment effect		-0.157***	-0.184***		-0.246***
		(0.025)	(0.034)		(0.043)
AKM residual		0.022**	0.049***	0.046***	-0.004
		(0.009)	(0.012)	(0.009)	(0.021)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No
Industry FE	Yes	Yes	Yes	No	No
Further Controls	No	No	Yes	No	No
Firm FE	No	No	No	Yes	No
Worker FE	No	No	No	No	Yes
Observations	244880	244880	153574	233090	109516

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log JOLTS vacancy duration

Log JOLTS vac. duration	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.036***				
	(0.007)				
AKM person effect		0.208***	0.199***	0.173***	
		(0.011)	(0.0142)	(0.013)	
AKM worker exp. effect		0.172***	0.154***	0.121***	0.074
		(0.012)	(0.014)	(0.013)	(0.061)
AKM establishment effect		-0.096***	-0.116***		-0.210***
		(0.019)	(0.025)		(0.028)
AKM residual		0.020***	0.039***	0.0372***	-0.014
		(0.007)	(0.009)	(0.008)	(0.014)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No
Industry FE	Yes	Yes	Yes	No	No
Further Controls	No	No	Yes	No	No
Firm FE	No	No	No	Yes	No
Worker FE	No	No	No	No	Yes
Observations	317692	317692	200317	301620	142770

Standard errors clustered at firm level in parentheses

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

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

Regressions w/ log duration (since posting)

Log vacancy duration	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.038***				
	(0.007)				
AKM person effect		0.214***	0.206***	0.177***	
		(0.011)	(0.014)	(0.013)	
AKM worker exp. effect		0.168***	0.146***	0.121***	0.059
		(0.011)	(0.014)	(0.013)	(0.060)
AKM establishment effect		-0.102***	-0.111***		-0.208***
		(0.019)	(0.025)		(0.028)
AKM residual		0.022***	0.042***	0.042***	-0.010
		(0.007)	(0.009)	(0.008)	(0.014)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Early Posting FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No
Industry FE	Yes	Yes	Yes	No	No
Further Controls	No	No	Yes	No	No
Firm FE	No	No	No	Yes	No
Worker FE	No	No	No	No	Yes
Observations	321569	321569	202909	305268	144341

Standard errors clustered at firm level in parentheses

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

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Agenda

1. Introduction
2. The Data
3. The Concept of a Vacancy and Vacancy Duration in the Data
4. Replication of Davis, Faberman and Haltiwanger (DFH)
5. Vacancy Durations and Wages in New Jobs
6. Theoretical Framework
7. Conclusion

Theoretical Framework

- Key findings:

  (1.) Starting wages and vacancy durations are positively correlated
  (2.) Vacancies with long durations are filled with high-wage workers
  (3.) High-wage firms fill vacancies more quickly

- In addition, we find that growing firms fill their vacancies faster (as DFH).

- To understand these findings, we extend the model of Kaas and Kircher (2015) to ex-ante worker heterogeneity.
  - Their model is a natural starting point because it (1) characterizes directed search in the context of firm heterogeneity and (2) was calibrated explicitly to match the facts documented in DFH.
  - Note that our finding (3) is also consistent with a model of random search (Burdett and Mortensen, 1998), but only if unemployed workers differ in reservation wage values.

Kaas and Kircher (2015) with Worker Heterogeneity

- There are N type of workers; there is a continuum of each type i.

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- Firms post fixed-wage long-term contracts and unemployed workers direct search toward most attractive offer.
- Job seekers and vacancies are matched according to matching function $m_i(\lambda_i) = (1 + k\lambda_i^{-r})^{-\frac{1}{r}}$. If contract attracts λ_i workers of type i per vacancy, then vacancy filling rate is m_i.

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- In equilibrium, unemployed workers of type i are indifferent between searching in different markets.
- There are exog. and endog. firm death ($\delta(x)$), and exog. and endog. layoffs for each type of worker i.

Calibration

- There are 5 types of firms. We assume the following shape of the production function and the vacancy cost function:

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

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

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- We calibrate the model for two types of workers, where we set c_i such that the job filling rate is 0.18 for the low-type and 0.16 for the high-type worker.
- In our baseline model with worker heterogeneity, we calibrate the parameters $a_i(x)$ to match the cross-sectional dispersion in AKM worker effects.

Calibrated Parameter Values in Kaas and Kircher (2015)

TABLE 1—PARAMETER CHOICES IN THE BENCHMARK CALIBRATION

Parameter	Value	Description
β	0.999	Annual interest rate 5 percent
k	6.276	Matching function scale parameter
r	1.057	Matching function elasticity parameter
α	0.7	Production function elasticity
c	8.317	Recruitment cost scale parameter
γ	2	Recruitment cost elasticity parameter
$\left(x_0^i\right)$	(0.366, 0.736, 1.166, 2.031, 4.138)	Employment shares (5 size classes)
$\left(\sigma^i\right)$	(98.82, 1.0, 0.153, 0.025, 0.002)%	Firm shares (5 size classes)
$\left(\delta^i\right)$	(1.71, 0.27, 0.16, 0.088, 0.016)‰	Exit rates
$\overline{x}$	0.312	Transitory productivity range
π	0.027	Adjustment probability
b	0.1	Unemployment income ($b/w \approx 0.7$)
K	329.6	Entry cost
s_0	0.48%	Quit rate

Source: Kaas and Kircher (AER, 2015).

▸ Calibration of c and a_i

Simulation Results, Model w/ Worker Heterogeneity

		Model Extension w/ Worker Heterogeneity		
	Data	$\gamma = 2$	$\gamma = 1.1$	$\gamma = 0.1$
Corr. of Worker and Firm Types	—	0.00	0.00	0.01
Elast. of Vacancy Duration to				

▸ Additional Results ▸ Results for Model w/ Positive Assortative Matching

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Elast. of Vacancy Duration to				
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... AKM Worker Effect	0.26	0.28	0.28	0.28

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... AKM Firm Effect	-0.16	-15.2	-11.0	-1.3
... AKM Residual	0.02	-23.3	-19.1	-10.2

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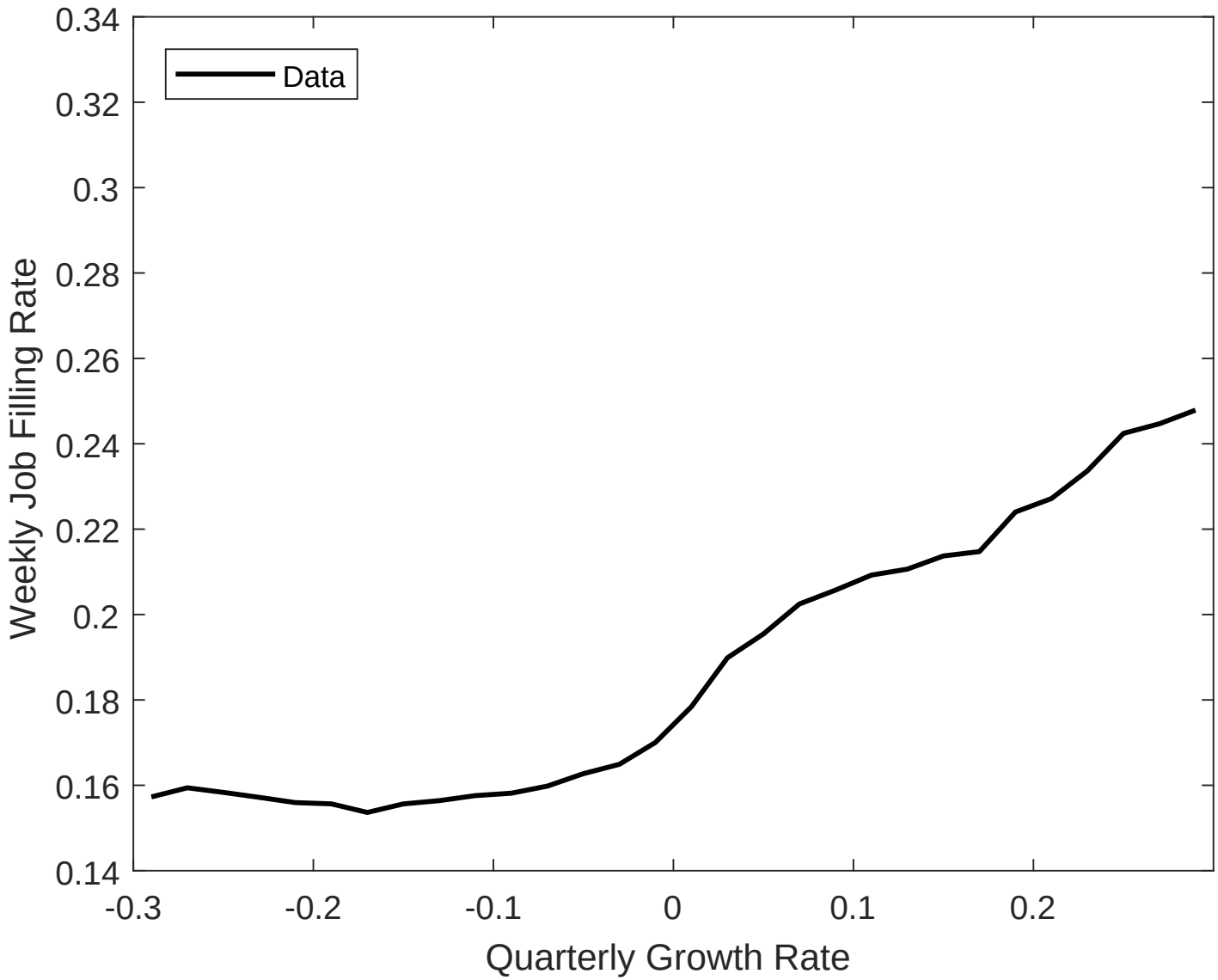
The Importance of the Vacancy Cost Elasticity γ



▸ Same Figures in Model w/ Worker Heterogeneity

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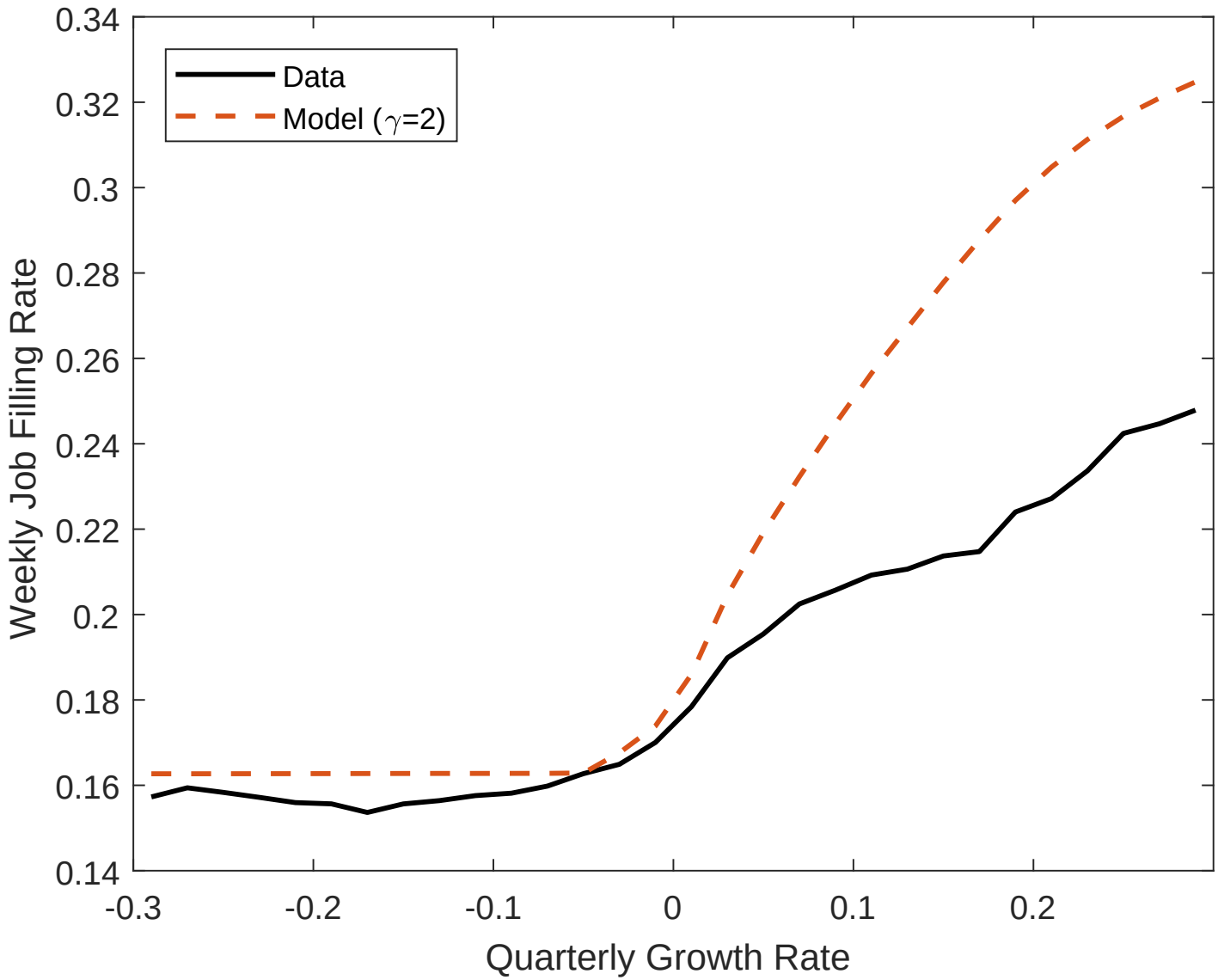

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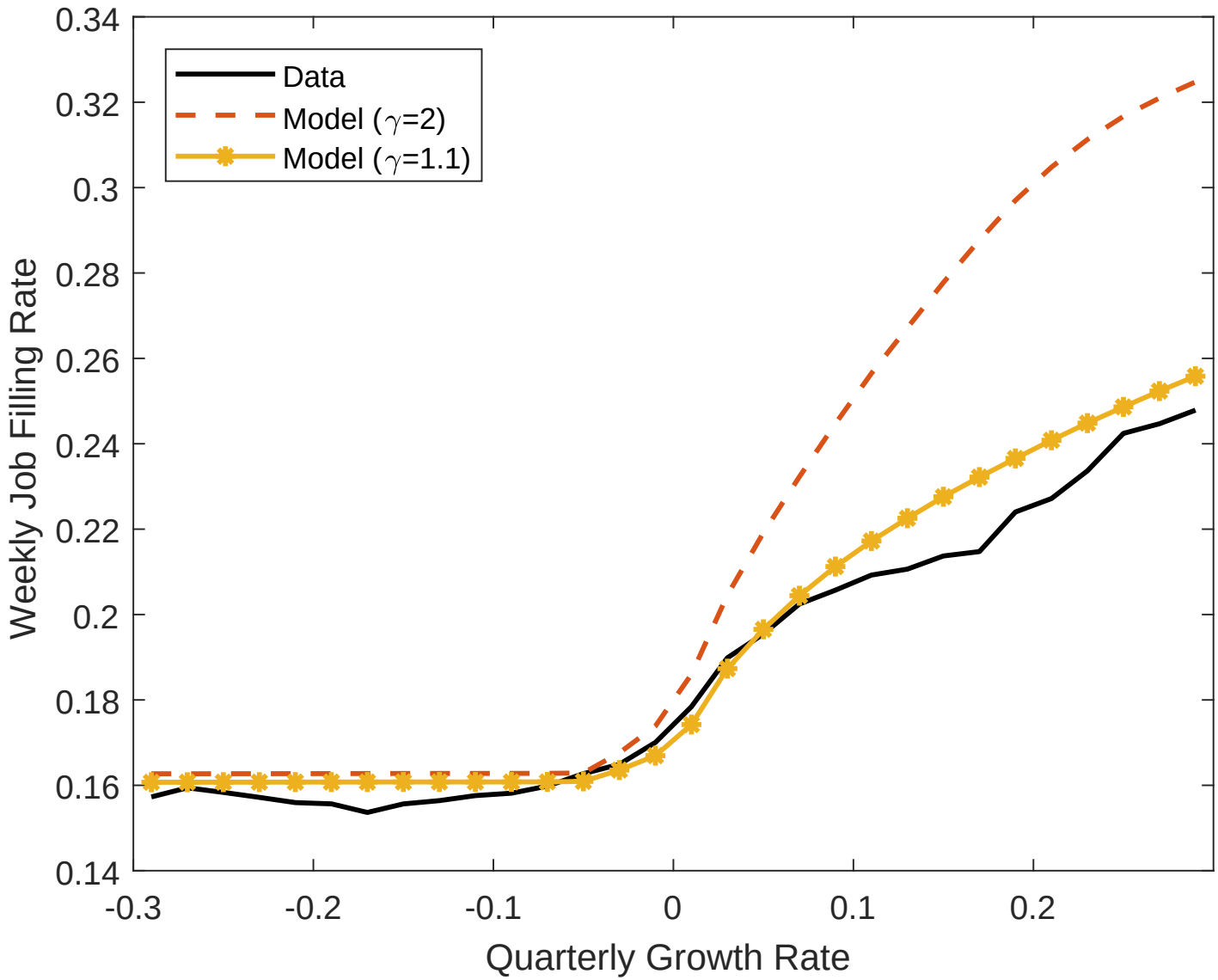

