Mis-Measuring Job Openings: Evidence from Swedish Plant Level Data*

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Abstract

In the textbook search and matching model job openings are a key component. Thus, when taking this model to the data we need an empirical counterpart to the theoretical concept of job openings. To achieve this, the literature relies on job vacancies measured either in survey or register data. Insofar, that this concept captures the concept of job-openings well we should see a tight relationship between vacancies and subsequent hires on the micro level. To investigate this, I construct a new dataset with hires and job vacancies on the plant level for Sweden covering the period 2001-2012. I show that vacancies contain little power in predicting hires above (i) whether the number of vacancies is positive and (ii) plant size. Building on these findings, I propose an alternative measure of job openings in the economy. This measure has the attractive feature of providing a better fitting matching function *vis-a-vis* the traditional vacancy measure. Using the new measure, it is less clear that the Beveridge curve has shifted outwards in the aftermath the Great Recession.

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1 IMF Introduction

One of the puzzles in macroeconomics after the Great Recession has been why unemployment in a number of advanced countries has been high, while job-vacancies at the same time has appeared to be plenty. This observation is captured by the notion that the so-called Beveridge curve has shifted outwards in many OECD countries (Figure TBD). In this paper, I argue that measurement problems can be part of the story in the case of Sweden. Using a novel dataset, I show that our vacancy measure is poorly related to hiring on the plant-level, and that the number of hires per vacancy (the *vacancy yield*) varies across plant characteristics. Moreover, I show that it is possible to construct an alternative measure of job-openings, which builds on the extensive margin of vacancies and plantsize. This measure performs better in predicting hiring on the plant level, and interestingly it also yields a better fitting matching function on the aggregate level. When using this measure to analyze the Swedish labor market after the Great Recession, the outward shift in the Beveridge curve is less pronounced.

Job-openings are a key concept in modern macroeconomic models. Within the search-matching framework, which is a important building block in modern macroeconomics, we need to know the number of job-openings to infer how tight the labor market is. And on the micro level a hire is made, when a job-opening and an unemployed worker are matched via the aggregate matching function.

Thus, when taking our models to the data we need to construct a mapping from the theoretical concept of a job-opening to an empirical counterpart. To achieve this mapping the literature relies on data for job-vacancies. These are either measured via surveys, where employers are asked about how many jobs they are currently trying to fill, or via register data on job vacancies made in newspapers or employment centers. We use these measures to guide our discussion about the aggregate state of the labor market, and to evaluate the predictions of our models. Yet so far, we know very little about how these vacancy measures relate to actual hiring on the micro level. Insofar that job-vacancies capture the notion of job-openings well, we should expect to see a rather tight relationship between job-vacancies and subsequent hires on the micro level.

This paper is one of the first to investigate this link. Specifically, I construct a novel Swedish dataset with hires and job-vacancies on the plant level. Using this data, I show that the relationship between job-vacancies and subsequent hiring is weak and concave, in contrast to linear as predicted by the standard search and matching model. That is, additional vacancies on the plant level predicts less and less hiring. Moreover, plants hire many workers than they post vacancies. I take these findings as evidence of vacancies being a poor measure of actual job-openings.

However, I also show that it is possible to construct a better measure of job-openings.

Indeed, by allowing job-openings to depend not only on listed vacancies, but also on plant size, I show that it is possible to improve the ability to predict hiring on the plant level by approx. 40 %.

Building on these findings, I propose an alternative measure for the aggregate number of job openings in economy. Motivated by the concave relationship between vacancies and hires, and the predictive power of plant size, I use the *number of plants with a positive number of vacancies weighted by size* as an alternative measure of job openings in the economy. I show, that this measure has the appealing feature of providing a better fitting aggregate matching function.

These findings have potentially important policy implications. As mentioned above an important policy discussion in the wake of the Great Recession has been why unemployment has been high in a number of OECD countries (including Sweden) in spite of the stock of vacancies also being high.

Figuring out why unemployment is high is first order, when designing policies to bring it down. If unemployment is high due to lack of demand, then more expansionary policies can be expected to bring it down. But what speaks against this hypothesis is the joint coincidence of high unemployment and vacancies. This has let some economists to argue that declining match efficiency, rather than demand deficiencies, is behind the high level of unemployment (Hall and Schulhofer-wohl, 2015; Sveriges Riksbank, 2012).

My findings provides a new perspective on this discussion. Using my alternative measure of job-openings the Swedish labor market appears less tight after the Great Recession. Moreover, the outward shift in the Beveridge is less pronounced. The reason is that the rebound in vacancies after the Great Recession was driven by smaller plants, where the vacancy yield is smaller. Consequently, after the Great Recession the traditional vacancy measure may have made the labor market look to tight and the outward shift in the Beveridge curve appear too large. *Ceteris paribus* this reduces the support of the hypothesis that the higher level of unemployment in Sweden is caused by a decline in matching efficiency.

Finally, I also provide some new evidence on the relationship between two often used empirical measures of job-openings: (i) survey data compiled by statistical agencies and (ii) register data on vacancies registered in databases maintained by public job-centers. The former type is often prefered, as this avoids the selection problems that can be present in the register data. However, due to limited availability of a survey based measure data from public job-centers are still often used as proxy, (Berman, 1997; Carlsson et al., 2013; Albaeck and Hansen, 2004; Wall and Zoega, 2002; Yashiv, 2000). Hence, an interesting question, which has not been investigated so far, is how the two vacancy measures relate on the plant level. I show that the relationship between openings registered at the Swedish

Public Employment Service (PES) and vacancies reported in the survey is weak on the firm level. Not surprisingly 47 % percent of the vacancies reported in the survey do not have a counterpart in the PES. More surprisingly is, however, that 37 % of all vacancies reported in the PES do not have a counterpart in the survey. Across firms there is also substantial heterogeneity in the use of PES opening, with the public sector and firm in the middle of the turnover and valueadded distribution having the largest share of PES to survey openings. During 2004-2012 the aggregate share of PES openings to survey openings in the sample varies in the interval 28-47 %.

Related literature

My study relates to at least three strands of literature.

First, a vast literature estimates matching function using the aggregate number of vacancies, unemployment and job-finding rates (Blanchard and Diamond, 1990; Berman, 1997; Yashiv, 2000; Albaeck and Hansen, 2004; Sunde, 2007; Gross, 1997; Entorf, 1998; Feve and Langot, 1996).[1]. My paper adds to this literature by discussing the micro-level properties of the vacancy data that goes into the estimation.

Second, a strand of literature discusses the duration of vacancies on the firm level, and how this duration is determined (Ours and Ridder, 1991; Burdett and Cunningham, 1998; Barron et al., 1997; Holzer, 1990). Here vacancies are studied on the micro level, but in isolation. My paper adds to this literature by investigating by investigating the link between vacancies and hiring on the micro-level.

Third, and closest in spirit, is the paper by Davis et al. (2013). They analyze the relationship between hires and a survey based measure of vacancies (JOLTS) on the plant level in the US. The document how hires per vacancy, the *vacancy yield*, behaves in the cross- and time-section. Moreover, they construct a *recruitment intensity*, and show how variations in this partly explains in the recent breakdown of the matching function. My paper takes a different approach. Instead of introducing a recruitment intensity measure that is varied to vary over time, I construct an alternative measure of job-openings which builds both on vacancies and plant-characteristics. As I will argue below, this measure has the advantages of (i) predicting hires better on the plant-level and (ii) yielding a better fitting aggregate matching function. In addition, my paper also makes a contribution by documenting the relationship between survey and register based vacancy measures on the firm level.

Fourth, my paper relates to the recent debate on the Beveridge curve movements. As documented by Hobijn and Sahin (2012) the Beveridge curve has shifted outwards in a number of OECD countries in the aftermath of the Great Recession. A number

[1]An overview of the literature is available in Pissarides (2000)

of, non-mutually excluding, hypothesizes have been put forward to explain this apparent puzzle. Hall and Schulhofer-wohl (2015) have argued that declining matching efficiency in the pre-crisis period is behind the outward shift in the Beveridge in the United States. Sveriges Riksbank (2012) has argued that a similar mechanism has been operating in Sweden. Another hypothesis has been put forward by Kroft et al. (2016). They argue that (i) duration dependent transition rates between employment, non-employment and non-participation can account for much of the outward shift in the Beveridge curve in the United States. Finally, Davis et al. (2013) have argued that variation in firms' recruitment intensity can explain parts of the outward shift. I add to this literature by arguing that mis-measurement of job-openings can explain much of the outward shift in the case of Sweden.

Organization

The paper proceeds as follows. In section 2, I describe the data sources and how the database is constructed. In section 3, I document the relationship between vacancies and hires on the plant level. However, to analyze this relationship properly one has to take the issue of time-aggregation into account. I do this in section 4, and show that this does not overturn the basic findings. In Section 5, I build on my findings from the previous two sections and propose a new measure of aggregate job-openings in the economy. In Section 6, I document the relationship between the survey and register based measure of vacancies on the firm level. Section 7 concludes.

2 Data

Job vacancies

For micro-data on job-vacancies I draw on two data sources: the Swedish Job Vacancy Survey and the database from the Swedish Public Employment Service (PES).

The Swedish Job Vacancy Survey is administered by Statistics Sweden and has been collected on a quarterly basis since 2001. In the survey a vacancy is defined as "a position which has been made available for external job-seekers via the newspapers, internet or another media". The survey further contains information on how many of the open positions that are currently manned and unmanned, respectively, and how many of the positions that are available immediately. The respondents are asked to report the number of vacancies medio of the reference month.[2] For the private sector the sampling is done on the establishment level with approx. 16 700 work places sampled each period.