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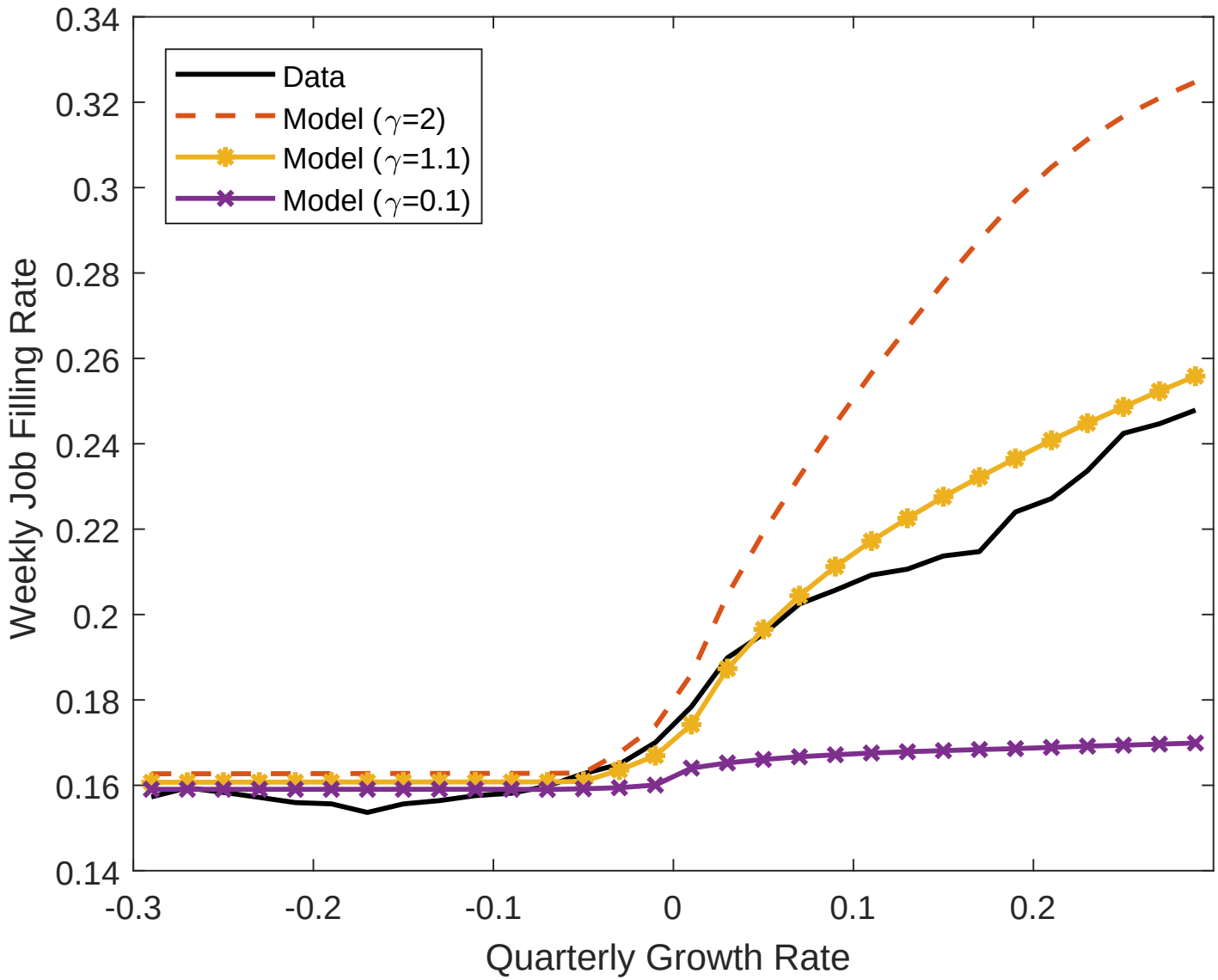

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Do firms not use posted wages as a recruiting tool?

A tentative conclusion: firms rely mostly on other recruiting channels for vacancy filling. This rests on important assumptions:

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3. With non-wage amenities, the starting wage is less informative about the value of the job?
   - Results in progress suggest that dispersion in non-wage amenities (as in Hall and Mueller, 2018) can reconcile results quantitatively.

Conclusion

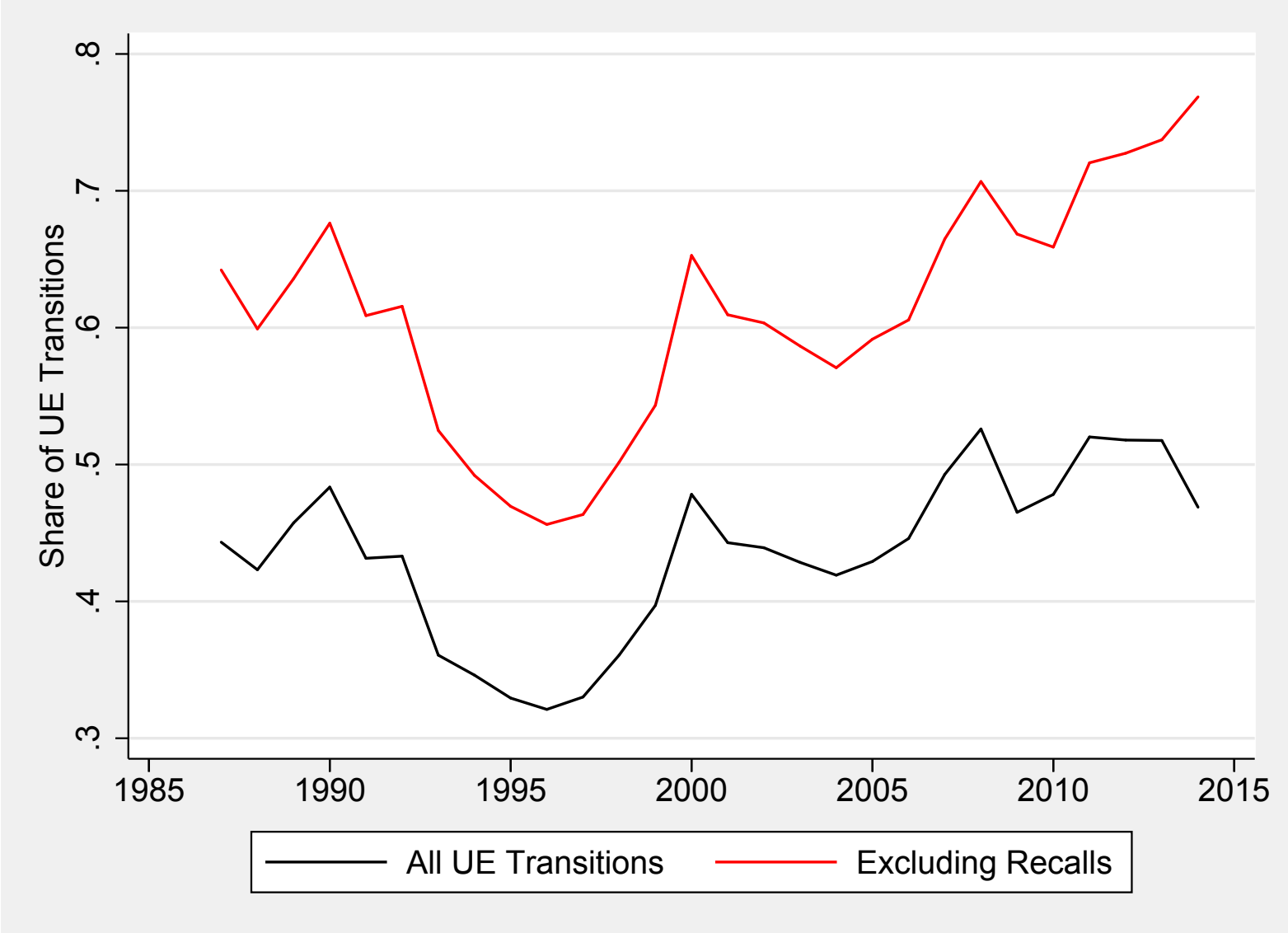
- We analyze a novel data source on vacancy posting and filling
- Three new findings stand out:

  (1.) Starting wages and vacancy durations are positively correlated
  (2.) Vacancies with long durations are filled with high-wage workers
  (3.) High-wage firms fill vacancies more quickly
- In addition, as DFH, we find that growing firms fill their vacancies faster.
- We extend the model of Kaas and Kircher (2015) to the case of ex-ante worker heterogeneity:
  - Qualitatively, the model matches our three findings
  - In the model, there is a tension between matching (1) the DFH-type evidence and (2) the response of vacancy filling to firm-level wages
  - With non-wage amenities, tension may resolve

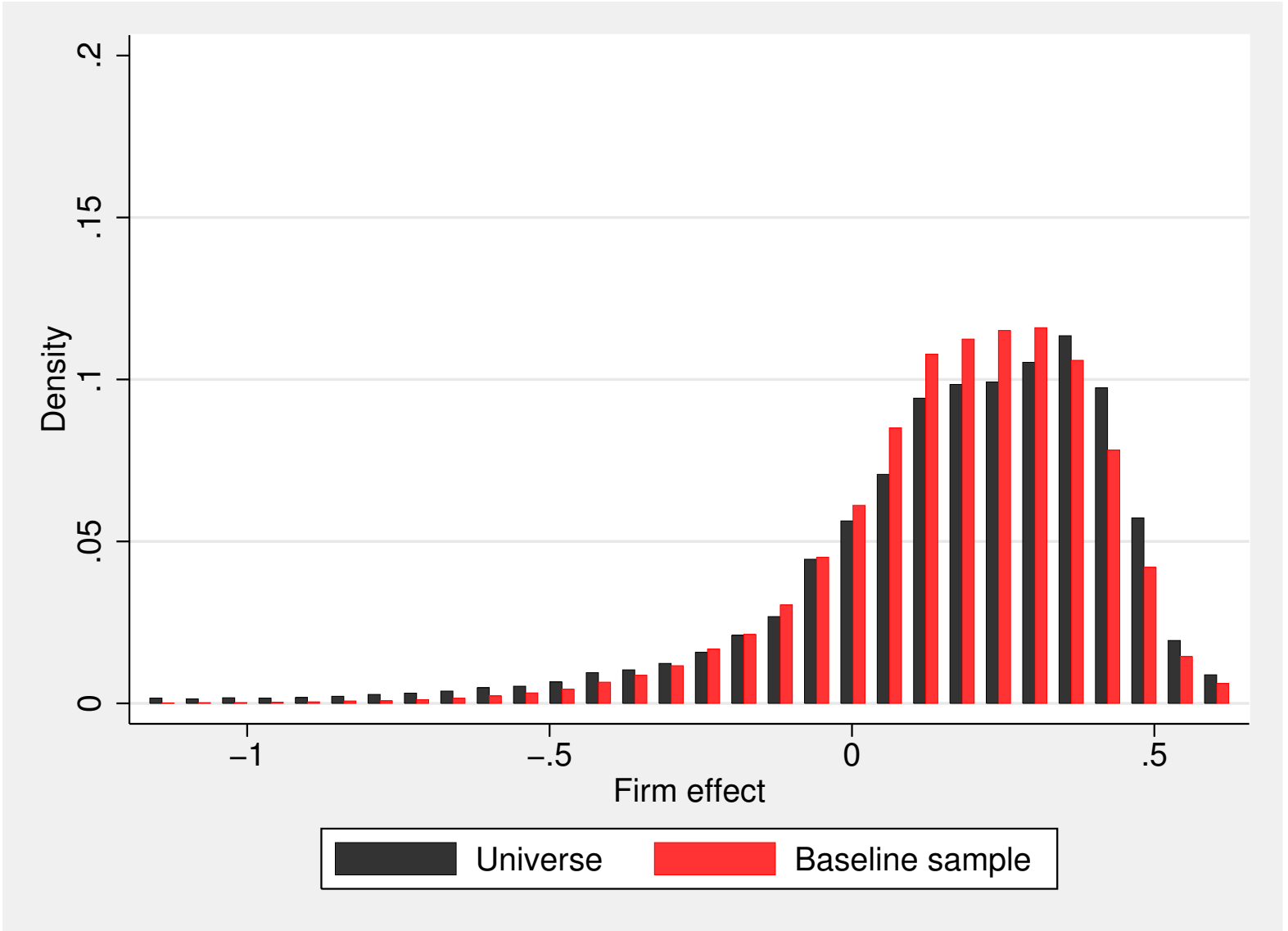
Other findings

- We find that the long-term unemployed workers are more likely to match to new vacancies than existing vacancies.
  - This finding supports stock-flow theories of the labor-market (Coles and Smith, 1998). ▸ Analysis
- The vacancies created during recessions are different from those created during booms and are filled by different workers (consistent with opportunistic "upskilling", see Modestino, Shoag & Ballance, 2015, and Hershbein and Kahn, 2016). ▸ Analysis

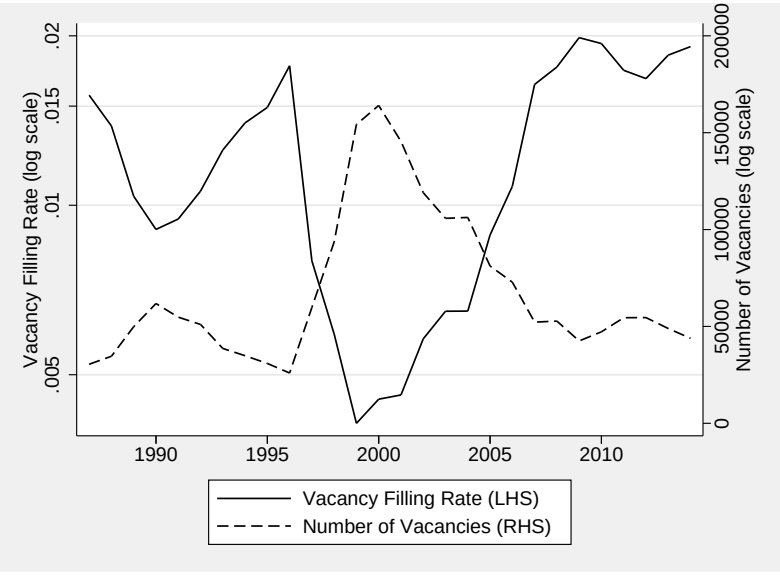
Filled vacancies in AMS data / UE transitions in ASSD



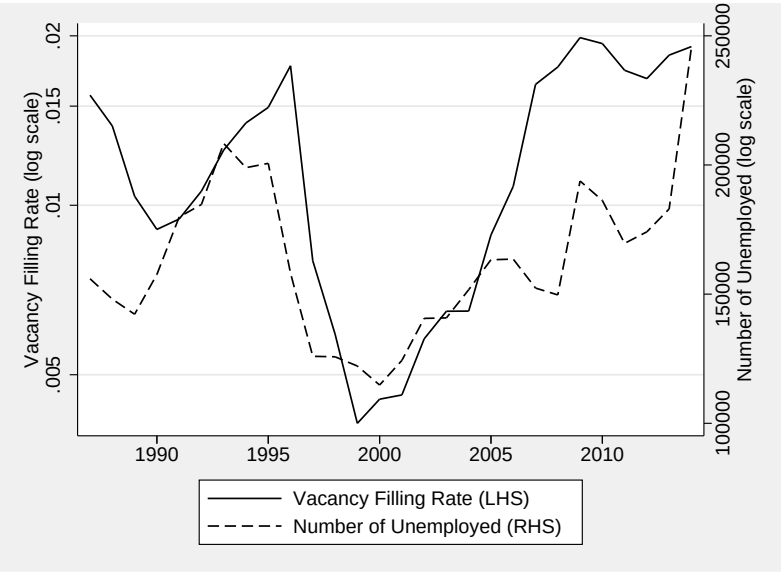
How does our sample compare to the universe of firms in ASSD?