[2]Specifically, the respondents are asked to report the number of job openings on the Wednesday closest to the 15th of the reference month.

For the public sector the sampling was also done on the work places level until 2006Q2. In 2006Q2 the sampling was changed to the organizational level and on this level 650 organizations are sampled each period. Units larger than 100 employees are asked to do the reporting for each month of the relevant quarter, whereas units with less than 100 employees only are asked to report in the reference month. Reporting takes place either via letter or online. Non-respondents are reminded via email, letter or a phone call. Until 2004 reporting was voluntary and the share of non-reporting units was 20 % (40 %) in the private (public) sector. In 2004 reporting became mandatory and currently the share of non-reporting units is 11 % in the private sector and 2 % in the public sector.

The database for vacancies administered by the Swedish Public Employment Service (PES) is the other source for job-openings. The PES maintains a database containing the universe of job-postings made at the agency since 2001. Specifically, the database contains a row for each posting made at the agency with information on the start and end date of the posting along with information on the number of workers the firm is searching for and information on job and firm type. In principle the database contains data on both the firm and plant level. However, for the majority of the observations plant identifiers are missing, why the database in practice only contains useful information on the firm level. To make the PES data comparable with the survey data, I compute the number of open positions at the PES medio each month.

The aggregate number for the two types of job openings is reported in Figure 2. As expected the the level of vacancies in the survey are consistently above the level of vacancies reported at the PES, and the share of PES to survey vacancies varies in the range 30-50 %.

Hires

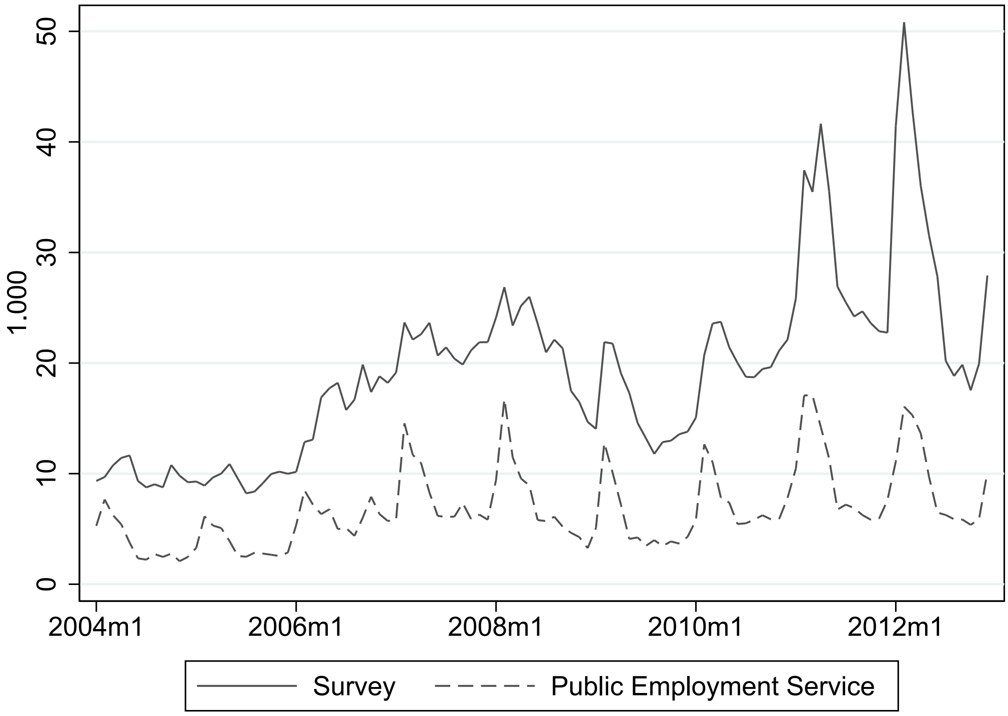
For hires I also have access to two data sources: a survey based measure from Statistics Sweden and a register based measure from the Swedish tax registry.

The survey based measure of hires stems from the *Short-term employment statistics* (Kortperiodisk sysselsätningsstatistik) as compiled by Statistics Sweden. This data is collected in combination with the job vacancy survey described above, and thus contains the same sample of plants and firms. This survey contains the number new hires as well as the number of workers currently employed at each plant.

The second measure for hires is register based and stems from the Swedish tax authorities. Specifically, IFAU[3] maintains a database containing the start and end month of all employment spells as reported to the Swedish tax authorities. Along with the spell length the database contains an identifier for person, firm and establishment. From this

[3]Institute for Evaluation of Labour Market and Education Policy

Figure 1: Monthly job openings in Sweden, 2004-2012



Notes: The figure shows the aggregate number of job openings in the survey and PES, respectively. The sample of firms is restricted to the firms sampled in the survey.
Source: The Swedish Public Employment Service and Statistics Sweden.

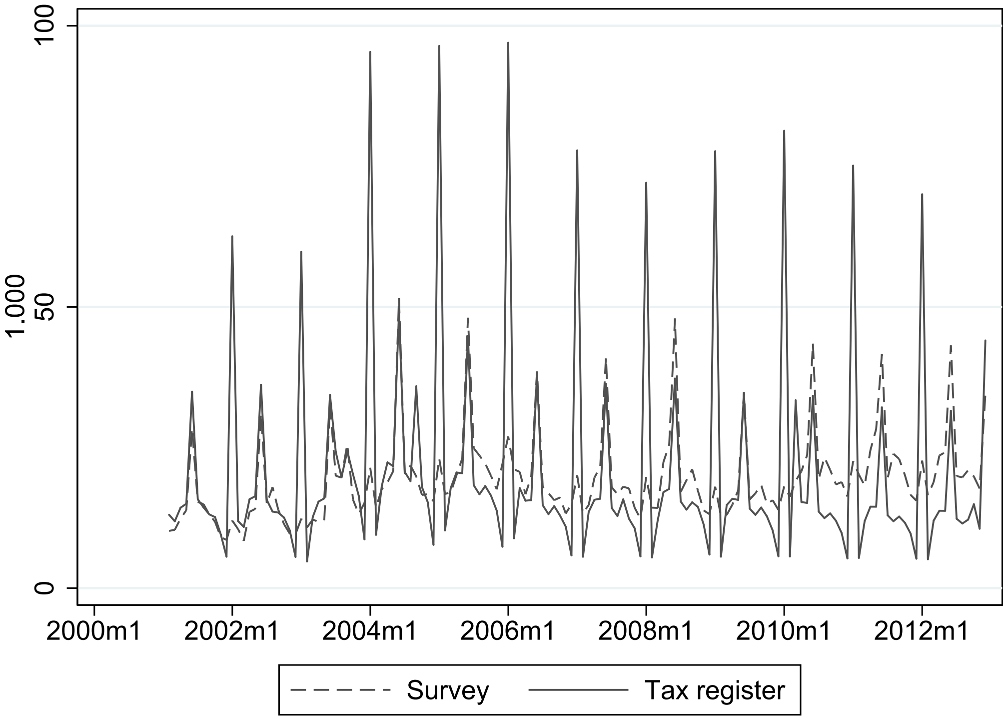
data I compute the number of monthly hires as the number of spells that starts in an establishment in a given month. To discard repeated, or interrupted, spells I remove all spells where the individual has been employed in the last 12 months. Moreover, I restrict the sample to the establishments also available in survey based measure of hires in the given month.

In most months the register and survey based measure of hires are closely related (Figure 2). However, the general exception is January, where the register based measure always exceeds that of the survey based. This is likely to be caused by mis-measurement in the former, as establishments reports spells as lasting for entire years instead of the correct duration in months.

Plant and firm background variables

From the *Short-term employment statistics* survey and the Swedish Firm Register (both administered by Statistics Sweden) I furthermore have access to background information on each plant and firm in the survey. In particular, this background information contains information on the number of employees and industry of each plant, while turnover and value-added is availiable on the firm level is from the firm register. A summary of these

Figure 2: Monthly hires in Sweden, 2001-2012



Notes: The figure shows the aggregate number of hires in the survey and tax data, respectively. The sample of firms is restricted to the firms sampled in the survey.
Source: IFAU and Statistics Sweden.

variables is presented in Table 7 in the appendix.

Data selection

Below I will work with two different selections of the data above.

In section 3, I relate the number of vacancies to the number of subsequent hires on the plant level. Here I use the data from the vacancy survey, and augment with hires in the next month from the tax register data. To ensure data quality of the hiring data, I cross-check the tax register data with the survey-based measure of hires in the *Short-Term Employment Statistics*. In particular, I restrict the sample to plants where the number of hires in the tax-register and survey data is the same for the month of vacancy measurement.[4]

In section 6, I relate the number of vacancies in the survey with the PES. This is straightforward for the public sector after 2006Q2, as collection of both measures is done on the firm level. However, for the private sector and the public sector before 2006Q2 the comparison is challenged by the fact that the survey data only is available on the

[4]I don't impose this restriction in the subsequent month, in which the relevant measurement of hiring is made, as the survey-data for hiring only is available in the same month as vacancies are measured.

plant level, while the latter only is available on the firm level. I address this problem by restricting the dataset to the sub-sample where only one plant per firm exists.