Vacancy Filling Rate and Labor Market Aggregates

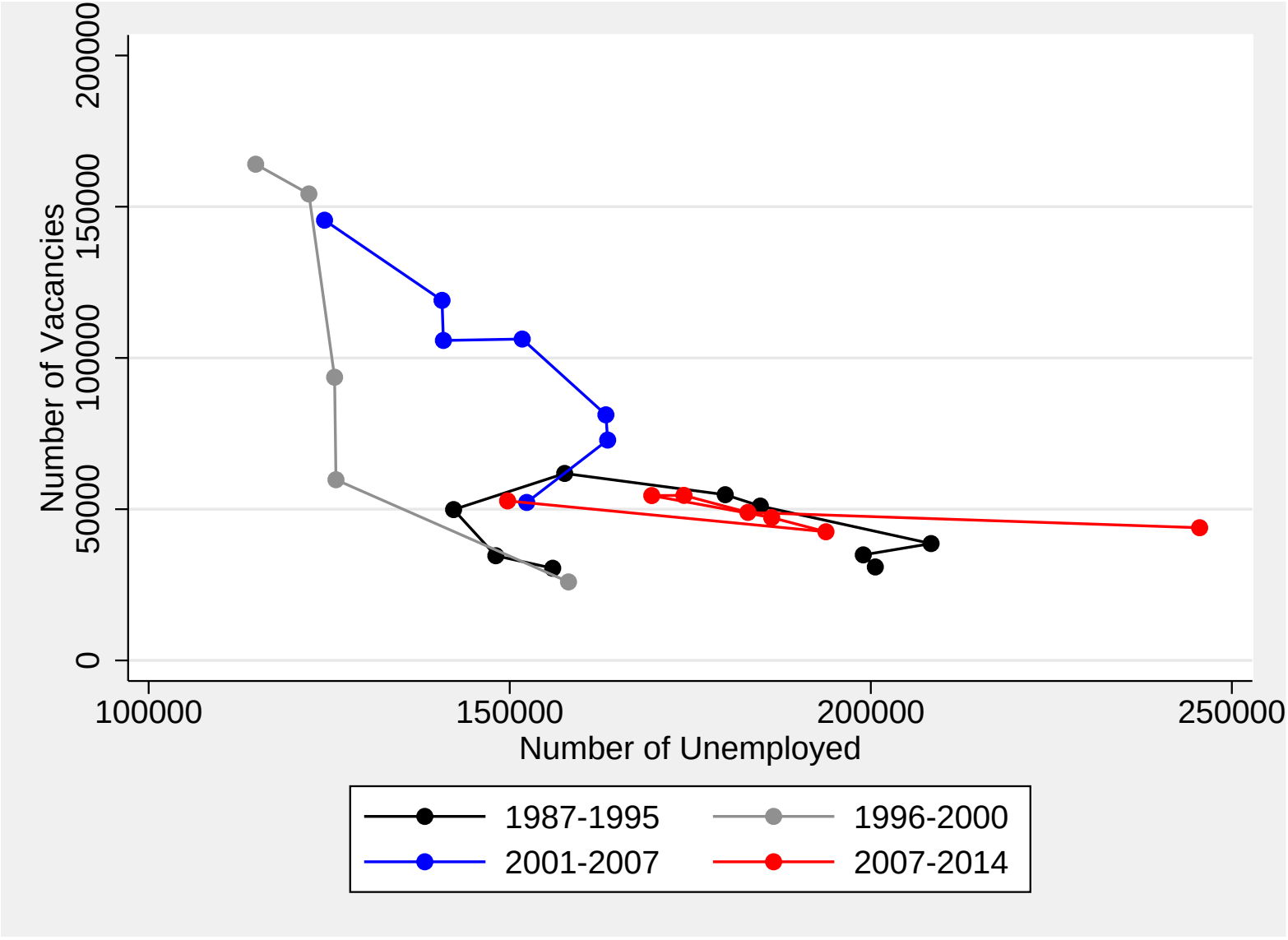


(a) Vacancy Filling Rate and Vacancies



(b) Vacancy Filling Rate and Unemployed

Beveridge Curve



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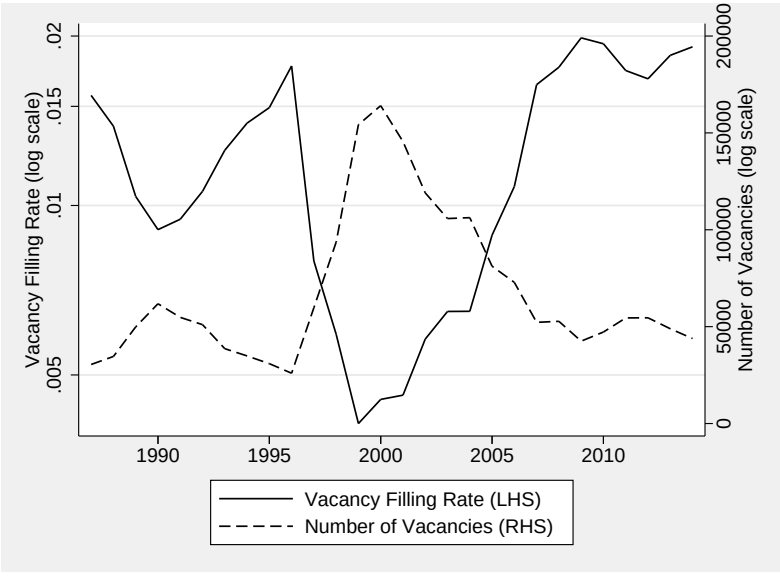

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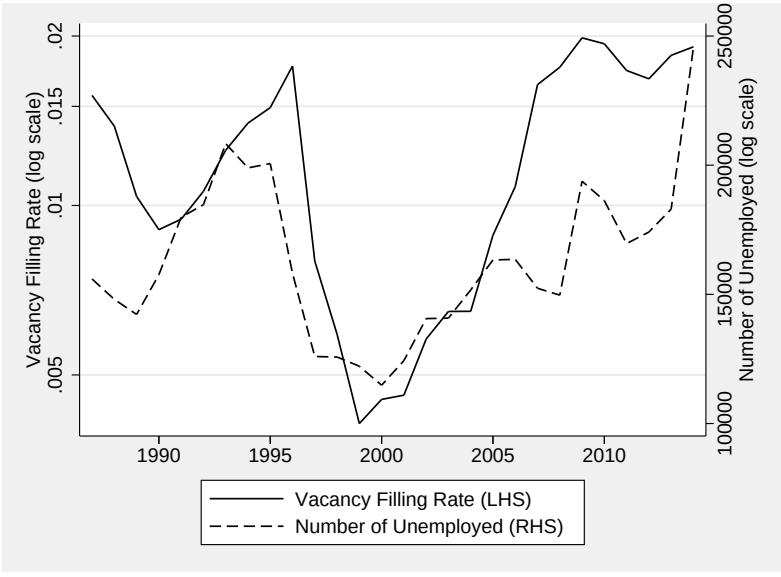


(b) Vacancy Filling Rate and Unemployed

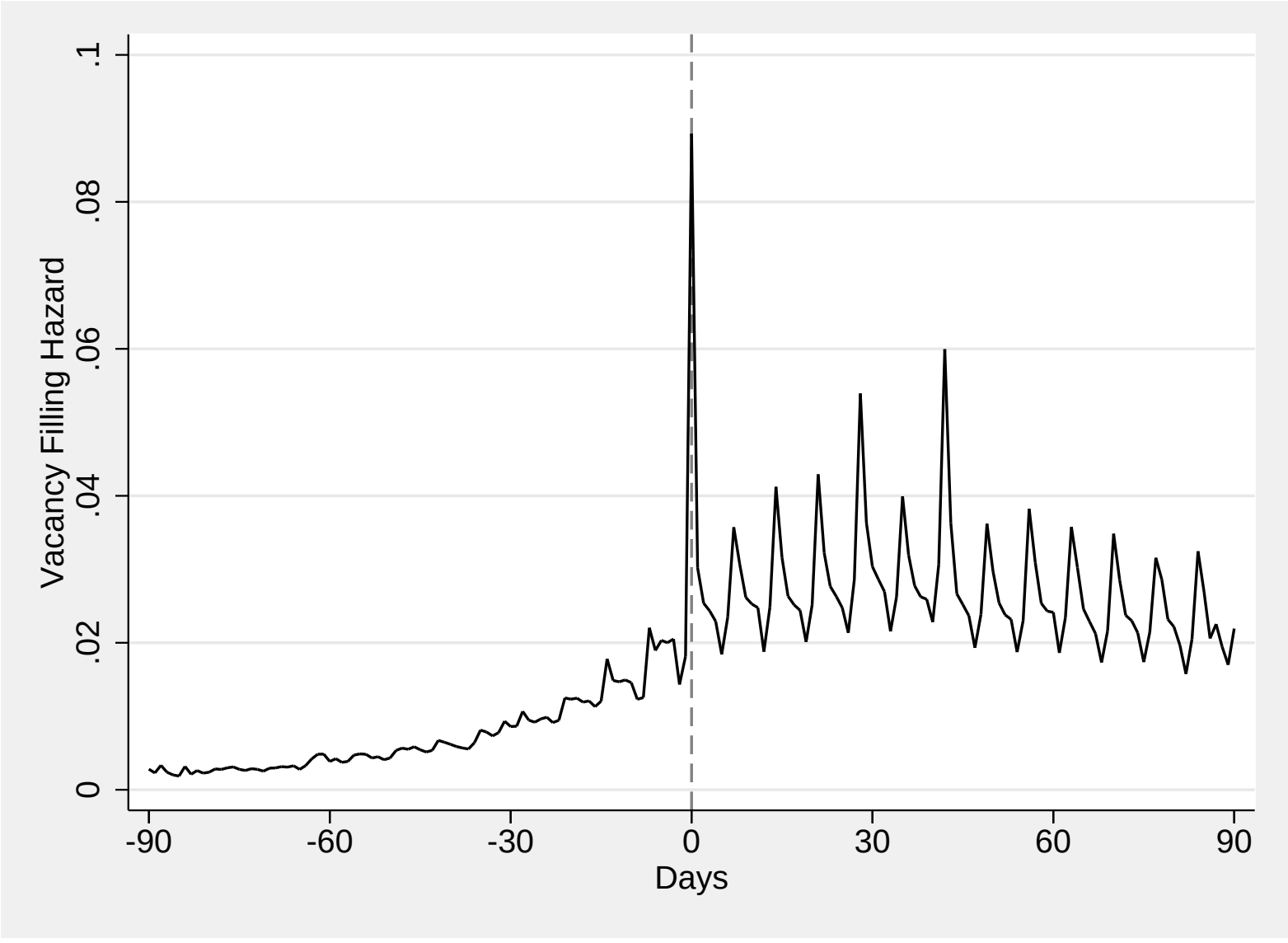
▸ Back

Summary statistics by sample restriction

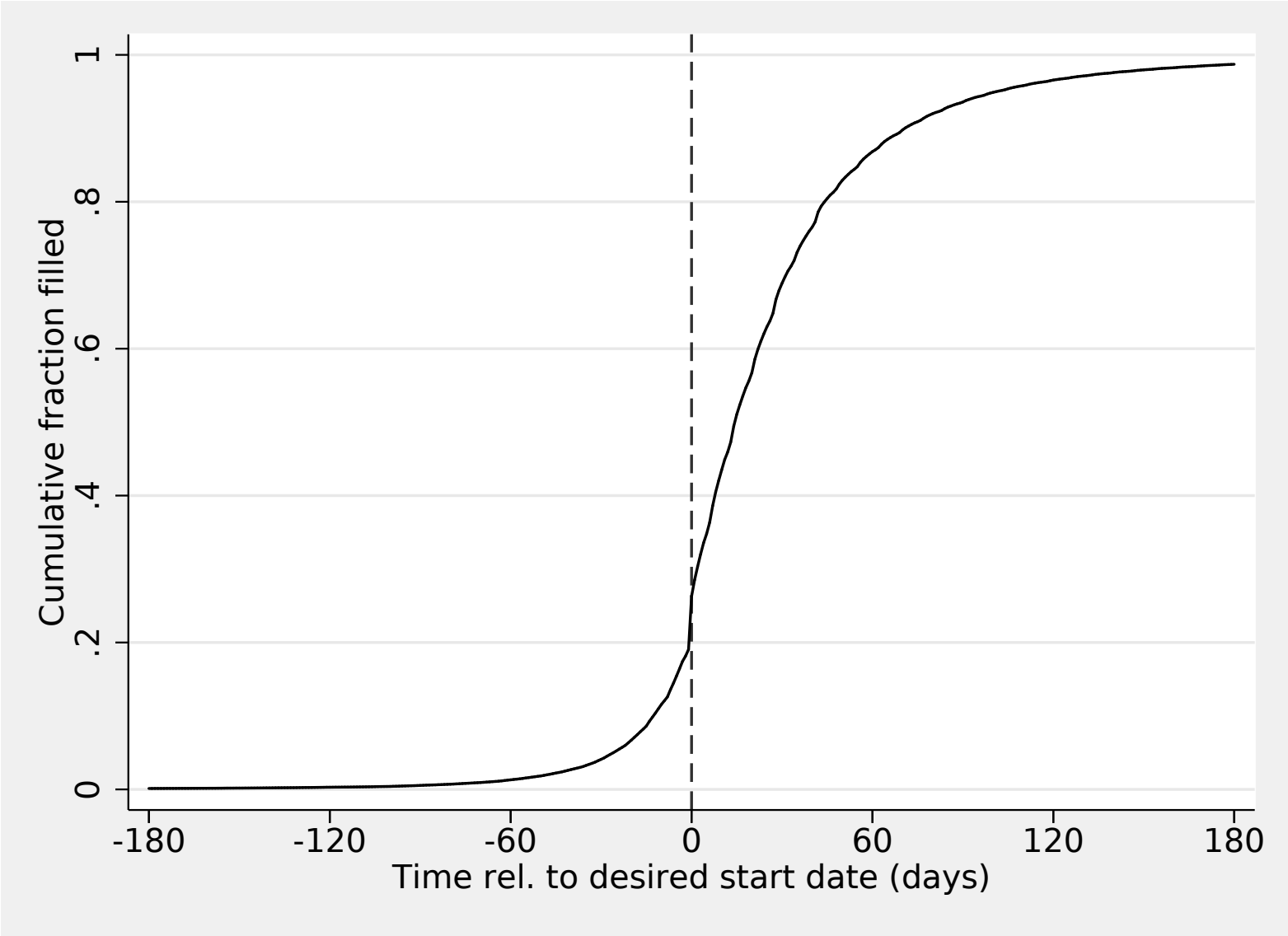
	All	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
At least apprenticeship (%)	48.21	43.97	43.33	46.18	47.65	48.11	48.88
Manufacturing (%)	34.92	41.09	38.65	37.14	44.15	44.25	41.94
Permanent contract (%)	79.97	77.85	82.36	81.63	79.90	80.36	83.37
Hired through system (%)	14.58	26.32	100.00	100.00	100.00	100.00	100.00
Fixed working time (%)	22.81	23.19	26.23	27.45	28.32	28.39	28.68
Small firm (%)	45.14	45.14	43.84	41.92	42.58	42.60	42.72
Vienna (%)	16.23	16.18	10.49	10.45	8.74	8.85	11.09
Full time (%)	80.55	76.20	79.23	100.00	100.00	100.00	100.00
Start of observation period	1997	1997	1997	1997	1997	1997	1997
Observations	9.60e+06	5.32e+06	1.11e+06	807482	441769	415726	278434

Table: Summary statistics by subsample

Vacancy filling rate, before and after the desired start date



Cumulative fraction filled, by time to desired start date

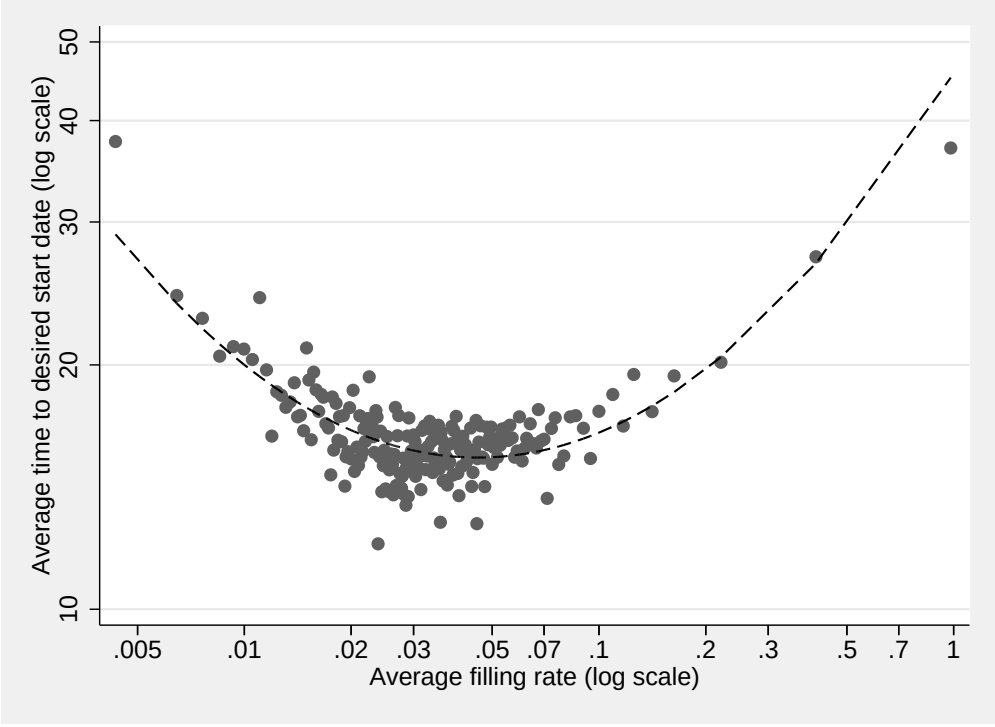


Summary Statistics of Vacancy Durations

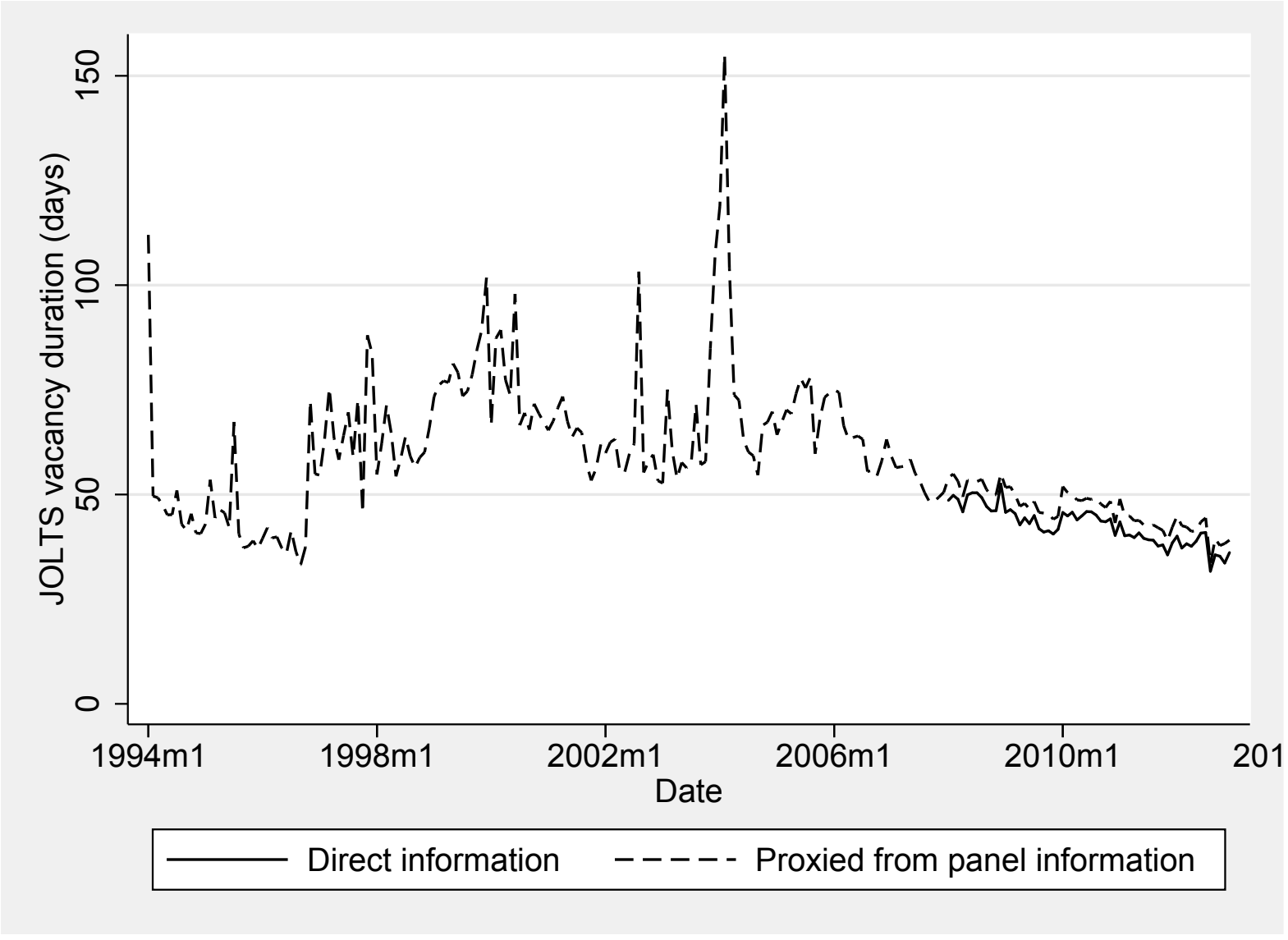
Table: Average and Median Vacancy Duration, in Days

	Mean	Mean (if >0)	Median	Median (if >0)
AMS Vacancy Duration	18.4	27.5	7	14
JOLTS Vacancy Duration	27.2	30.4	18	21
Vacancy Dur. Since Posting	34.6	38.3	19	22

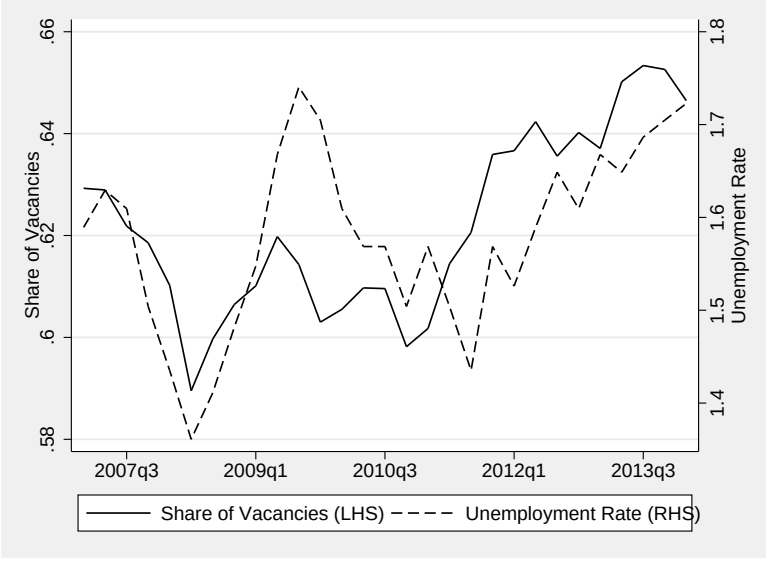
Early Posting and the Vacancy-Filling Rate