3 Plant-level relationship between vacancies and hires

Descriptive statistics

Table 1 presents the hiring rate, the vacancy rate and the vacancy yield in the cross-section of plants. The hiring and vacancy rate is expressed as the number of hires and vacancies per employee, while the vacancy yield is the number of hires per vacancy. Across industries the vacancy yield is lowest in construction with a yield of 1.37 hires per vacancies, while it is highest in the manufacturing sector with a rate of 3.43. Across plant size, as measured by number of employees, larger firms hire more workers per vacancies. Indeed, while the plants in the decile with fewest employees, measured in number of employees, only hire 0.3 workers per vacancy, the plants in the decile with most employees hire 4.02 workers per vacancy. Across turnover, measured on the firm level, a similar pattern is seen: plants in firms with larger turnover have a larger vacancy yield.

TBD: Why is yield not just hires/vacancies? TBD: Do Table 1 with PES vacancies

There are a number of potential explanations behind the observed heterogeneity in vacancy yields. First, plants may rely on other recruitment channels than vacancies such as uninvited applications or informal social networks. In case the reliance on such alternative recruitment varies across plant characteristics this may give rise to the pattern observed in Table 1. For example Cahuc and Fontaine (2009) construct a model where the probability of matching a job is increasing in the size of the social network. To the extent that larger plants have larger networks this can potentially explain why the vacancy yield is increasing plant size. Second, plants may rely on one vacancy to report more than one worker. If a plant is attempting to hire homogenous workers, it may only report one vacancy in spite on an intention to hire more than one worker. Such a behavior would predict a higher vacancy yield in industries with more homogeneity in the required skill set of workers.

Next, I show how number of hires varies with vacancies in the cross section of plants. Figure 3 depicts the raw relationship between vacancies and hires in the following month on the plant level. Here each dot on the y-axis represents the average number of hires for the number of vacancies represented on the x-axis. This relationship appears concave, rather than linear, which suggests that an additional vacancy predicts less and less hiring. TBD: In Figure 10 in the Appendix, I depict the similar relationship but for each year. For most years the concave relationship is still seen.

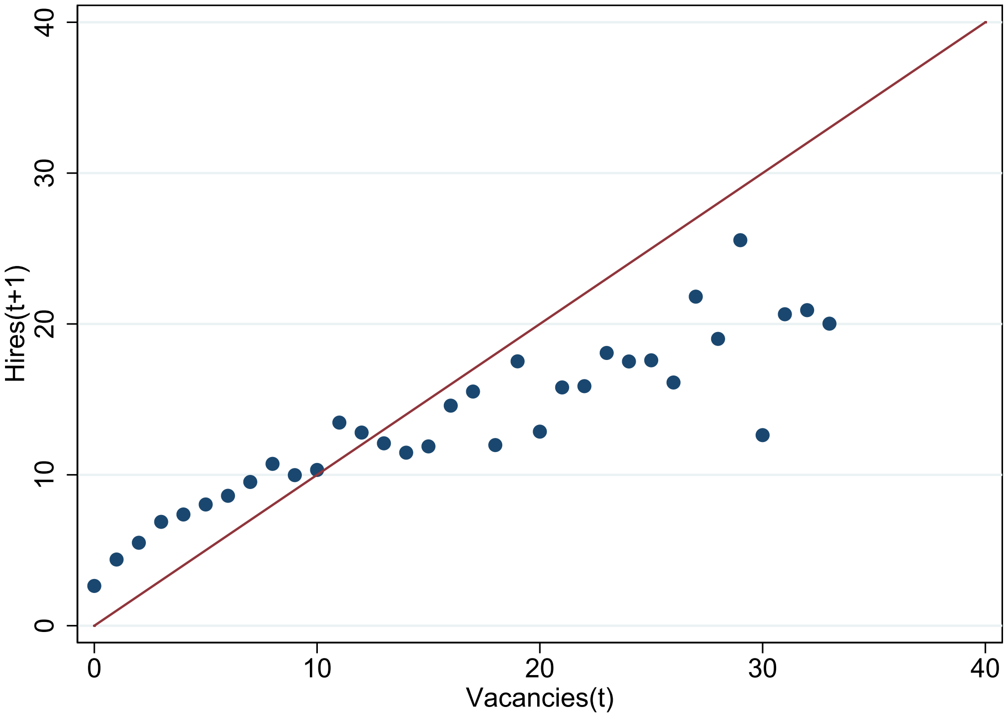
Table 1: Hiring rate, vacancy rate and vacancy yield across industries, plant size and firm turnover, 2001-2010

	Hiring rate (%)	**Vacancy rate** (%)	**Vacancy yield** (#)
	By industry		
Farming	10.26	1.96	1.97
Manufactoring	3.61	0.87	3.43
Energy	3.91	1.14	1.73
Construction	4.71	1.40	1.37
Trade, hotel and restaurants	7.07	1.38	2.80
Transportation, mail and telecom	4.05	1.14	2.24
Finance and business service	6.45	1.72	2.04
Public and personal services	9.72	1.75	2.89
Total	6.22	1.42	2.31
	By number of employees (deciles)		
1	12.64	2.41	0.30
2	6.69	1.64	0.34
3	5.16	1.51	0.52
4	4.27	1.34	0.73
5	4.09	1.25	1.07
6	3.35	1.07	1.40
7	2.67	1.01	1.64
8	2.44	0.97	2.05
9	2.29	0.89	2.62
10	1.93	0.66	4.02
Total	4.55	1.27	1.47
	By turnover (deciles)		
1	6.17	1.55	1.90
2	7.40	1.87	0.33
3	5.96	1.63	0.53
4	4.80	1.41	0.79
5	4.24	1.21	1.41
6	2.98	1.06	1.75
7	2.90	0.98	1.87
8	2.58	1.02	2.25
9	2.58	0.86	2.67
10	2.96	0.90	3.03
Total	4.26	1.25	1.65

Notes: The hiring rate is the fraction of hires to the plant size. The vacancy rate is the average fraction of vacancies to plant size. The vacancy yield is the average fraction of vacancies to plant size. Public sector has been dropped in tabulation by turnover.

Source: Own calculation from Statistics Sweden

Figure 3: Relationship between number of vacancies and hires, 2001-2012

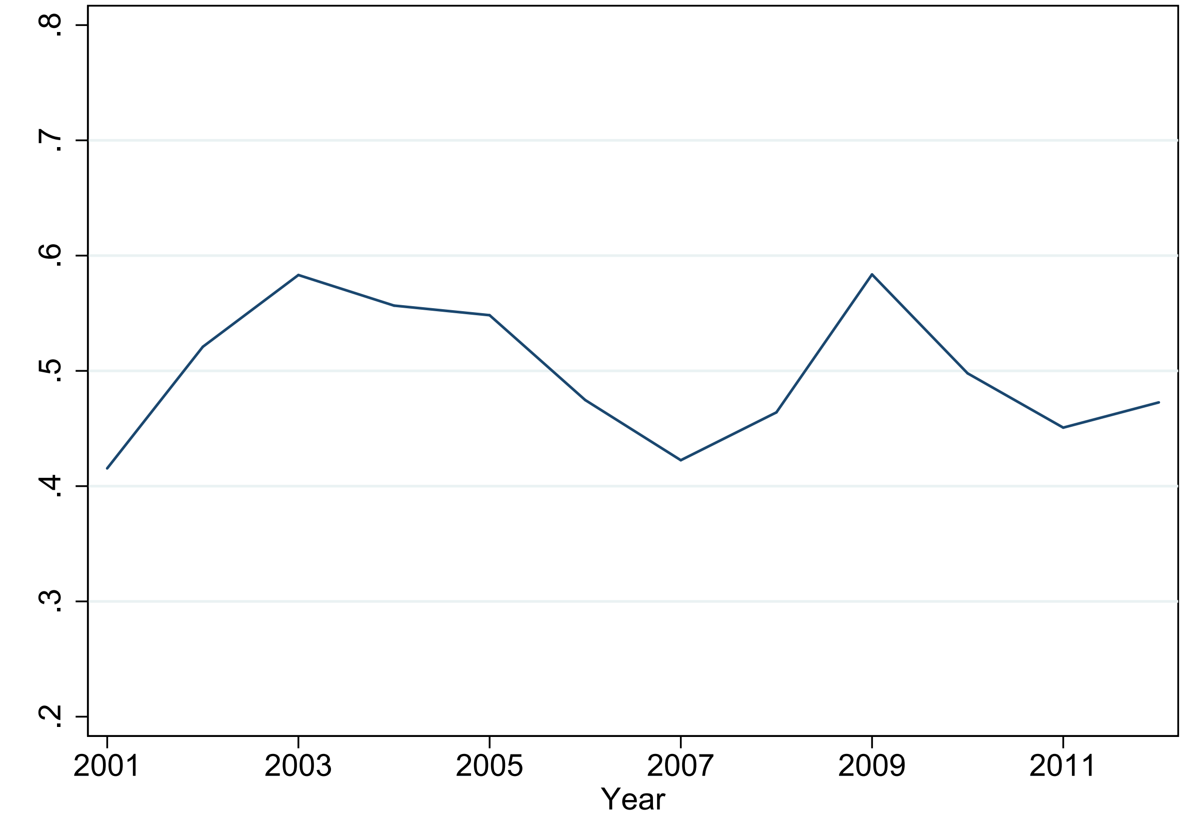


Notes: The figure shows the average number of hires (y-axis) for each number of vacancies in the previous month (x-axis). TBD: Insert standard deviations.
Source: Own calculation on data from Statistics Sweden.