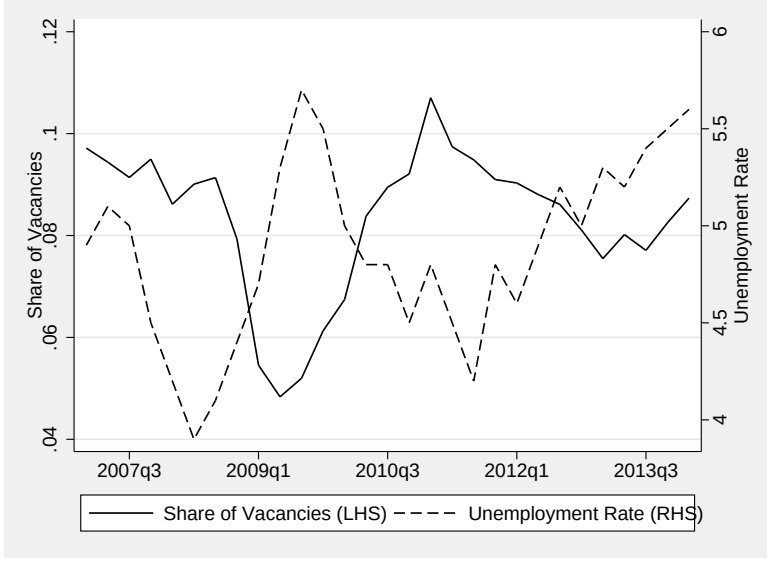
JOLTS vacancy duration



Vacancy Characteristics over the Business Cycle



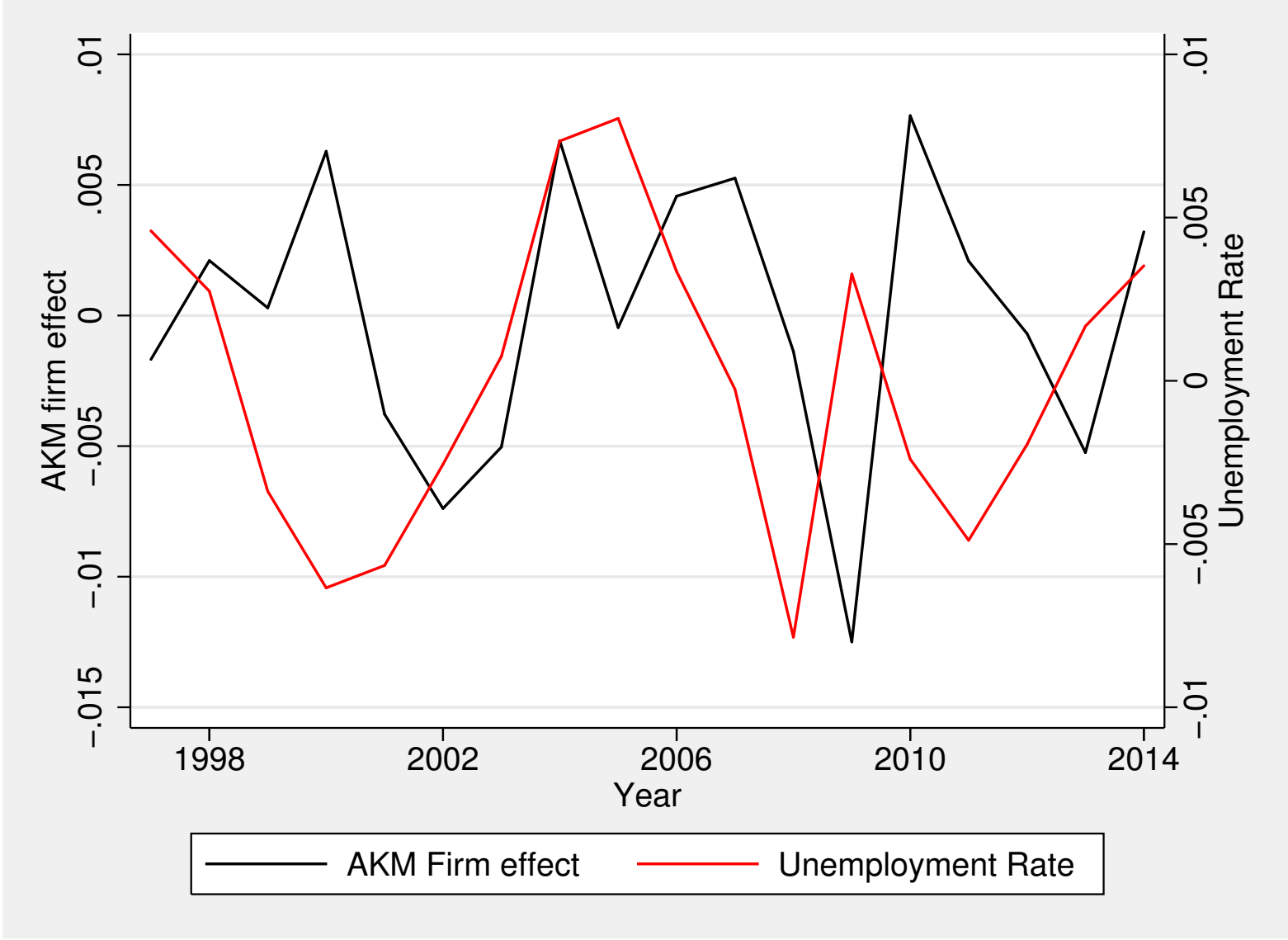
(a) Requires at least apprenticeship



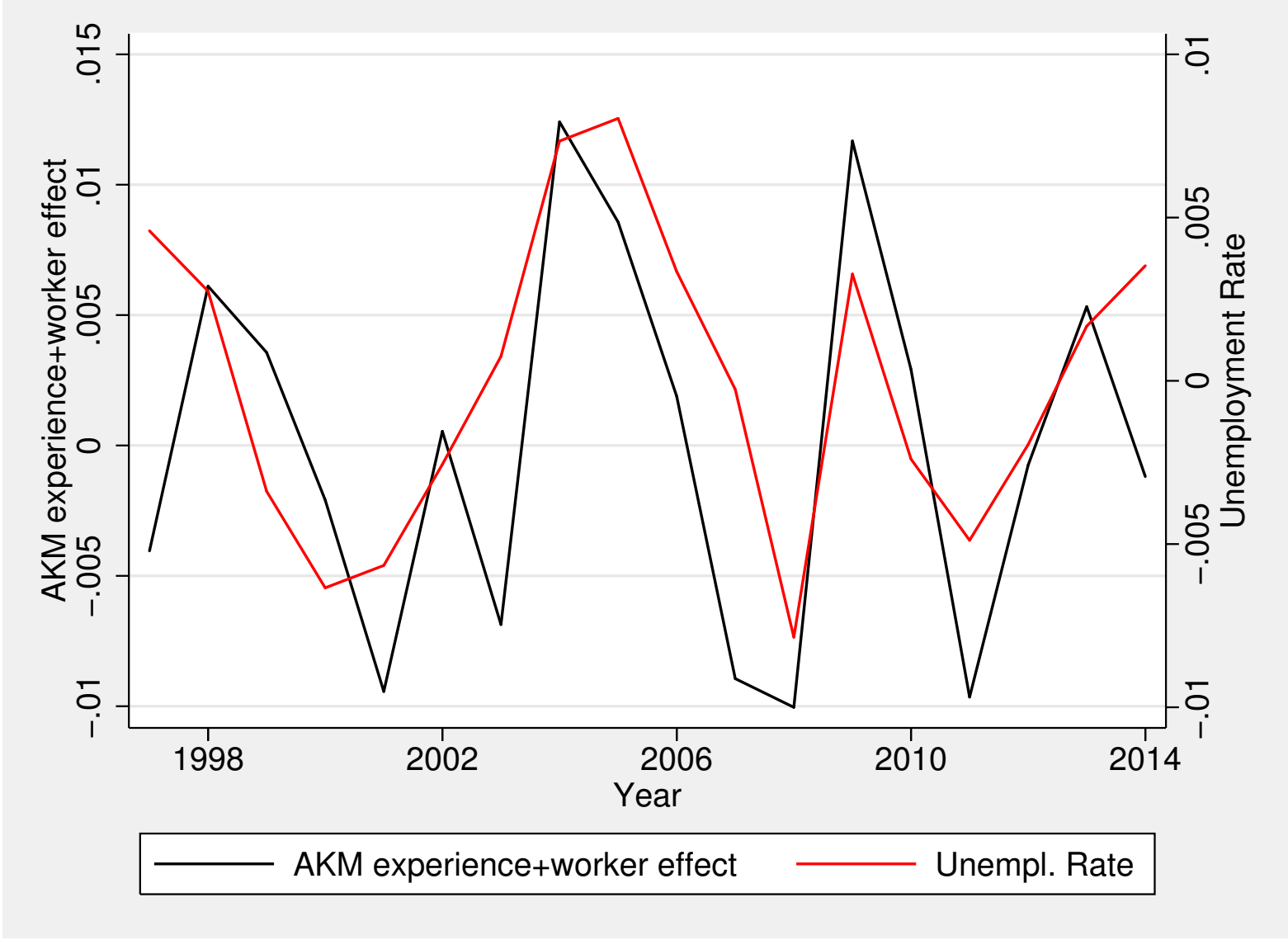
(b) Shift work

▸ Back

AKM Firm Effect Among Matched Vacancies



AKM Worker Effect Among Matched Vacancies



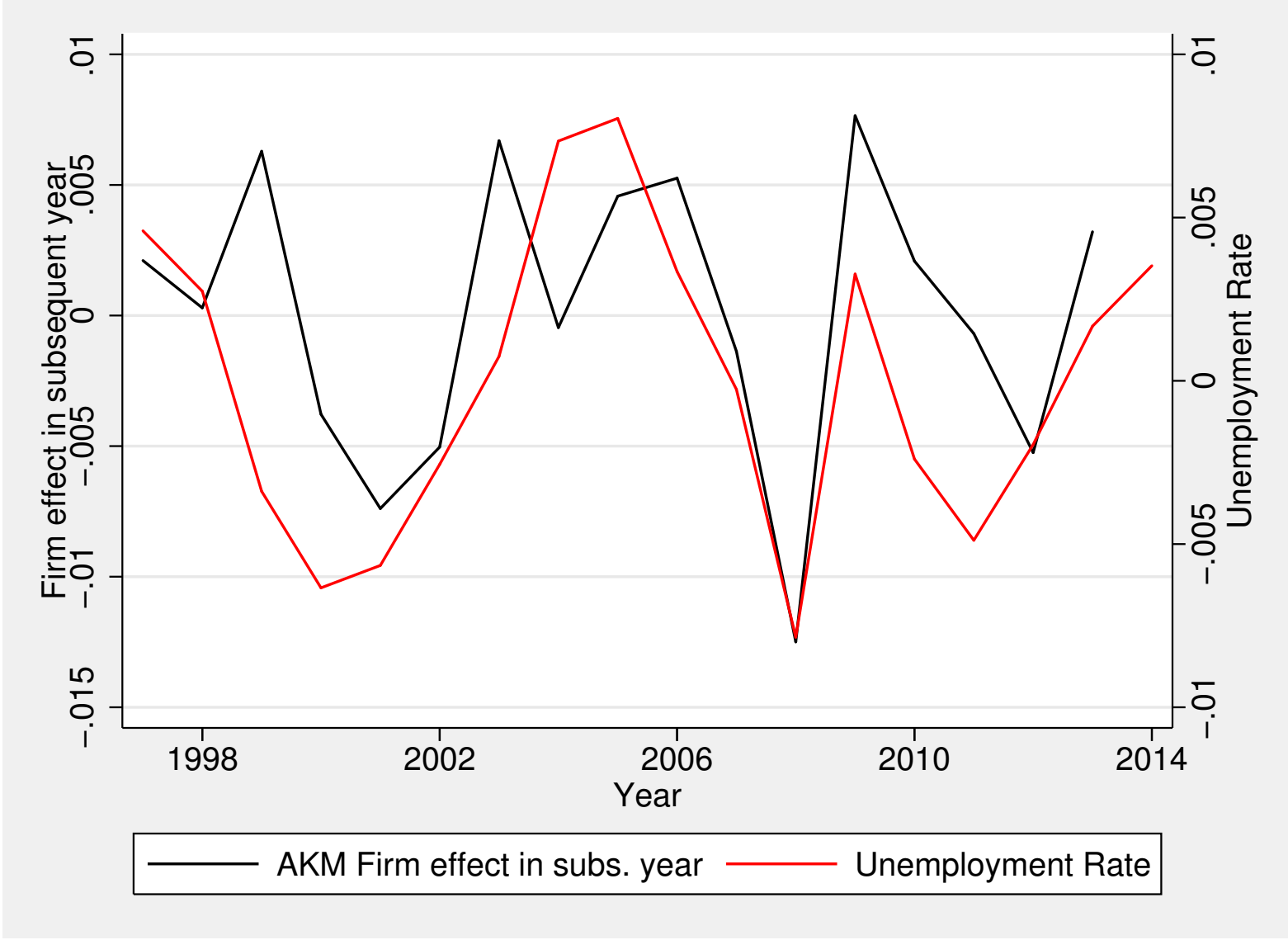
Vacancy Characteristics over the Business Cycle

During recessions, (i) firms require higher education, (ii) vacancies are filled by higher-wage workers, and (iii) firms post fewer jobs involving routine tasks.

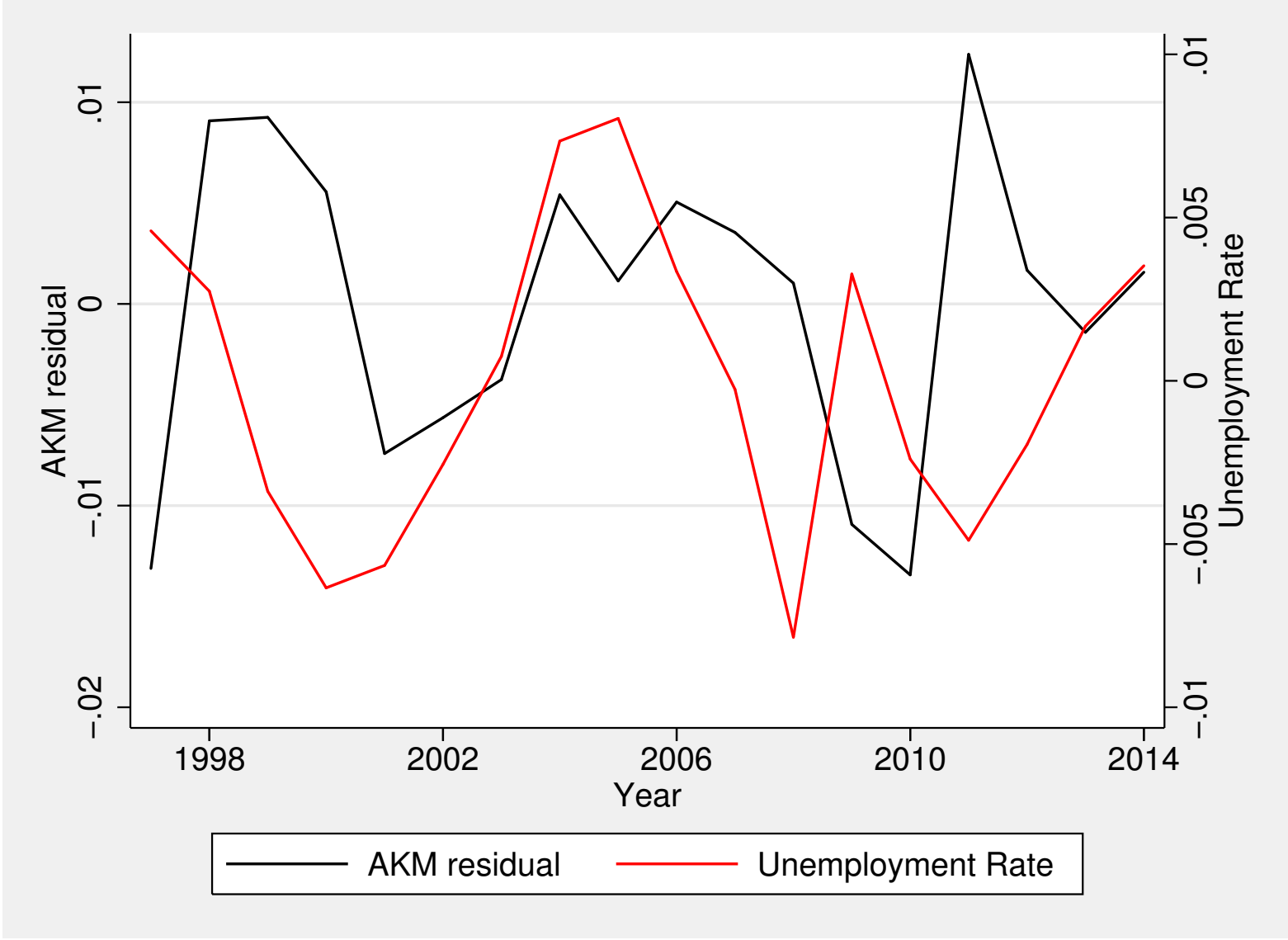
- Patterns consistent with opportunistic "upskilling" (Modestino, Shoag & Ballance, 2015; Hershbein and Kahn, 2016)
- Upskilling may be response to composition of unemployed tilting toward high-wage workers in recessions (see Mueller, 2017)

Back

Vacancy Characteristics over the Business Cycle



Vacancy Characteristics over the Business Cycle

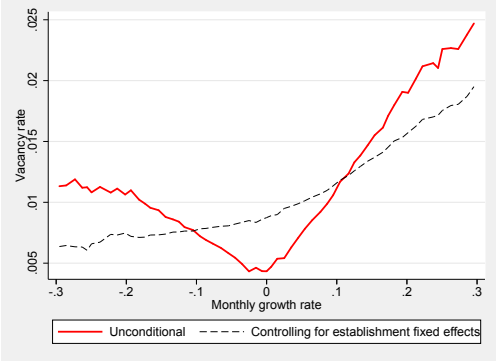


Hiring Intensity and Establishment Growth

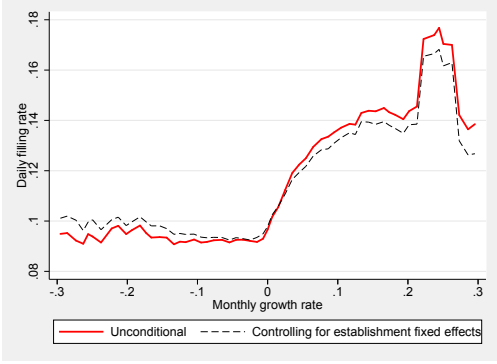
- Davis, Faberman and Haltiwanger (2013) document that growing firms increase their hiring intensity: not only higher vacancy rate, but also more hires per posted vacancy. Results are based on survey data.

- Using administrative data, we can confirm their findings. We can also show that the vacancy filling rate increases for growing firms.

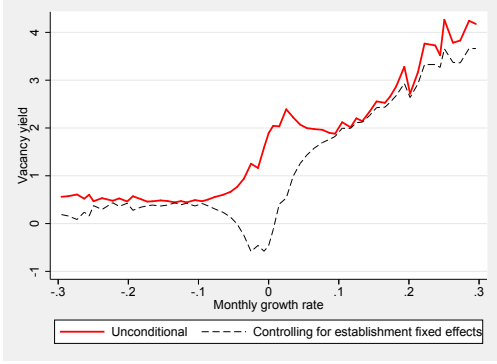
Hiring Intensity and Establishment Growth



(a) Vacancy Rate

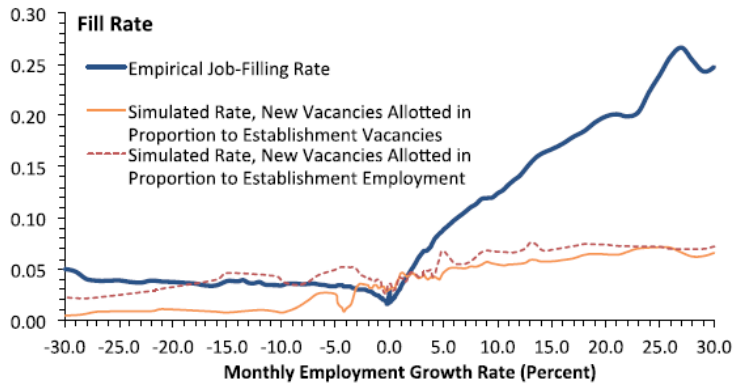


(b) Vacancy-filling rate

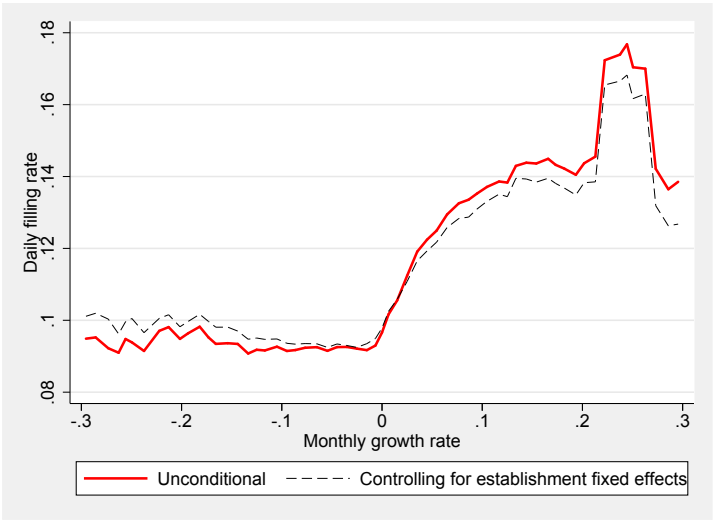


(c) Hires per vacancy (vacancy yield)

Hiring Intensity and Establishment Growth

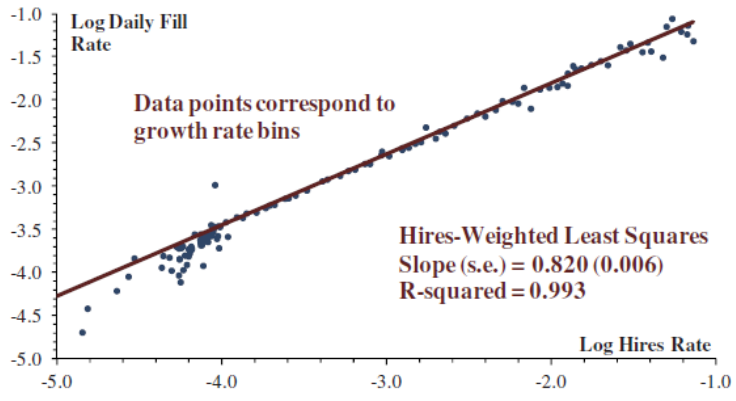


(a) Vacancy-filling rate in DFH (Figure 8)

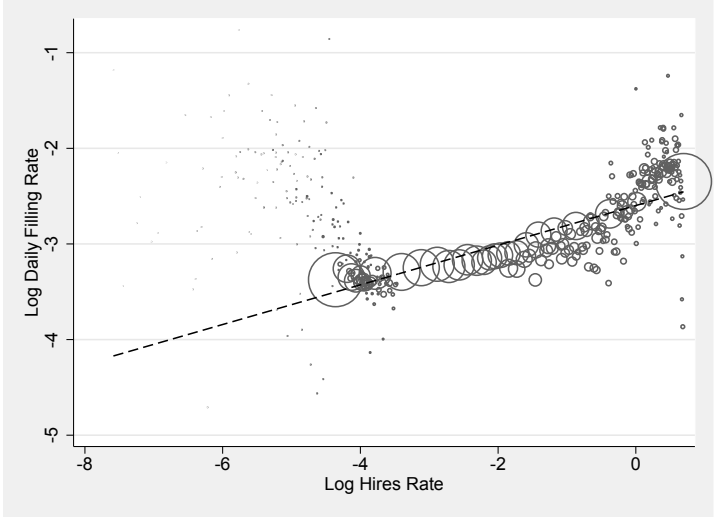


(b) Vacancy-filling rate in Austrian data

Elasticity of vacancy filling rate to hires rate



(a) Figure 9 from DFH



(b) Austrian data

Elasticity in Austrian data is 0.26.