In addition many hires happen in plants with did not report any vacancies. Figure 4 shows the share of all hires that are made in plants that did not report any vacancies in the preceding month. This share varies in the interval 40 % - 50 %, and falls to 30 % - 40 % if counting the share of hires that are made without any vacancies in the two preceding months (TBD: Add figure). Some of these hires can be accounted by hiring out of other channels than vacancies, but some might also be explained by time-aggregation issues. Indeed, since we only observe the stock of vacancies at a given point in time hiring may happen out of newly created vacancies that do not enter into the dataset. I will address this issue in Section 4.

These initial descriptive statistics hint at (1) the distribution of vacancies play an important role and (2) our vacancy may not capture all job-openings in the economy. Usually, we look at the sum of all vacancies to gauge the number of job-openings in the economy. However, the descriptive statistics reported above suggests that this is potentially misleading. Indeed, if the observed variation the vacancy yield is caused by variation in the underlying number of actual job-openings, then we need to account for the distribution when using vacancies as a measure of job-openings in the economy. Moreover, the large share of hiring in plants without preceding vacancies suggests that vacancies may

Figure 4: Share of all hires without vacancies in the preceding month, 2001-2012



Source: Own calculation on data from Statistics Sweden.

be an incomplete measure of job-openings.

Estimating a hiring equation on the plant level

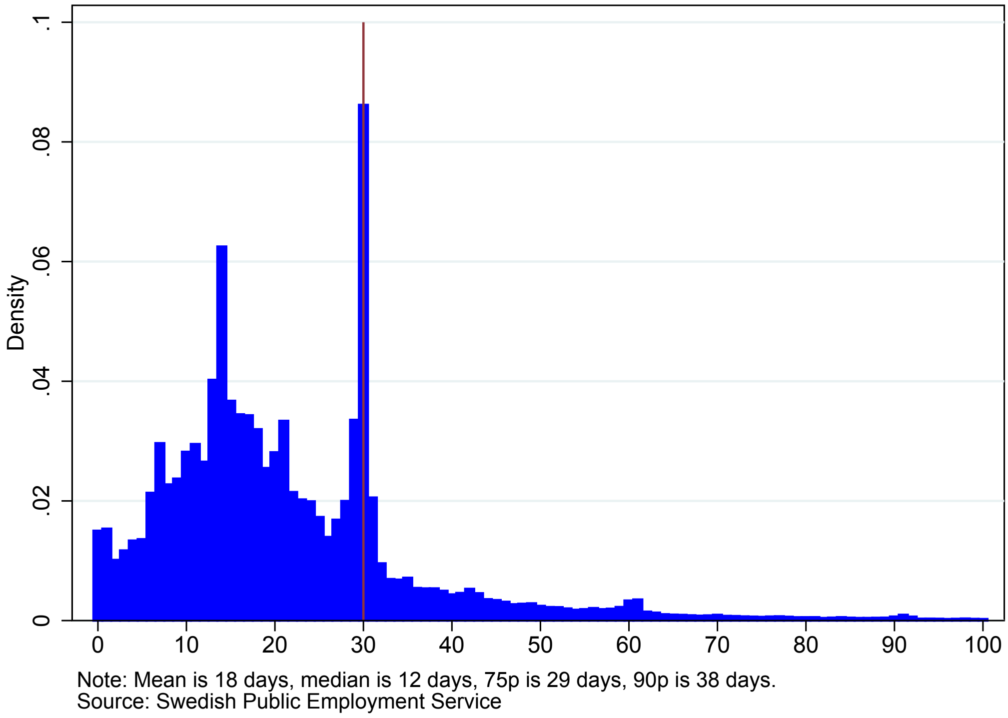
I now turn to the estimation of the relationship between vacancies and hires on the plant level. In the standard search and matching model[5] aggregate hiring is determined via the matching of unemployed workers (U) and job-openings (V) via an aggregate matching function with constant returns to scale $M(U, V)$. Assuming plant homogeneity, the number of hires in plant j at time t will then be a function of (1) tightness on the aggregate labor market and (2) number of job-openings posted by plant j.

$$H(t, j) = \underbrace{\frac{M(U(t-1), V(t-1))}{V(t-1)}}_{(1)} \underbrace{V(t-1, j)}_{(2)} \tag{1}$$

Two predictions follow from this equation. First, a plant's number of hires , $H(t, j)$, should be linear in the number of job-openings posted by the plant, $V(t-1, j)$. The coefficient

[5] As presented *e.g.* in Pissarides (2000)

Figure 5: Duration of vacancies at the Public Employment Service, 2001-2012



Notes: The figure shows the histogram of the interval between start and end date of all vacancies registered at the Public Employment Service during the period 2001-2013.
Source: The Swedish Public Employment Service.

on job-openings is inversely related to labor market tightness[6], such that a tighter labor market predicts fewer hires per job-opening. Second, we should only see hiring in plants with a positive number of job-openings. As explained above these predictions appear to be at odds with the data. Below, I will address these problems in turn.

When estimating 1 one has to take a stance on the appropriate interval between vacancy and relevant hire. To guide this choice, I rely on information on the duration of vacancies posted at the Public Employment Service (Figure 5). The average duration of vacancies posted here is 18 days, and 85 % of all durations are less than a month. Informed by these findings, I set the interval between vacancy and hire to month. I will however vary this interval to check robustness.

To estimate (1) in a flexible manner, I will estimate the following equation using the plant-level data.

$$H(t, j) = \alpha(t-1)V(t-1, j)^{\gamma} \tag{2}$$

Here $\alpha(t-1)$ is a time fixed effect, which captures the aggregate conditions (1) in equation

[6]The definition of labor market tightness is often cause of confusion. Here I follow conventions and define labor market tightness as *number of job-openings per unemployed worker.*

(1). γ is an exponent on plant-level vacancies, which allows for the possibility of a non-linear relationship between hires and vacancies. Insofar, that the relationship is linear we should estimate γ to be equal to one.

Estimating (2) involves a choice of estimation strategy. One option is to estimate (2) in logs using ordinary least squares. This, however, comes at the cost of loosing all observations with zero hires and/or vacancies. Another option is to estimate (2) in levels using non-linear least squares. This allows for the inclusion of all observations in the regression. However, one should note that the model in any case restricts hires to be zero when vacancies are zero. Below I report the results from both estimation methods.

The estimation results are reported in the first column of Table 2 and 3. In both estimations the exponent on vacancies is far below unity, which speaks against a linear relationship between vacancies and hires. Notice that the fit of the model estimated via ordinary least squares is substantially better than that estimated via non-linear least squares, which is witnessed by the much lower Adjusted R^2 in Table 3 *vis-a-vis* Table 2. This is explained by the fact that the Non-Linear Least Square estimator includes all observations with zero hires or vacancies, while these observations are excluded in the Ordinary Least Square estimator. Given the functional form of 2 this is bound to decrease the fit of the model. Also notice that most of the explanatory power in both estimations stems from the time-fixed effect. Indeed, in the estimation using ordinary least squares the adjusted R^2 falls from 0.27 to TBD, when removing the time-fixed effects. Similarly, In the non-linear least square the adjusted R^2 falls from 0.03 to TBD.

TBD: Para on measurement error.

Table 2: Plant level hiring regression, Ordinary Least Squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires(t+1)	Hires(t+1)	Hires(t+1)	Hires(t+1)	Hires(t+1)
Vacancies(t)	0.27***	0.05***	0.05***	0.00	0.00
	(0.011)	(0.011)	(0.011)	(0.01)	(0.01)
Plant size (t)		0.41***	0.40***	0.49***	0.50***
		(0.011)	(0.011)	(0.011)	(0.02)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Value-added dummies	No	No	No	Yes	Yes
Turnover dummies	No	No	No	No	Yes
Observations	123819	123788	123788	79097	79097
Adjusted R^2	0.28	0.41	0.41	0.37	0.37
AIC	360422	335545	334656	205583	205425

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are clustered on the firm level.

Table 3: Plant level hiring regression, Non-Linear Least Squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires(t+1)	Hires(t+1)	Hires(t+1)	Hires(t+1)	Hires(t+1)
Vacancies(t)	0.49***	0.04***	0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Plant size (t)		0.66***	0.68***	0.91***	0.91***
		(0.01)	(0.01)	(0.01)	(0.01)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Value-added dummies	No	No	No	Yes	Yes
Turnover dummies	No	No	No	No	Yes
Observations	693451	693451	693451	482784	482784
Adjusted R^2	0.03	0.05	0.05	0.08	0.03
AIC	6036235	6022939	6022387	3686250	3708815

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Can measure of job-openings be improved?

The findings above show that the relationship between vacancies and hires on the plant level is weak and non-linear. Moreover, the descriptive statistics pointed to the distribution being important for the job-content of the sum of observed vacancies. Specifically, the number of hires per vacancy was increasing in the plant size. A natural next question is thus, whether it is possible to construct an alternative measure of job-openings, which is able to better predict hiring on the plant level.

To investigate this, I will allow job-openings to be a function of not only vacancies, but also of plant size as well as other plant and firm level characteristics. Specifically, I will estimate the following relationship.

$$H(j,t) = \frac{M\left[U(t-1), V(t-1)\right]}{V(t-1)} F\left[V(j,t-1), \mathbf{x}(t-1)\right] \tag{3}$$

$$F\left[V(j,t-1), \mathbf{x}(t-1)\right] = V(j,t-1)^{\gamma_1} \times S(j,t-1)^{\gamma_2} \times T(j,t-1)^{\gamma_3} \times Va(j,t-1)^{\gamma_4}$$

This relationship between hires and job-openings is an augmented version of that in equation (1). Whereas job-openings in equation (1) were translated into posted vacancies, job-openings in (3) it is here allowed to be However, here I allow job-openings to be a function of not only reported vacancies, but also firm and plant characteristics. Specifically, in equation (3) job-openings is denoted $F\left[V(j,t-1), \mathbf{x}(t-1)\right]$, and is a function of posted vacancies $V(j,t)$, plant size S_{jt}, firm turnover T_{jt} and firm value-added Va_{jt}. Aggregate labor market conditions are again captured in the term $\frac{M[U(t-1),V(t-1)]}{V(t-1)}$ and will be modelled as a time-fixed effect in the regressions.

Equation (3) is estimated using ordinary least squares as well as non-linear least squares in Table 2 and 3. TBD: In column (2)-(4) of Table 2 and 3, I gradually allow job-openings to be a function of firm and plant level characteristics in addition to vacancies. Two results stand out from this exercise. First, the ability to predict hiring on the plant level is substantially improved when allowing job-openings to depend also on plant and firm characteristics. This is witnessed by the increase in the adjusted R^2. Second, including these additional plant and firm variables decrease the exponent on vacancies towards 0. These two results are especially driven by plant size. Indeed, most of the increase in the fit, and decrease in the exponent on vacancies, comes from the inclusion of plant size in the regression. Relatively little additional fit is achieved from including the other firm and plant level variables.

One might be concerned that these results are driven by data selection, rather than explanatory power from the firm and plant level characteristics. Indeed, the number of observations drop as more variables are included Table 2 and 3. Hence, one concern is that the better fit is not driven by the inclusion of plant and firm characteristics, but instead the drop in number of observations. TBD: To ensure this is not the case, in Table X I restrict attention to the subset of data where all variables are available. We see that this does not alter my results.

The results in this section suggest that we can improve our measure of job-openings by taking plant characteristics as well as vacancies into account. Indeed, as we have seen above allowing job-openings to be a function of vacancies and plant size substantially improves our ability to predict hiring on the plant level. Specifically, the regressions showed that a measure of job-openings, which combines posted vacancies and plant size in the following manner form

$$F(V_{jt}, size_{jt}) = V_{jt}^{a} size_{jt}^{b} \tag{4}$$

outperformed the traditional vacancy in its ability to predict hiring on the plant level. In (4) a is effectively zero and b is between 0.4 and 0.5, is a superior measure of firms j's willingness to hire *vis-a-vis* V. That a is effectively zero means that V_{jt}^{a} effectively takes the form of a 0/1 variable, which is 0 when the plant reports 0 vacancies and 1 as soon as the plant reports a positive number of vacancies. This binary variable is then multiplied with $size_{jt}^{b}$, which is a concave function of plant size.

Thus, the takeaway from the regressions in this section is that we should be concerned about three questions when wanting to predict to predict hiring in a given plant: (1) what are the aggregate conditions on the labor market[7], (2) whether or not the plant has any vacancies and (3) the size of the plant.

4 Dealing with time-aggregation

An issue I have alluded to, but not dealt with so far, is that of time-aggregation. In section 3, I associated hiring in period t with the number of vacancies posted in the middle of period $t-1$. This approach could be problematic for two reasons. First, a vacancy posted medio month $t-1$ might be filled before the beginning of month t. Second, a hire made in period t might be associated with a vacancy which was created after vacancies were counted medio month $t-1$.

To address this problem of time-aggregation, I take the approach developed by Davis et al. (2013). They set up a simple model, which captures the daily dynamics of vacancies and hires. Using a calibrated version of this model it is possible to compute (1) the number of vacancies in the end of month $t-1$, and (2) the number of hires in month t associated with newly created vacancies in period t.

Specifically, Davis et al. (2013) model the daily dynamics of of hires and vacancies using the following system of equations.

$$h_{s,t} = f_t v_{s-1,t} \tag{5}$$

$$v_{s,t} = (1-f_t)(1-\delta_t)v_{s-1,t} + \theta_t \tag{6}$$

here $h_{s,t}$ is the number of hires at day s in month t, $v_{s,t}$ is the number of vacancies at day s in month t, f_t is the daily job-filling rate, δ_t is the daily and θ_t is the inflow of new

[7]As captured in the term $M(U(t), V(t))/V(t)$, which in the regressions is modelled as a time fixed effect.

vacancies each day. Both f_t, δ_t and θ_t are assumed to be constant throughout each month. Equation (5) is thus telling us that the number of hires at day s in month t is equal to the number of vacancies yesterday multiplied by the vacancy filling rate. Likewise, equation (6) tells us that the number of vacancies at day s in month t is equal to the number of vacancies from yesterday, which were not filling nor depleted, plus the inflow of new vacancies.

Solving (5) and (6) forward yields an expression for stock of vacancies and the flow of hires in month t.

$$v_t = (1 - f_t - \delta_t + \delta_t f_t)\, v_{t-1} + \theta_t \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta f_t)^{s-1} \tag{7}$$

$$h_t = f_t v_{t-1} \sum_{s=1}^{\tau} (1 - f_t - \delta_t + \delta_t f_t)^{s-1} + f_t \theta_t \sum_{s=1}^{\tau} (\tau - s)\,(1 - f_t - \delta_t + \delta_t f_t)^{s-1} \tag{8}$$

where τ is the number of days per months. The first expression on the righthand side of equation (7) denotes the number of vacancies from month $t-1$ that carried over to month t. The second expression captures the remainder from the flow of newly created vacancies. Likewise, the first righthand side expression in equation (8) denotes hires out of vacancies posted in period $t-1$, while the second expression denotes hires out of newly created vacancies.

The task is now to solve the equation system, (7)-(8), numerically for $\{f_t, \theta_t\}$. This is possible given τ and time-series for the triplet of variables $\{\delta_t, h_t, v_t\}$. h_t and v_t are available from the data and I set $\tau = 22$ (working days per month). δ_t is less obvious how to compute, but I follow Davis et al. (2013) and set $\tau\delta_t$ equal to monthly job-destruction rate.[8] However, as robustness I vary $\tau\delta_t$ in the interval $[0, 10\%]$. This impacts very little on the calibrated values for f_t and θ_t.

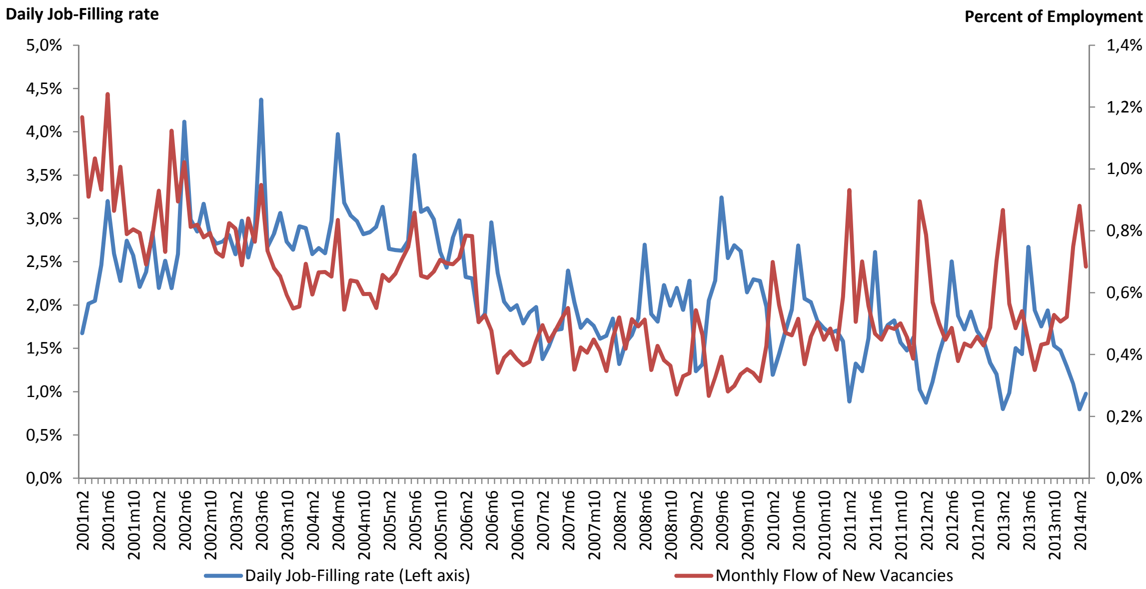
Given τ and time series for the triplet $\{\delta_t, h_t, v_t\}$ one can solve this equation system numerically the time series for $\{f_t, \theta_t\}$. h_t and v_t is available from the data and I set $\tau = 26$ (working days per month). δ_t is less obvious how to compute, but as of now I follow Davis et al. (2013) and $\tau\delta_t$ equal to monthly job-destruction rate.[9] TBD: However, as robustness I vary $\tau\delta_t$ in the interval $[0, 10\%]$ and show that this impacts very little on the calibrated values for f_t and θ_t.