Starting wage by growth bin

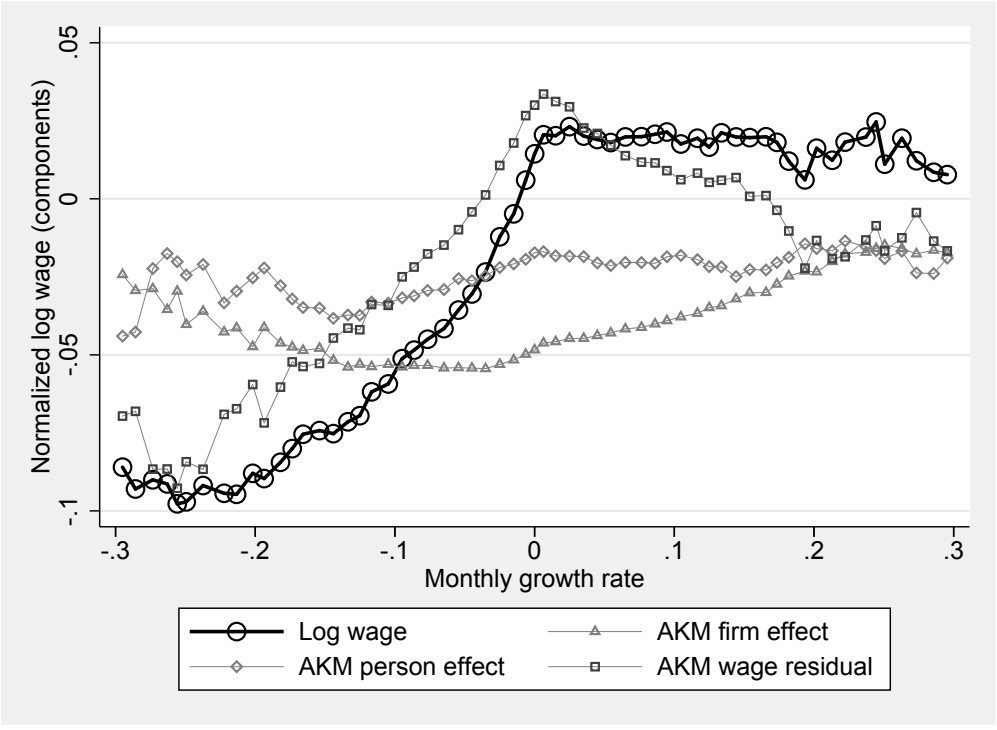


Figure: Starting wage and its components per firm growth bin

DFH results but controlling for AKM firm effects

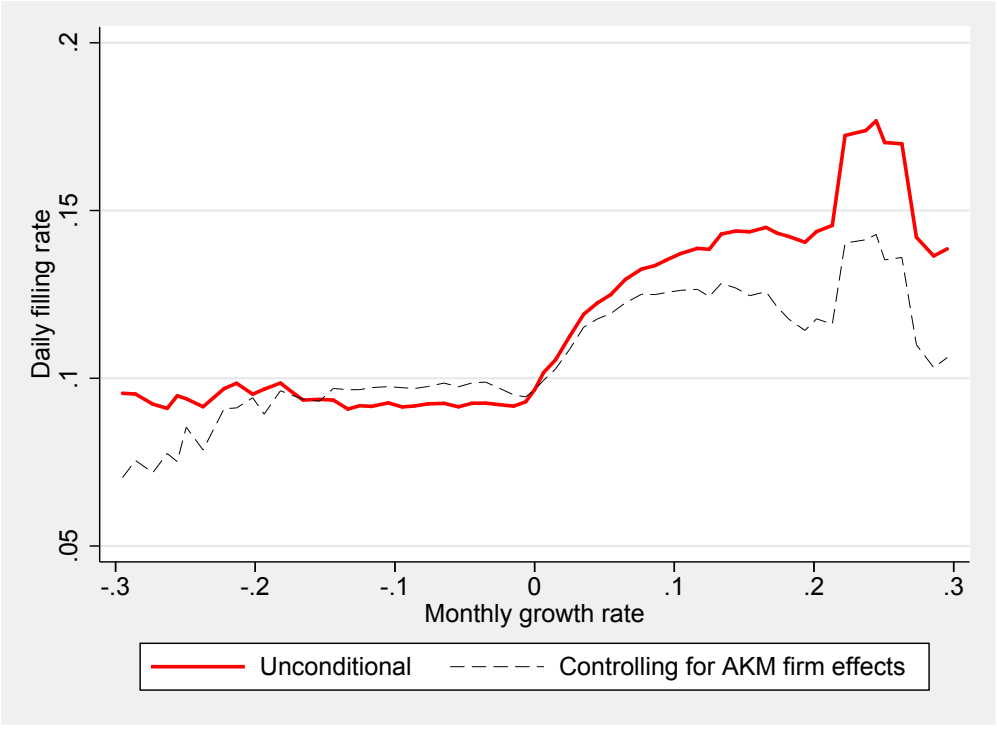
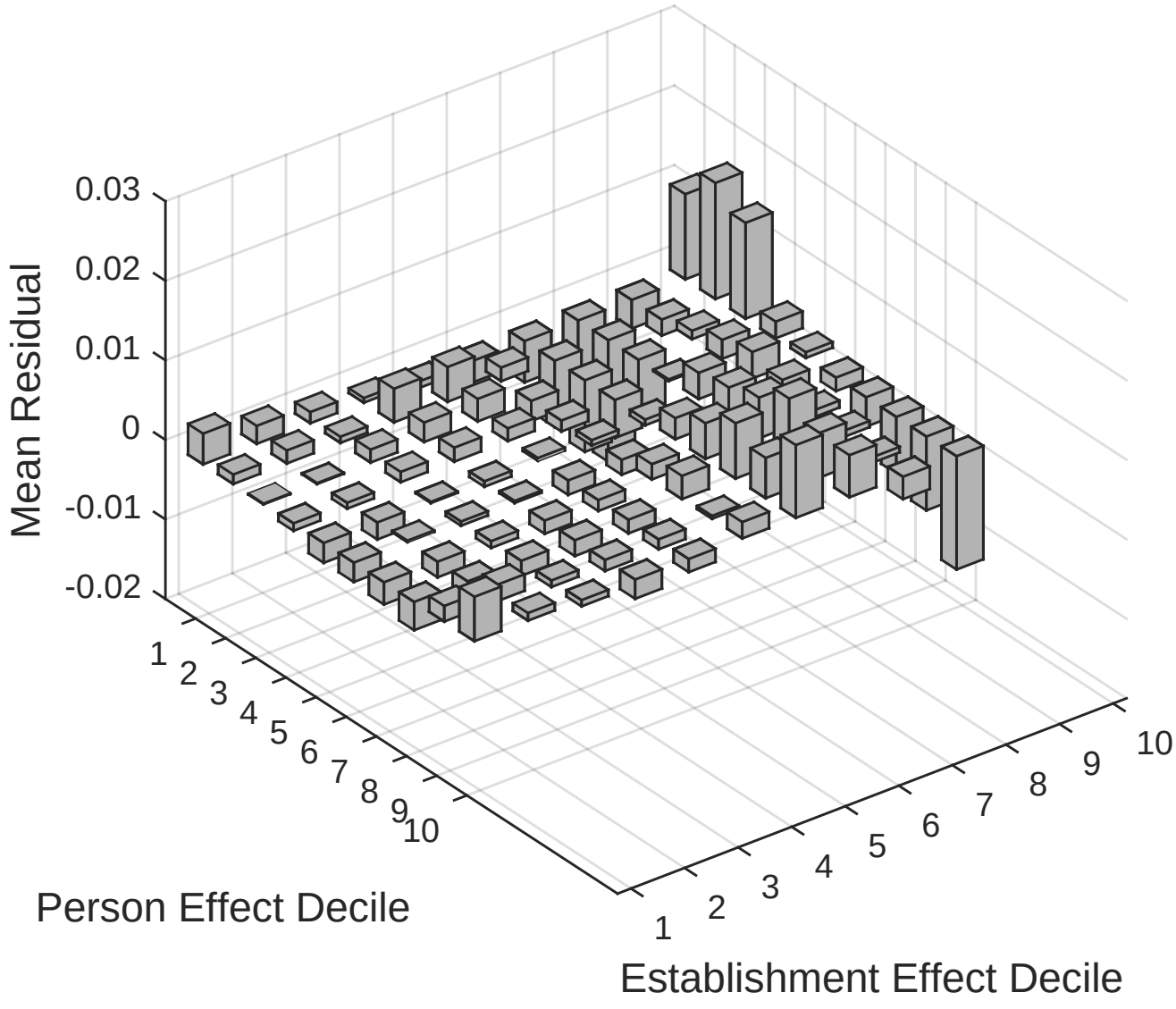


Figure: Filling rate per growth rate bin, controlling for AKM firm effects

AKM residuals



Regressions w/ log vacancy duration

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

Standard errors clustered at firm level in parentheses
Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regressions w/ log(vac. dur. + 1)

	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.0659***				
	(0.0114)				
AKM person effect		0.441***	0.0319*	0.0710***	0.0645***
		(0.0175)	(0.0182)	(0.0177)	(0.0197)
AKM experience effect		0.317***	0.128***	0.0990***	0.0885***
		(0.0145)	(0.0186)	(0.0175)	(0.0198)
AKM establishment effect		-0.112***	-0.180***	-0.305***	-0.312***
		(0.0373)	(0.0385)	(0.0351)	(0.0367)
AKM residual		0.0876***	-0.0270**	-0.0517***	-0.0446***
		(0.0111)	(0.0108)	(0.0127)	(0.0152)
Wage growth					-0.0701**
					(0.0347)
Log job duration					0.00595*
					(0.00318)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Further Controls	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	415726	415726	402988	366740	286299
Adjusted R^2	0.000	0.026	0.039	0.062	0.064

Standard errors clustered at firm level in parentheses
Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Restricted sample: at least 25 firm and 10 worker observations

	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.164***				
	(0.0168)				
AKM person effect		0.509***	0.330***	0.319***	0.288***
		(0.0241)	(0.0257)	(0.0247)	(0.0288)
AKM worker experience effect		0.368***	0.255***	0.220***	0.196***
		(0.0220)	(0.0300)	(0.0268)	(0.0313)
AKM establishment effect		-0.123***	-0.118***	0.108***	0.143***
		(0.0448)	(0.0425)	(0.0412)	(0.0435)
AKM residual		0.110***	0.0183	0.0442***	0.0550***
		(0.0182)	(0.0166)	(0.0155)	(0.0162)
Wage growth (on job)					-0.0190
					(0.0440)
Log job duration					0.0392***
					(0.00365)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Further Controls	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	88215	88215	88205	88205	64345
Adjusted R^2	0.010	0.017	0.047	0.081	0.078

Standard errors clustered at firm level in parentheses

Regressions w/ I(vac. dur. ≥ 1)

	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.0103***				
	(0.00300)				
AKM person effect		0.0668***	-0.0265***	-0.0145***	-0.00947*
		(0.00436)	(0.00520)	(0.00502)	(0.00561)
AKM experience effect		0.0514***	0.00821	0.00736	0.0154***
		(0.00377)	(0.00541)	(0.00510)	(0.00566)
AKM establishment effect		0.00785	-0.0106	-0.0499***	-0.0478***
		(0.00948)	(0.00954)	(0.00842)	(0.00886)
AKM residual		0.0201***	0.00242	-0.00425	0.00340
		(0.00277)	(0.00289)	(0.00350)	(0.00416)
Wage growth					-0.0319***
					(0.0102)
Log job duration					-0.00687***
					(0.000865)
Quarter FE	No	Yes	Yes	Yes	Yes
Further Controls	No	No	Yes	Yes	Yes
Region/Industry FE	No	No	No	Yes	Yes
Observations	415726	415726	402988	366740	286299
Adjusted R^2	0.000	0.021	0.026	0.046	0.047

Standard errors clustered at firm level in parentheses
Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regressions w/ JOLTS vacancy duration

	(1)	(2)	(3)	(4)	(5)
Log starting wage	0.0558***				
	(0.00796)				
AKM person effect		0.294***	0.198***	0.188***	0.175***
		(0.0128)	(0.0129)	(0.0126)	(0.0141)
AKM worker experience effect		0.164***	0.146***	0.115***	0.0840***
		(0.0106)	(0.0135)	(0.0125)	(0.0140)
AKM establishment effect		-0.137***	-0.145***	-0.0782***	-0.0758***
		(0.0218)	(0.0219)	(0.0204)	(0.0210)
AKM residual		0.0396***	-0.0394***	-0.0255***	-0.0247***
		(0.00861)	(0.00822)	(0.00767)	(0.00857)
Wage growth (on job)					0.113***
					(0.0270)
Log job duration					0.0436***
					(0.00211)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Further Controls	No	No	Yes	Yes	Yes
Region/Industry FE	No	No	No	Yes	Yes
Observations	280503	280503	272418	272418	211975
Adjusted R^2	0.008	0.012	0.039	0.063	0.064

Standard errors clustered at firm level in parentheses
Controls: Requ. ed. FEs, gender, age, age squared, year of labor market entry
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Calibration of Key Parameter Values

			Model Extension w/ Worker Heterogeneity	
	Parameters	Model	(1)	(2)
Worker Productivities:	$a_1(x_1)/a_2(x_1)$	1/1	0.8/1.2	1.0/1.0
	$a_1(x_2)/a_2(x_2)$	1/1	0.8/1.2	0.9/1.1
	$a_1(x_3)/a_2(x_3)$	1/1	0.8/1.2	0.8/1.2
	$a_1(x_4)/a_2(x_4)$	1/1	0.8/1.2	0.7/1.3
	$a_1(x_5)/a_2(x_5)$	1/1	0.8/1.2	0.6/1.4
Vacancy Posting Costs:	c_1	1.8	2.0	2.1
	c_2	1.8	1.8	2.0

Back

Simulation Results, Model w/ Worker Heterogeneity

		Model Extension w/ Worker Heterogeneity		
	Data	$\gamma = 2$	$\gamma = 1.1$	$\gamma = 0.1$
Corr. of Worker and Firm Types	—	0.00	0.00	0.01
Elast. of Vacancy Duration to				
... Starting Wage	0.16	0.23	0.25	0.28
... AKM Worker Effect	0.26	0.28	0.28	0.28
... AKM Firm Effect	-0.16	-15.2	-11.0	-1.3
... AKM Residual	0.02	-23.3	-19.1	-10.2
Elast. of Hiring to Job Filling	0.26	0.39	0.25	0.03

Back

Simulation Results, Model w/ Worker Heterogeneity

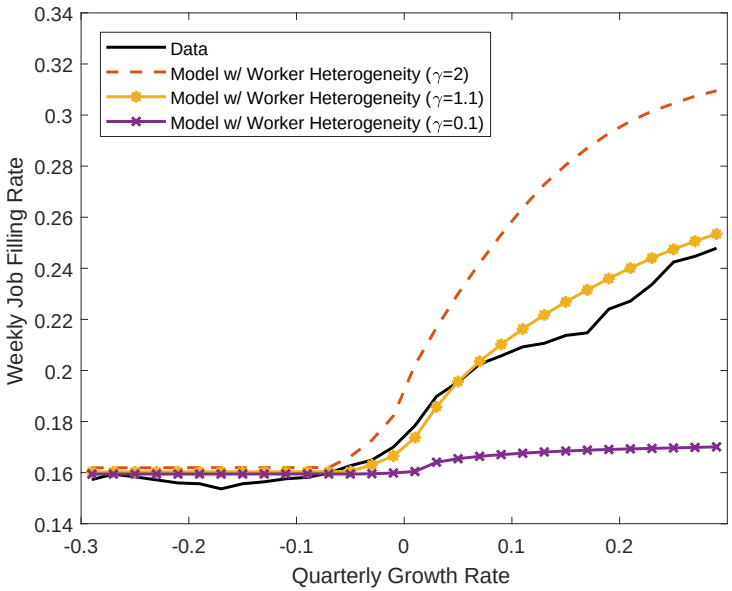
w/ positive complementarities between high-x firms and high-skilled workers

.