Figure 6 shows the calibrated time-series for f_t and θ_t. The calibrated monthly inflow of new vacancies is 0.6% of the labor force on average and varies in the interval $0.2-0.8\%$. The daily fill-rate of vacancies has an average of 2.5%, which corresponds to an average

[8]Specifically, I set $\tau\delta_t$ equal to the monthly probability of not staying in a regular contract. This data is available the Swedish labor market survey.

[9]Specifically, I set $\tau\delta_t$ equal to the monthly probability of not staying in a regular contract. This data is available the Swedish labor market survey.

Figure 6: Daily Job-Filling Rates and Flow of New Vacancies, 2001-2012



Source: Own calculations on data from Statistics Sweden.

duration of 40days, and varies in the interval $1 - 3.5\%$.

Using the calibrated model I now address the problem of time-aggregation. First, I use the calibrated job-filling and vacancy creation rates to compute the predicted number of vacancies at each plant in the end of each month.

$$v_{t,ultimo} = (1 - f_t - \delta_t + \delta_t f_t)^{\tau/2} v_{t,medio} + \theta_t \sum_{s=1}^{\tau/2} (1 - f_t - \delta_t f_t)^{s-1} \quad (9)$$

Second, I compute hires in each month corrected for the number of hires that are predicted to be associated with newly created vacancies.

$$h_{t,corr} = h_t - f_t \theta_t \sum_{s=1}^{\tau} (\tau - s) (1 - f_t - \delta_t + \delta_t f_t)^{s-1} \quad (10)$$

To compute $v_{t,ultimo}$ and $h_{t,corr}$ in (9) and (10) I use values for f_t and θ_t calibrated on the industry level. I let f_t be identical across all plants in a given industry, while I compute a plant specific value of θ_t by weighting the value computed on the industry level with the plant's share of employment in the given industry.

Having computed $v_{t,ultimo}$ and $h_{t,corr}$ I can now redo the analysis from Section 3. In Table 8, I re-estimate the relationship between hiring and vacancies while gradually increasing the number of plant- and firm-level characteristics. The pattern remains unchanged: (1) The relationship between hires and vacancies is concave, not linear, (2) the exponent on vacancies goes towards zero as I increase the number of plant- and firm-level

Table 4: Plant level hiring regression, corrected for time-aggregation, Ordinary Least Squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)
Vacancies (t)	0.23***	-0.00	0.01	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Plant size (t)		0.33***	0.30***	0.36***	0.37***
		(0.01)	(0.01)	(0.02)	(0.02)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Value-added dummies	No	No	No	Yes	Yes
Turnover dummies	No	No	No	No	Yes
Observations	307872	307841	307841	211773	211773
Adjusted R^2	0.25	0.28	0.29	0.25	0.25

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Hires: hiring in month $t + 1$ corrected for hires associated with newly created vacancies. Vacancies: Vacancies computed at the end of month t.

characteristics and (3) the fit of regression is improved by allowing job-openings to be a function of plant-size as well as of posted vacancies.

TBD: Insert this table as NLS

Additional robustness checks

In addition, I conduct two other robustness checks in the Appendix.

First, in spite of the evidence presented above, one might question the choice of relating vacancies in one month to hires in the next month only. To address the sensitivity of my analysis with respect to this choice, I redo the analysis in Table 2 and 3 while relating the number of vacancies in a given month the the *average number of hires over the next months*. This analysis is presented in Table TBD in the Appendix, and does not overturn the results from Table 2 and 3.

Second, a shortcoming of my dataset is the lack of a panel structure for vacancies. This makes it impossible to aggregate both vacancies and hires to the annual level, and then relate the yearly number of hiring to the yearly number of vacancies. However, for some plants I more than one observation per year. As a robustness check I therefore restrict my sample to plants, where I have at least three observations per year. Using this sample I relate the average number of hires per year to the average number of vacancies per year. The results from the exercise is also presented in Table TBD in the Appendix, and do also not overturn the results from Table 2 and 3.

5 Aggregate implications

The findings above have potential important implications for how we should measure job-openings on the aggregate level. Indeed, my findings on the plant level suggest that an indicator variable for whether or not a plant has any vacancies multiplied by a concave function of plant size is a superior measure of job-openings *vis-a-vis* the number of vacancies posted by the relevant plant. Taken to the aggregate level this suggests that the number of plants with a positive number of vacancies, weighted by a function of their respective sizes, provides a better measure of job-openings in the economy than the sum of all vacancies.

To test this hypothesis, I rely on estimated matching function using aggregate data. Specifically, I follow the search-matching literature and assume that the aggregate matching function takes the following form.

$$M(U(t), V(t)) = AU(t)^{\alpha} V(t)^{1-\alpha} \tag{11}$$

Consequently, the job-finding rate can be written as

$$\frac{M(U(t), V(t))}{U(t)} = AU(t)^{\alpha-1} V(t)^{1-\alpha} \tag{12}$$

which in log terms takes the following form

$$\log\left(\frac{M(U(t), V(t))}{U(t)}\right) = \log(A) + (1-\alpha)\log\left(\frac{V(t)}{U(t)}\right) \tag{13}$$

In Table 5 I report the estimated matching function (13) using both the standard vacancy measure and my alternative measure for job-openings. The matching function is estimated on Swedish data during the period 2001Q1-2012Q4. Across the columns I vary my measure of job-openings. In column 1, I use the traditional measure from the vacancy survey. In column 2, I instead use the number of plants with a positive number of vacancies. And in column 3, I use the number of plants with a positive number of vacancies weighted by their size.

Interestingly, the alternative measures of job-openings perform better than the traditional vacancy measure. Indeed, compared to the traditional measure of vacancies (column 1) the fit of the matching function is improved by 13 % when using the number of plants with a positive number of vacancies (column 2), and 30 % when using the number of plants with a positive number of vacancies weighted by size (column 3). Although the fit of the matching function is improved when using the alternative measure of job-openings, the three models still yield roughly similar coefficients. Thus, both the micro and macro level evidence points to the alternative measure of job-openings being superior to the traditional vacancy measure.

TBD: Change labeling and notes

These findings have potentially important implications for how we should think about

Table 5: Regression table

	(1) log(jfr)	(2) log(jfr)	(3) log(jfr)
log(v/u)	0.39**		
	(0.07)		
log(plants/u)		0.41**	
		(0.09)	
log(plants, weighted/u)			0.46**
			(0.08)
Observations	48	48	48
R^2	0.15	0.17	0.21

Standardized beta coefficients; Standard errors in parentheses
* $p < 0.05$, $^{**}p < 0.01$, *** $p < 0.001$

the recent developments on the labor market. Figure TBD shows the time-serie for tightness[10] on the Swedish labor market using the traditional and the alternative measure for job-openings, respectively. Importantly, the labor market, as measured using the traditional measure, was equally tight before and after the Great Recession. This is however not the case when using the alternative measure to gauge labor market tightness. Here the Swedish labor market was substantially less tight after the Great Recession.

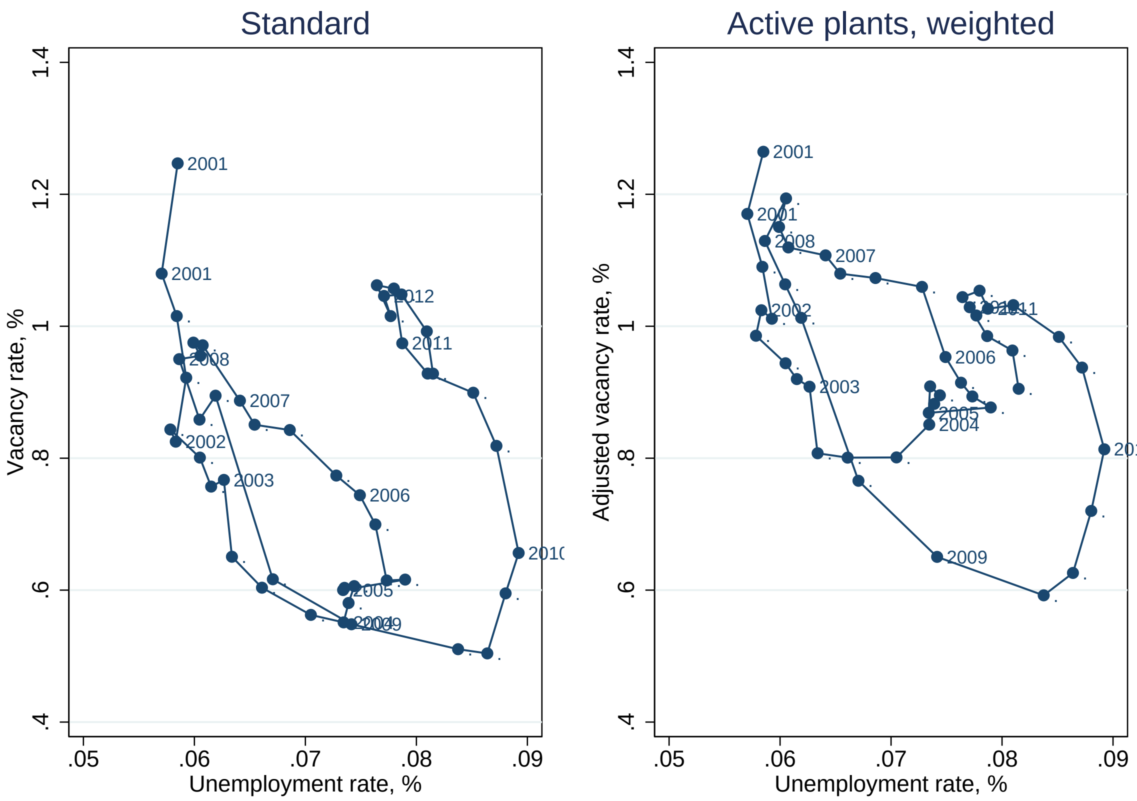
The difference is perceived tightness stems from the distribution of vacancies. After the Great Recession vacancies bounced back, but less so in larger plants where, as documented above, the vacancy is higher than in smaller plants. This implies that the apparent surge in vacancies after the Great Recessions may partly have been deceptive: Vacancies soared, but primarily in plants where the vacancy yield was low. Consequently, the traditional vacancy measure may have made the labor market look tighter than it actually during the post-crisis recovery.

My findings also call for a re-interpretation of the recent developments in the Swedish Beveridge curve. As mentioned in the introduction, one of the puzzles in macroeconomics after the Great Recession has been why the Beveridge curve in a number of advanced countries, including Sweden, moved out in the aftermath of the crisis (Figure TBD). In line with what have been hypothesised about the case of the United States, some Swedish economists and policymakers have argued that the shift can have been caused by declining matching efficiency on the labor market (Sveriges Riksbank, 2012; Hå kanson, 2014). However, if we look at the Swedish Beveridge curve through the lens of the alternative measure for job-openings the outward shift is less pronounced (Figure TBD). Using this measure there was also an outward after 2008, but it was smaller and in recent years the Beveridge curve has been operating close to a level where it also operated around 2006.

[10]Measured as job-openings per unemployed worker

In sum, my findings suggest that part of the recent movements in the Swedish Beveridge curve can be explained explained by measurement issues. Vacancies quickly bounced back after the crisis, but less so in larger plants where the vacancy yield is highest. This may have made the Swedish labor market look tighter after the Great Recession than what it actually was. Using my alternative measure of job-openings, which in a simple way accounts for the variation in the vacancy yield, the outward shift in the Swedish Beveridge curve is less clear.

Figure 7: Beveridge curves



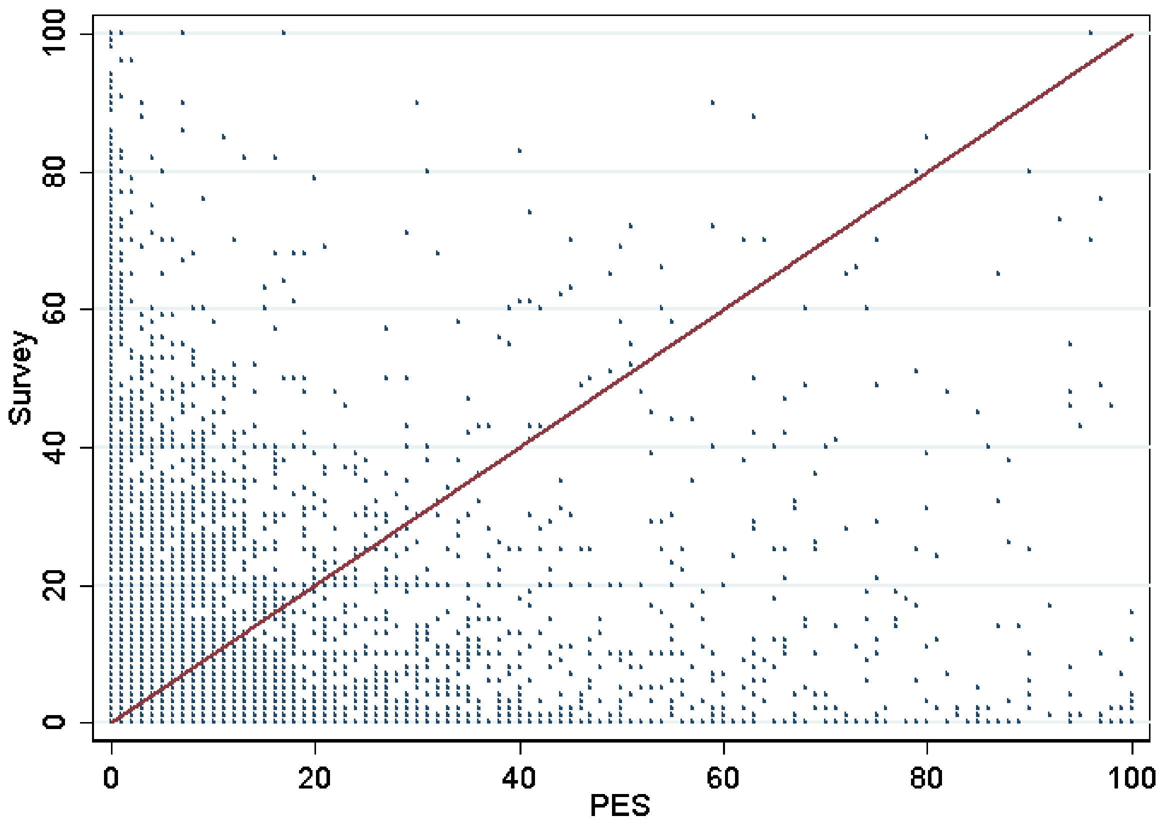
Source: Own calculation on data from Statistics Sweden.

6 Relationship between vacancies in survey and PES

In this section, I document the relationship between vacancies as measured in the (i) survey and in the (ii) register of the PES on the firm level.

Figure 9 shows a cross-plot between these two measures on the firm level. If the two measures are identical, we should see the observations line up on the 45-degree line. Evidently, this is not the case. Instead, regressing the two measures on each other yields a R^2 of only 0.06. Moreover, 47 % of the vacancies registered in the survey are not registered in the PES. This is unsurprising given that not all firms can be expected to use the Public Employment Service as recruitment channel, which creates the problem of selection in the PES data. What is, however, more surprising is that 37 % of the vacancies registered at the PES are not counted in the survey.

Figure 8: Cross plot of vacancies registered in the survey and the PES register, firm-level, 2004-2012



Notes: The sample is restricted to firms with only one plant.
Source: Own calculation on data from Statistics Sweden and Swedish Public Employment Service.

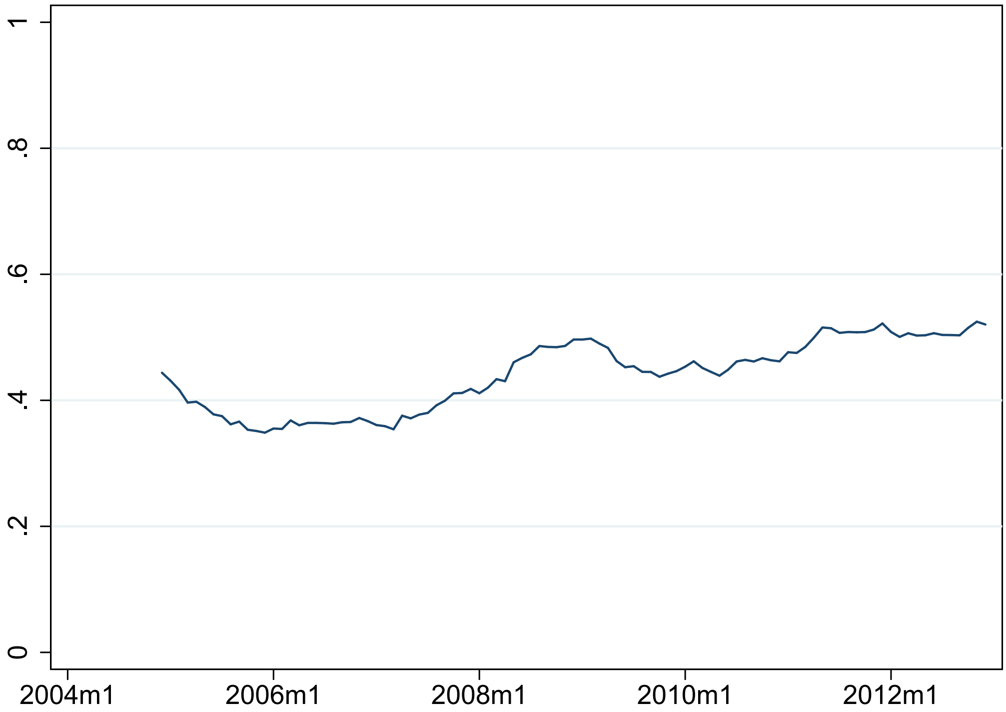
Table 6 documents the heterogeneity in the ratio of vacancies registered the PES to the number counted in the survey. Overall, this table suggests at the use of the PES as recruitment channel varies substantially across firm characteristics. The share of PES to survey vacancies is largest within *Public and personal services* and smallest within construction. Indeed, the former industry accounts for 42 % of all vacancies at the PES. Across plant size there is not clear pattern, while the use across the turnover and value-added deciles peaks in the middle of the distribution.

Finally, Figure 9 documents the time-series for the aggregate share of vacancies registered at the PES *vis-a-vis* the number in the survey. From 2004-2012 this share has varied in the interval $28 - 47$ % and has displayed a increasing trend over time.