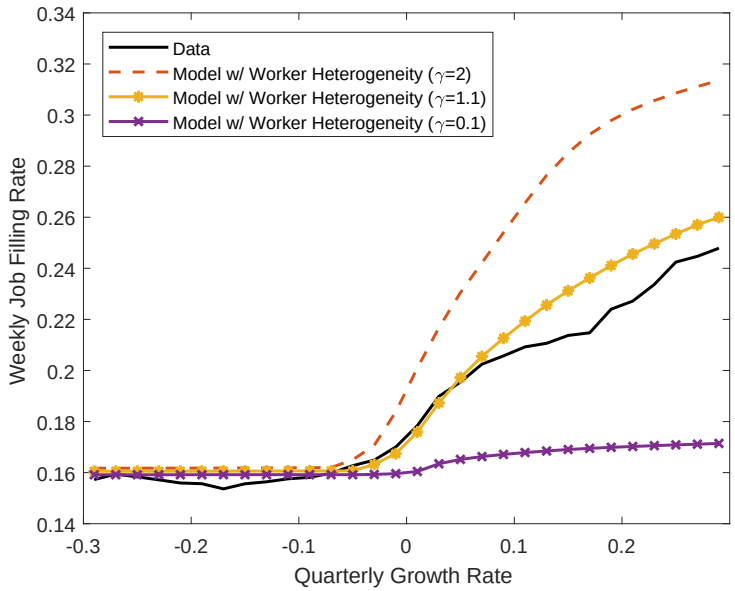
		Model Extension w/ Worker Heterogeneity		
	Data	$\gamma = 2$	$\gamma = 1.1$	$\gamma = 0.1$
Corr. of Worker and Firm Types	—	0.51	0.50	0.48
Elast. of Vacancy Duration to				
... Starting Wage	0.16	0.18	0.22	0.36
... AKM Worker Effect	0.26	0.04	0.07	0.35
... AKM Firm Effect	-0.16	-14.2	-11.7	-0.9
... AKM Residual	0.02	-22.7	-17.8	-8.4
Elast. of Hiring to Job Filling	0.26	0.41	0.26	0.03