Table 6: Survey and Public Employment Service vacancies on the firm-level,2004-2012

	PES share (%)	Average PES (#)	Average Survey (#)	Share of PES (%)	Share of survey (%)
			By industry		
Farming	42.12	0.43	1.02	0.70	0.77
Manufactoring	23.70	0.70	2.96	16.72	32.65
Energy	18.33	0.76	4.14	0.94	2.39
Construction	17.26	0.17	0.96	0.63	1.70
Trade, hotel and restaurants	32.68	0.50	1.54	5.66	8.02
Transportation, mail and telecom	35.51	1.37	3.86	6.33	8.25
Finance and business service	57.48	1.68	2.93	26.12	21.04
Public and personal services	78.90	3.29	4.16	42.90	25.18
			By number of employees (deciles)		
1	51.60	0.05	0.09	0.39	0.35
2	66.36	0.09	0.14	0.66	0.46
3	52.01	0.13	0.26	0.99	0.88
4	46.93	0.25	0.53	1.78	1.75
5	49.50	0.51	1.04	3.81	3.56
6	35.47	0.53	1.49	3.82	4.99
7	36.89	0.71	1.93	5.27	6.61
8	41.20	1.27	3.07	9.36	10.52
9	37.16	1.59	4.28	11.68	14.55
10	51.15	8.35	16.32	61.51	55.69
			By turnover (deciles)		
1	19.10	0.21	1.09	1.29	3.12
2	54.28	0.09	0.17	0.57	0.49
3	77.49	0.23	0.29	1.39	0.83
4	82.34	0.62	0.76	3.84	2.16
5	87.95	1.19	1.35	7.34	3.86
6	66.18	1.12	1.70	6.93	4.85
7	58.43	1.12	1.91	6.89	5.46
8	45.66	1.17	2.55	7.18	7.28
9	36.69	1.46	3.99	9.01	11.37
10	28.91	3.49	12.07	21.48	34.41
			By valueadded (deciles)		
1	20.42	0.28	1.35	1.70	3.85
2	51.91	0.08	0.16	0.50	0.45
3	51.24	0.13	0.25	0.79	0.72
4	50.74	0.24	0.47	1.48	1.35
5	72.85	0.67	0.91	4.10	2.60
6	58.60	0.82	1.40	5.06	4.00
7	59.60	1.11	1.86	6.82	5.29
8	55.02	1.29	2.35	7.96	6.70
9	38.03	1.48	3.88	9.08	11.06
10	34.82	4.62	13.26	28.43	37.81

Figure 9: Ratio Public Employment Service to survey vacancies, 2004-2012



Notes: The figure shows a 12-month moving average of the aggregate ratio of PES to survey vacancies in the sample.
Source: Own calculation on data from Statistics Sweden and Swedish Public Employment Service.

7 Conclusion

This paper studied the relationship between vacancies and hires on the plant level using Swedish data. According to basic search-matching theory we should see no hiring without job-openings and we should expect the relationship between hiring and job-openings to be linear. When taking these predictions to the data we first need to translate the theoretical concept of a job-opening into an empirical counterpart. The preferred way to this in the empirical literature is via a survey based measure of vacancies. To the extent that this measure captures the concept of job-openings well, we should expect to see a tight relationship between vacancies and subsequent hires. I show that the relationship in the data is concave, rather than linear as predicted by the model, as one additional vacancy associated with less and less hiring. I also show the prediction of hiring on the plant level can be improved substantially by allowing plants' willingness to hire to depend not only on posted vacancies but also on plant size.

These observations motivates the formulation of an alternative measure of aggregate job-openings. Instead of using the sum of all vacancies, I use the the sum of all plants with a positive number of vacancies weighted by their size. This measure has the attractive feature of providing a better fitting aggregate matching function. The alternative measure also provides a new perspective on the outward shift in the Swedish Beveridge curve observed in the wake of the Great Recession. Some have suggested that this was caused by a deterioration of the matching efficiency. The findings in this paper however puts this hypothesis into doubt. Indeed, an alternative explanation is that the traditional vacancy measure has become a less good measure for the number of job-openings in the economy.

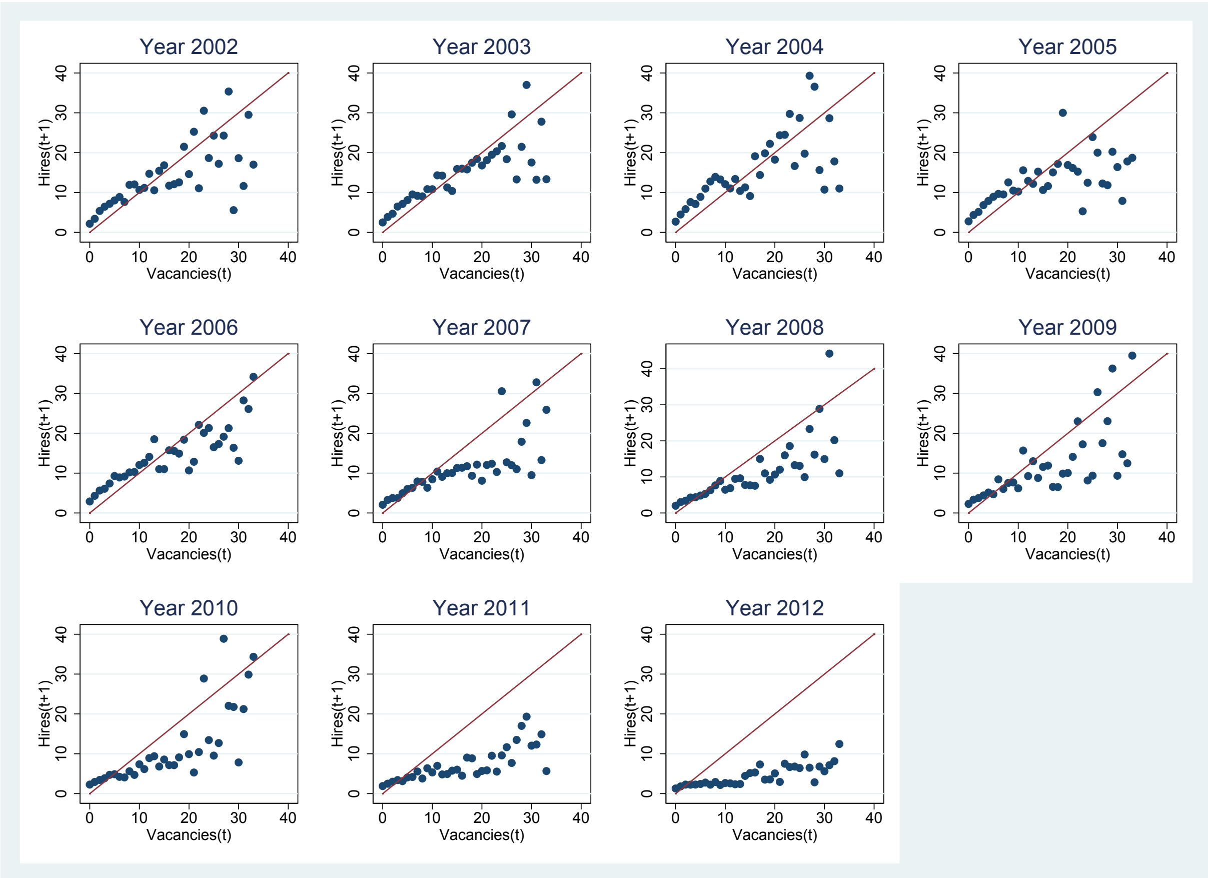
Overall, this paper suggests that more work is needed on how to best measure job-openings in the economy. Indeed, the finding that a substantial amount of hiring happens without vacancies in the preceding month, and that 37 % of all vacancies registered at the PES do not have a counterpart in the survey data point to a reliability problem in our vacancy data. Better understanding the hiring that happen without vacancies is a first step towards addressing this problem.

1 Appendix

Table 7: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Employees	159	450	0	14.368	693.417
Turnover	2.084.064	7.298.369	0	107.805.024	482.750
Valueadded	525.587	1.890.874	-12.151.558	39.204.988	482.750

Figure 10: Relationship between number of vacancies and hires, 2001-2012



Notes: The figure shows the average number of hires (y-axis) for each number of vacancies in the previous month (x-axis). TBD: Change background color.
Source: Own calculation on data from Statistics Sweden.

TBD:

Table 8: Plant level hiring regression, corrected for time-aggregation, Ordinary Least Squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)
Vacancies (t)	0.23***	-0.00	0.01	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Plant size (t)		0.33***	0.30***	0.36***	0.37***
		(0.01)	(0.01)	(0.02)	(0.02)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Value-added dummies	No	No	No	Yes	Yes
Turnover dummies	No	No	No	No	Yes
Observations	307872	307841	307841	211773	211773
Adjusted R^2	0.25	0.28	0.29	0.25	0.25

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Hires: hiring in month $t + 1$ corrected for hires associated with newly created vacancies. Vacancies: Vacancies computed at the end of month t.

Table 9: Plant level hiring regression, corrected for time-aggregation, Ordinary Least Squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)	Hires (t+1)
Vacancies(t)	0.327***	0.0408***	0.0441***	-0.0157	-0.0209**
	(0.0146)	(0.0114)	(0.0116)	(0.0107)	(0.0106)
Plant size (t)		0.497***	0.489***	0.611***	0.621***
		(0.0120)	(0.0126)	(0.0212)	(0.0213)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	Yes	Yes	Yes
Value-added dummies	No	No	No	Yes	Yes
Turnover dummies	No	No	No	No	Yes
Observations	154542	154492	154492	100443	100443
Adjusted R^2	0.243	0.421	0.423	0.382	0.384
AIC	478696.5	437069.3	436659.9	273805.9	273364.0

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Hires: The average number of hires in month t and $t + 1$.

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