▸ Back

The Importance of the Vacancy Cost Elasticity γ



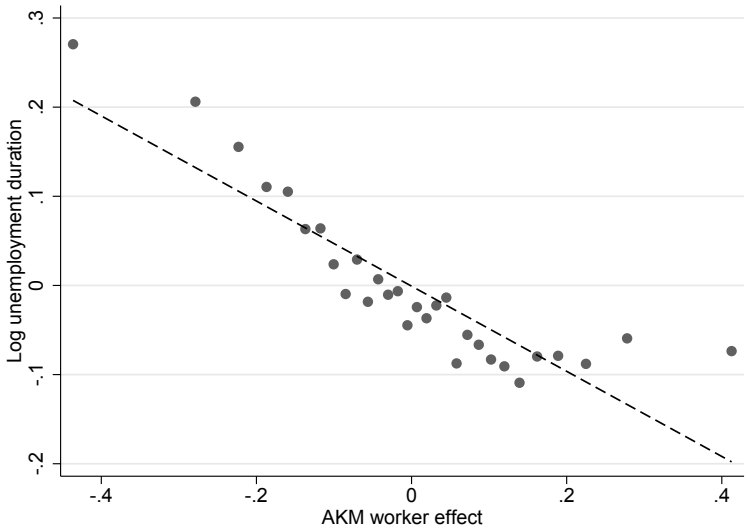
(a) Model w/o PAM



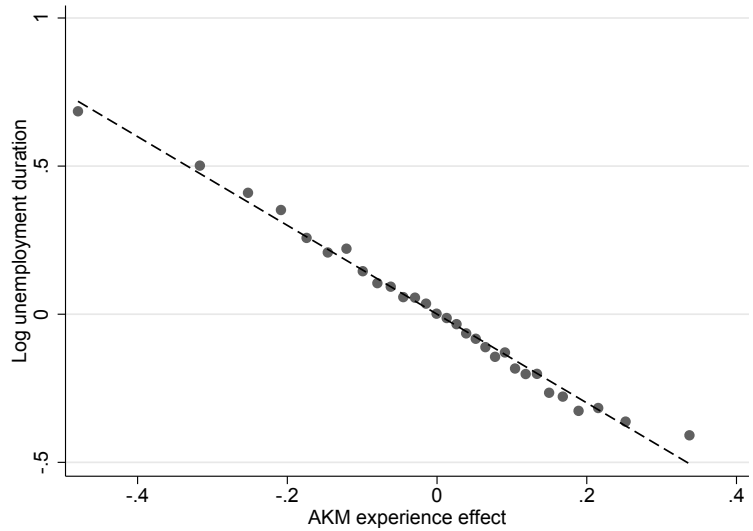
(b) Model w/ PAM

▸ Back

Unemployment Duration and AKM worker effects

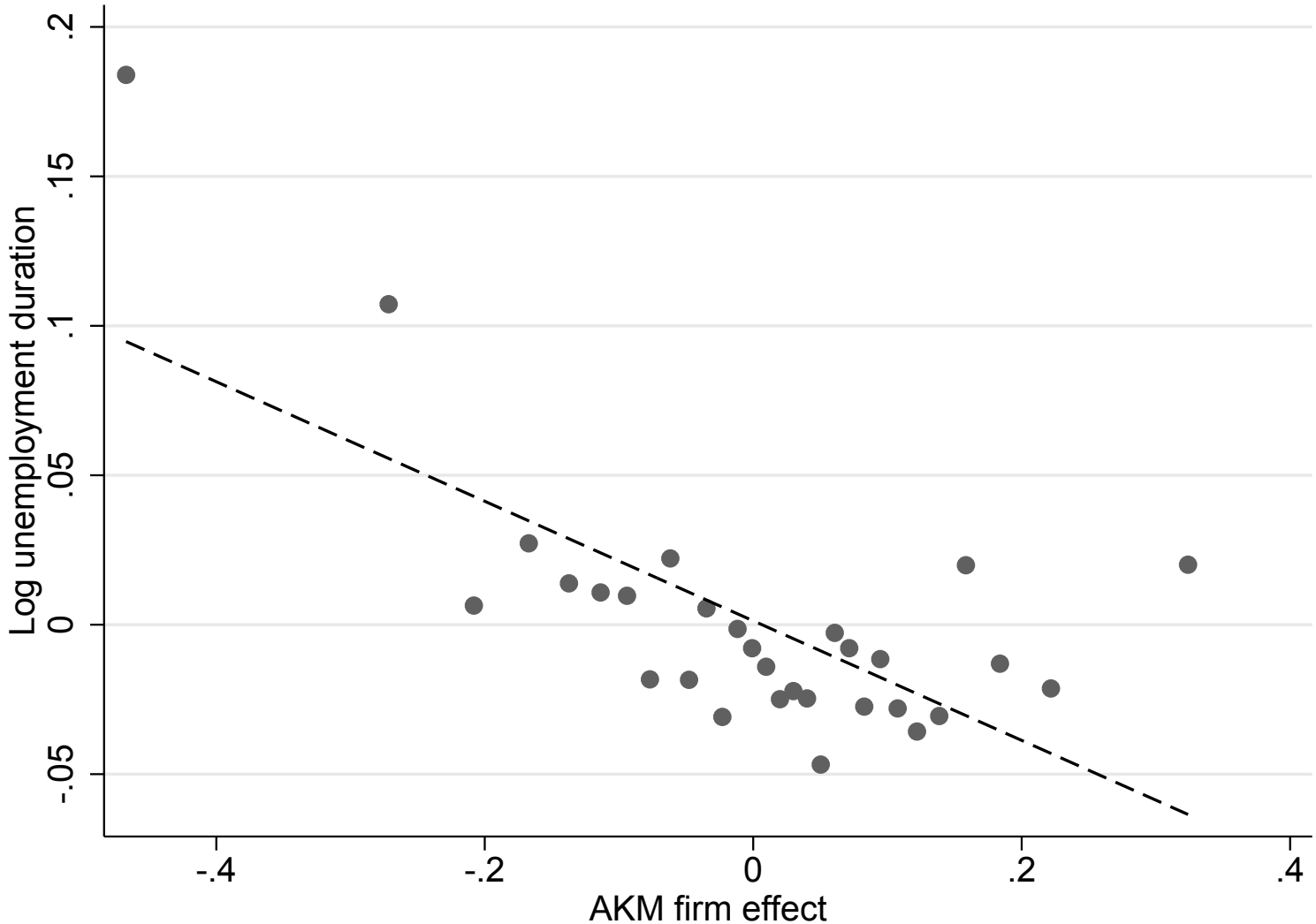


(a) Worker effects

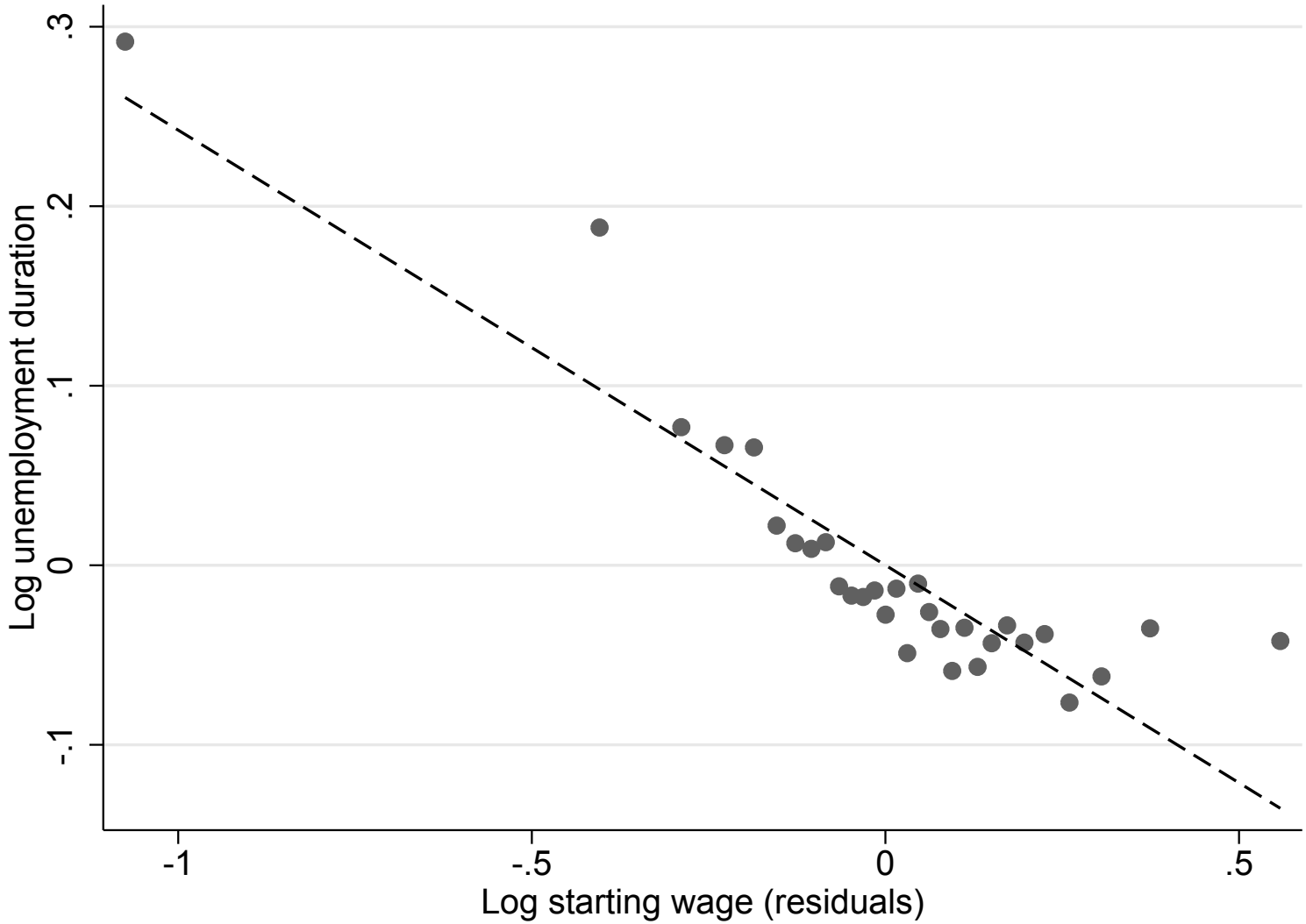


(b) Experience effects

Unemployment Duration and AKM firm effects



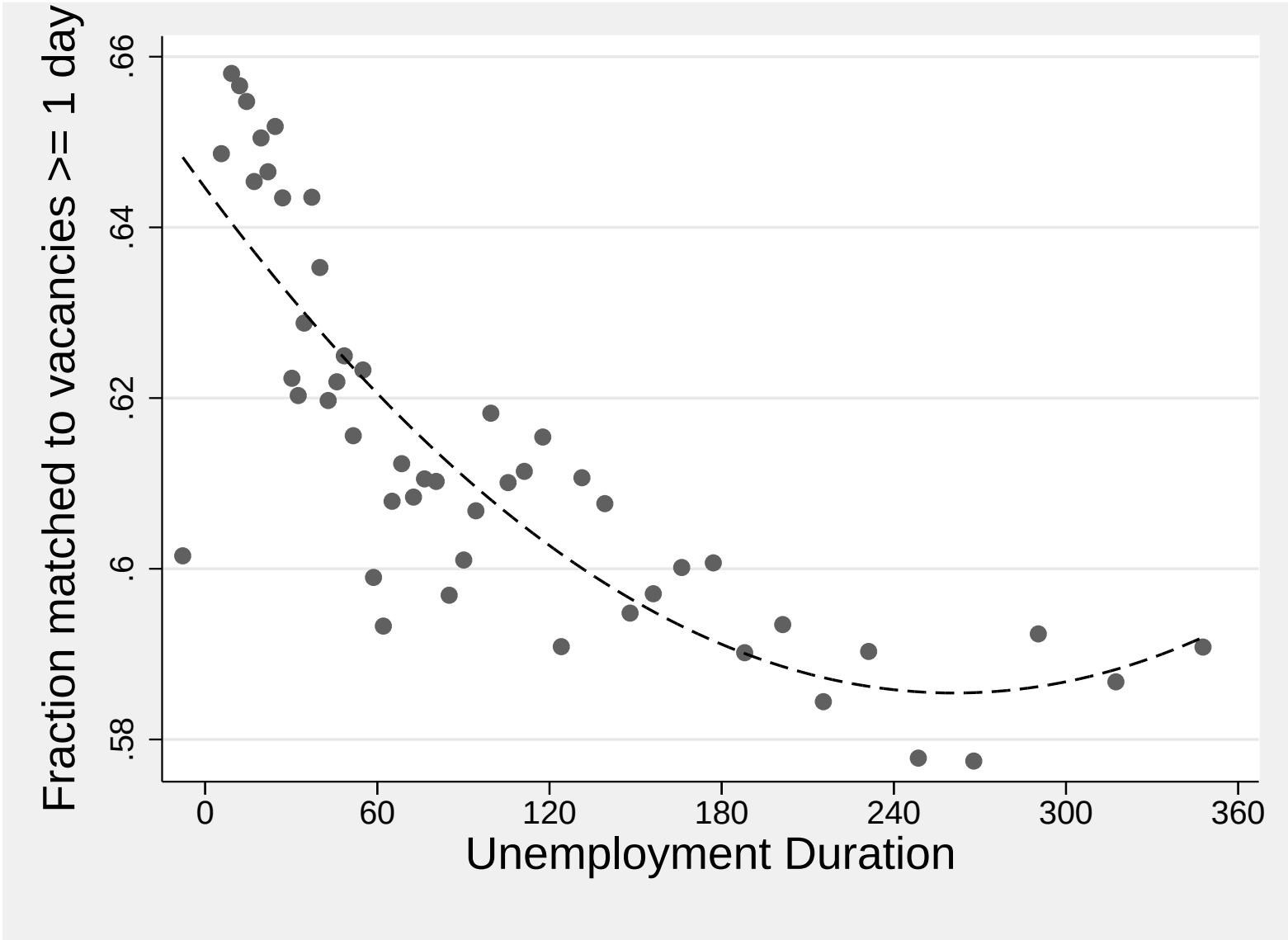
Unemployment Duration and AKM residual



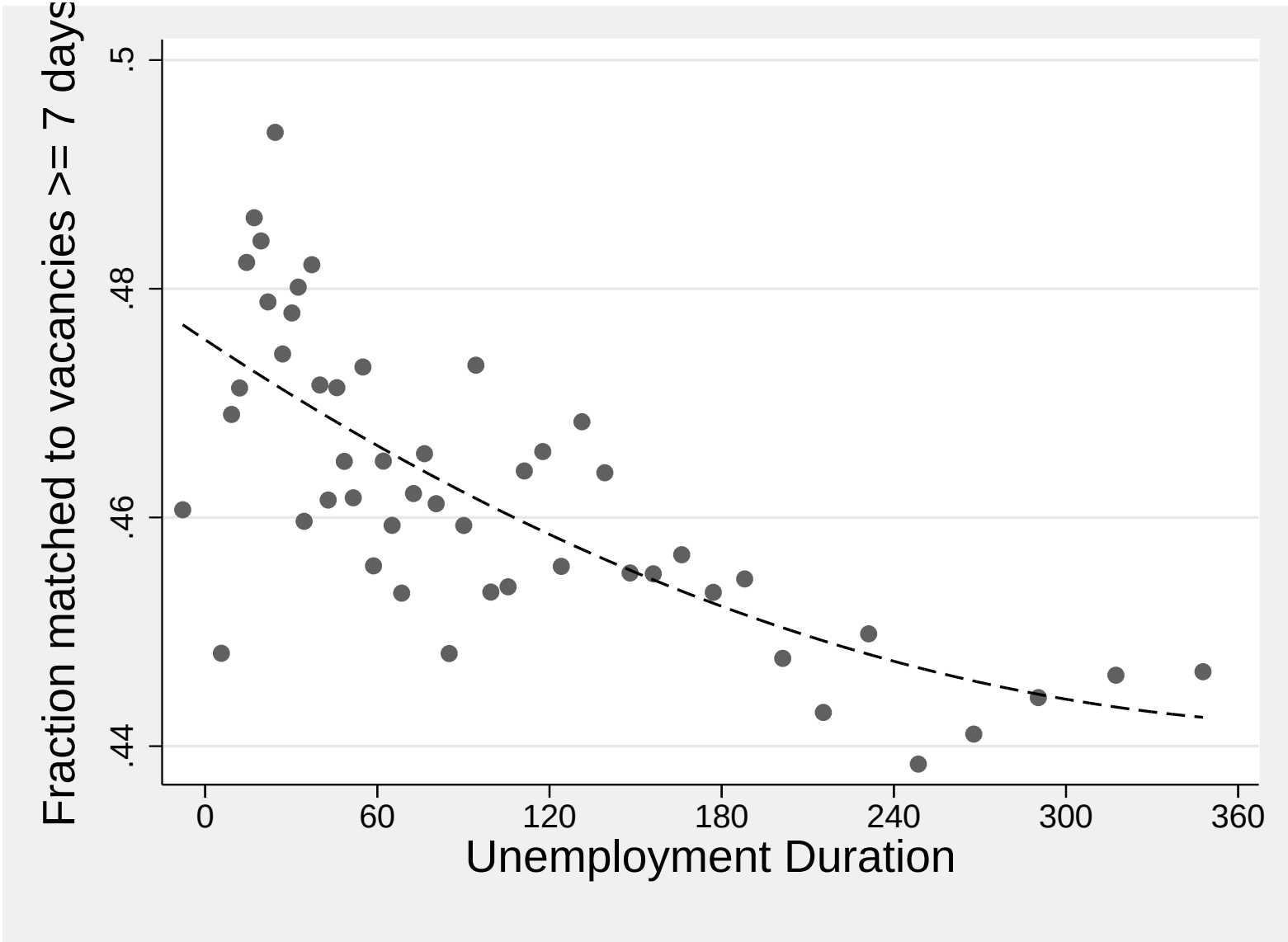
Stock-Flow Matching

- Theory of stock-flow matching posits that unemployed workers (resp. firms) are more likely to match to the inflow of vacancies (resp. unemployed) than the stock of vacancies (resp. unemployed).
  - Main references: Coles and Smith (1998), Lagos (2000), ...
- Underlying idea is that - within a submarket - workers and firms find out immediately about suitable matches.
- Implies duration dependence in job finding rates and vacancy filling rates.
- We evaluate the presence of stock-flow matching by relating vacancy duration to the unemployed worker's unemployment duration at the time of the match.
  - We use all data from 2007, where we have a precise measure of the match date for unemployment duration.

Fraction matched to vacancies $\geq$ 1 day, by unemployment duration



Fraction matched to vacancies $\geq$ 7 days, by unemployment duration



Regressions w/ fraction matched to vacancies ≥ 1 day

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

Standard errors clustered at firm level in parentheses

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

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

Implications of stock-flow matching for duration dependence

The probability of finding a job at duration d can be written as

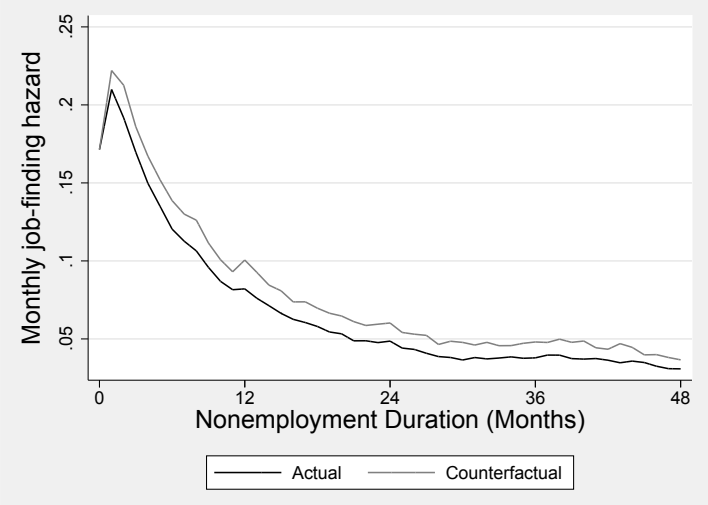
$$f(d) = f_0(d) + f_1(d) = f_0(d)(1 + f_1(d)/f_0(d)),$$

where $f_0(d)$ is the hazard of being matched with the flow of vacancies and $f_1(d)$ is the hazard of being matched with the stock.

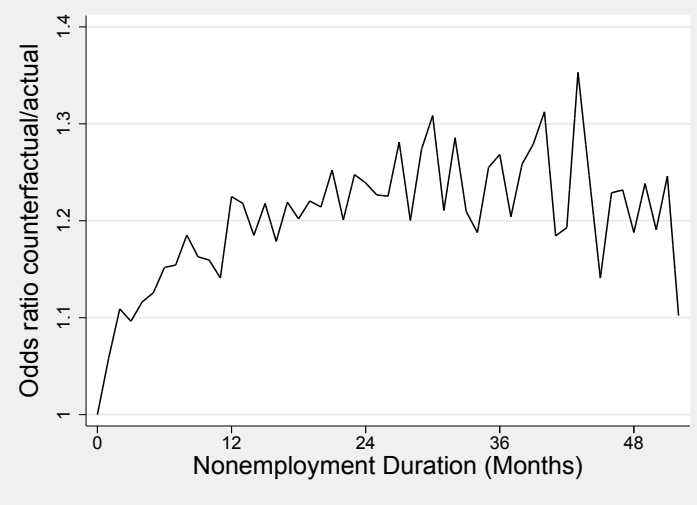
Under random matching, $f_1(d)/f_0(d)$ is independent of duration d, and thus we can compute a counterfactual hazard rate

$$\tilde{f}(d) = f_0(d)(1 + f_1(0)/f_0(0)).$$

Actual and counterfactual job-finding rates



(a) Actual vs. counterfactual



(b) Odds ratio

Summary

- The long-term unemployed are more likely to match with vacancies with short durations.
- Patterns consistent with some degree of stock-flow matching and may account for about 20 percent of the job finding rate of the long-term unemployed.
- We have developed a nonparametric test based on this intuition: Rejects the null that observed patterns are generated by random matches for nearly all time periods.

Testing Random Search

- Under random search, conditional on matching, the probability of an unemployed matching with a vacancy of type j is independent of the unemployed's type.

- Therefore, the probability of a match between an unemployed of type i and a vacancies of type j is:

$$P_t^{ij} = P_t^i P_t^{j|i} = P_t^i P_t^j,$$

- Thus, under random matching,

$$log \frac{P_t^{ij}/P_t^{ik}}{P_t^{lj}/P_t^{lk}} = 0.$$

- Note: This allows for arbitrary differences in search and recruiting effort.

Testing Random Search

- We apply this test to two types of unemployed $i \epsilon [s, l]$ and two types of vacancies $j \epsilon [s, l]$.

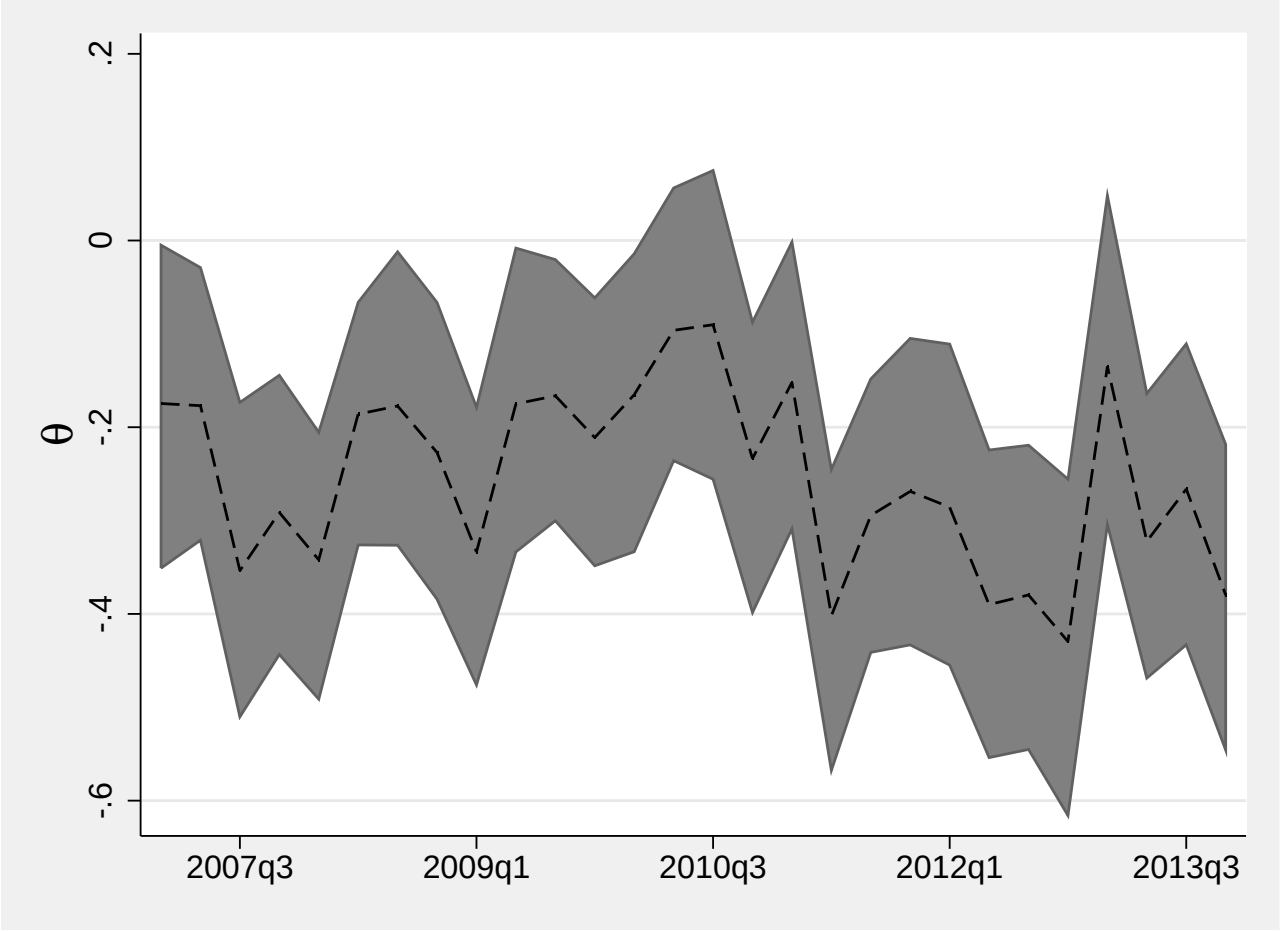
- Therefore, under the null hypothesis of random matching,

$$\theta_t \equiv log \frac{\hat{P}_t^{ss} / \hat{P}_t^{sl}}{\hat{P}_t^{ls} / \hat{P}_t^{ll}} \rightarrow 0.$$

  where $\hat{P}_t^{ij}$ is the fraction of matches between unemployed of type i and vacancies of type j.

- Intuitively, under random search, a short-term unemployed worker s should have the same odds-ratio of matching with short vs. long duration vacancies as a long-term unemployed worker l.

The test statistic θ_t and bootstrapped confidence intervals



The results imply that, conditional on matching, the long-term unemployed are more likely to match with a short-term vacancy than the short-term unemployed.

Regressions w/ fraction matched to vacancies ≥ 7 days

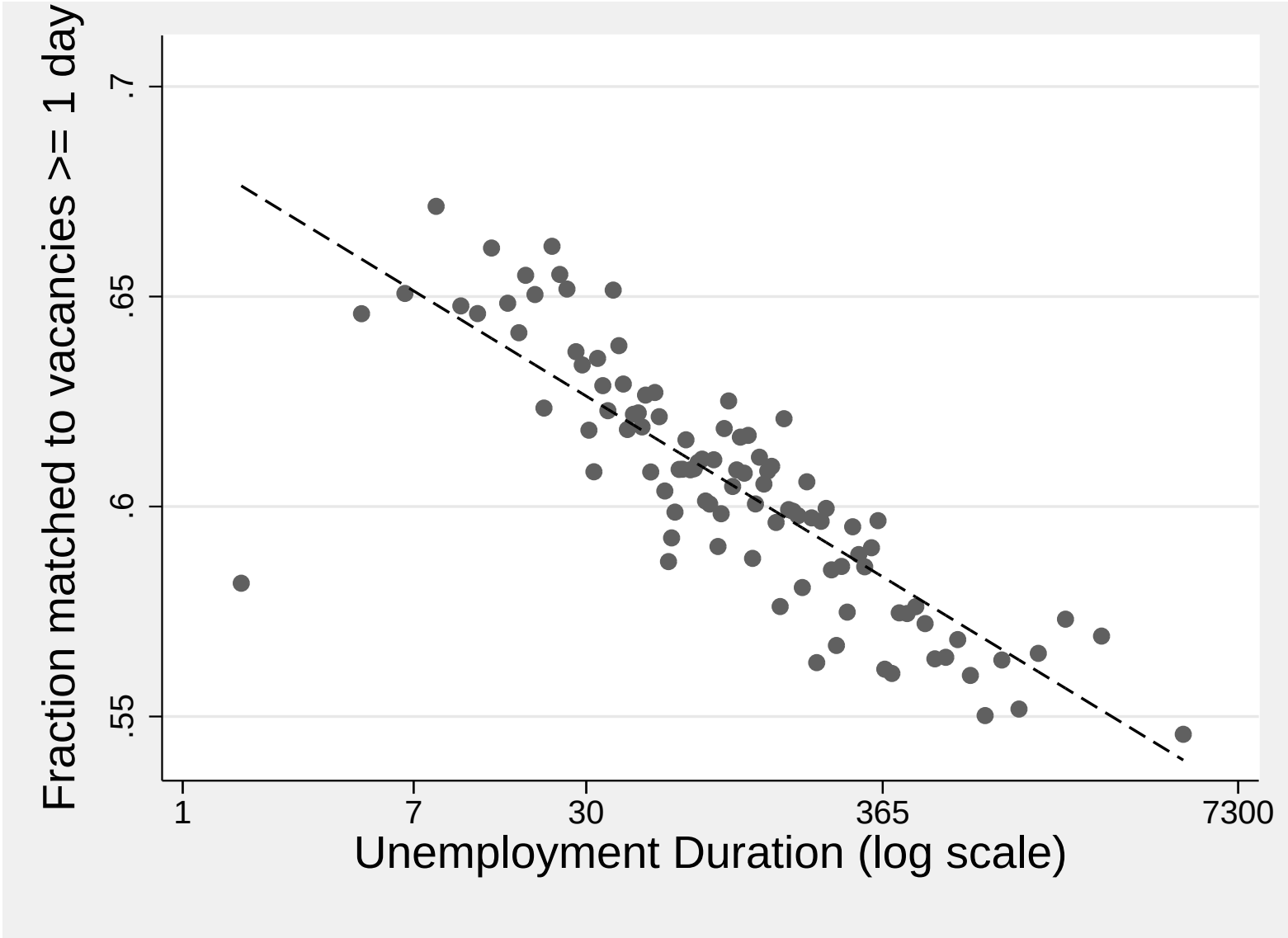
	(1)	(2)	(3)	(4)
Log nonemployment duration	-0.0207***	-0.0167***	-0.0103***	-0.0237***
	(0.00131)	(0.00116)	(0.00134)	(0.00297)
Controls	No	Yes	Yes	Yes
Region/Industry FE	No	Yes	No	No
Firm FE	No	No	Yes	No
Worker FE	No	No	No	Yes
Observations	185164	172484	163605	80689
Adjusted R^2	0.003	0.059	0.140	0.072

Standard errors clustered at firm level in parentheses

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

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

Fraction matched to vacancies $\geq$ 1 day, by unemployment duration



Fraction matched to vacancies $\geq$ 7 days, by unemployment duration