Mis-Measuring Job Openings: Evidence from Plant Level Data

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Abstract

In modern macroeconomic models job openings are a key component. Thus, when taking these 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 on Swedish hires and job vacancies on the plant level 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 features of (i) better predicting hiring on the plant level and (ii) providing a better fitting aggregate matching function *vis-a-vis* the traditional vacancy measure. Using the new measure, the outwards shift in the Swedish Beveridge curve after the Great Recession is less pronounced.

1 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 *Beveridge curve* has shifted outwards in many OECD countries. 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 construct an alternative measure of job-openings, which builds on the extensive margin of vacancies and plant size. This measure outperforms the traditional vacancy measure 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, job-openings were less plenty and the outward shift in the Beveridge curve was less pronounced.

Job-openings are a key concept in modern macroeconomic models. Within the search-matching framework, which is an 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 these models to the data we need to construct a mapping from the theoretical concept of a job-opening in 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 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 predict less and less hiring. Moreover, plants hire many more workers than they post vacancies. I take these findings as evidence of vacancies being a poor measure of actual job-openings.

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 capability to predict hiring on the plant level by up to 40 %.

Building on these findings, I also propose an alternative measure for the aggregate number of job openings in economy. Motivated by the concave relationship between vacancies and hires on the plant level, 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 matching function on the aggregate level.

These findings potentially have 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 the joint incidence of high unemployment and vacancies speaks against this hypothesis. This has let some economists and policymakers 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 the alternative measure of job-openings developed in this paper, 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 vacancy postings in smaller plants, where the vacancy yield is lower. Consequently, after the Great Recession the traditional vacancy measure may have overstatede the number of job-openings in the economy and made the outward shift in the Beveridge curve appear too large. *Ceteris paribus* this reduces the support for the hypothesis that the higher level of unemployment in Sweden after the Great Recession was caused by a decline in matching efficiency on the labor market.

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 preferred, as this avoids the selection problems that can be present in the register data. However, due to limited availability of the survey-based measure (Elsby et al., 2015) the 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 important question, which has not been investigated so far, is how the two vacancy measures relate to each other on the micro level. I show that the relationship between openings registered at the Swedish Public Employment Service 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 database of the Public Employment Service. More surprisingly is that 37 % of all vacancies reported in the database of the Public Employment Service do not have a counterpart in the survey data. Across firms there is also heterogeneity in the use of the Public Employment Service, with the public sector and middle-sized firms having the largest share of openings in the Public Employment Service.

Related literature

My study relates to at least four strands of literature.

First, there exists a vast literature which estimates matching functions using the aggregate number of vacancies, unemployment and job-finding rates. A review of this literature is available in Pissarides (2000), but some key papers include Blanchard and Diamond (1990); Berman (1997); Yashiv (2000); Albaeck and Hansen (2004); Sunde (2007); Gross (1997); Entorf (1998); Feve and Langot (1996). My paper adds to this literature by discussing the micro-level properties of the vacancy data that goes into the estimation.

Second, another 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 the *link* between vacancies and hires on the micro level.

Third, and closest related, 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 United States. They document how hires per vacancy, the *vacancy yield*, behaves in the cross- and time-section. Moreover, they construct a measure of the *recruitment intensity*, and show how variations in this partly explains in the recent breakdown of the matching function in the United States. My paper takes a different approach. Instead of introducing a time-varying measure of recruitment intensity, 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) better predicting hires on the plant-level and (ii) yielding a better fitting matching function on the aggregate level. In addition, my paper also makes a contribution by documenting how survey and register-based measures of vacancies relate to each other on the micro level.

Fourth, my paper relates to the recent debate on the Beveridge curve movements after the Great Recession. 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. Some, 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 curve 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 duration dependence in workers' 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 some of the outward shift in the case of Sweden.

Organization

The paper proceeds as follows. In Section 2, I describe my 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. Section 6 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.

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 respondents are asked to report the number of vacancies in the middle of the reference month.[1] For the private sector the sampling is done on the plant level with approximately 16 700 work places sampled each period. For the public sector the sampling was also done on the plant level until 2006Q2. In 2006Q2 the sampling was changed to the organizational level and on this level 650 organizations are sampled each

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

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 happens 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 40 % in the public sector and 20 % in the private 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 registered at the Swedish Public Employment Service is my other source of vacancies. The Public Employment Service maintains a database containing the universe of job-vacancies 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 the plant identifiers are missing, why the database in practice only contains useful information on the firm level. To make the data from the Public Employment Service comparable with the survey data, I compute the number of open positions at the Public Employment Service in the middle of each month.

The aggregate numbers of the two vacancy measures are reported in Figure 1. As expected the level of vacancies in the survey is consistently above the level of vacancies reported at the Public Employment Service, and the share of Public Employment Service to survey vacancies varies in the range 30-50 %.

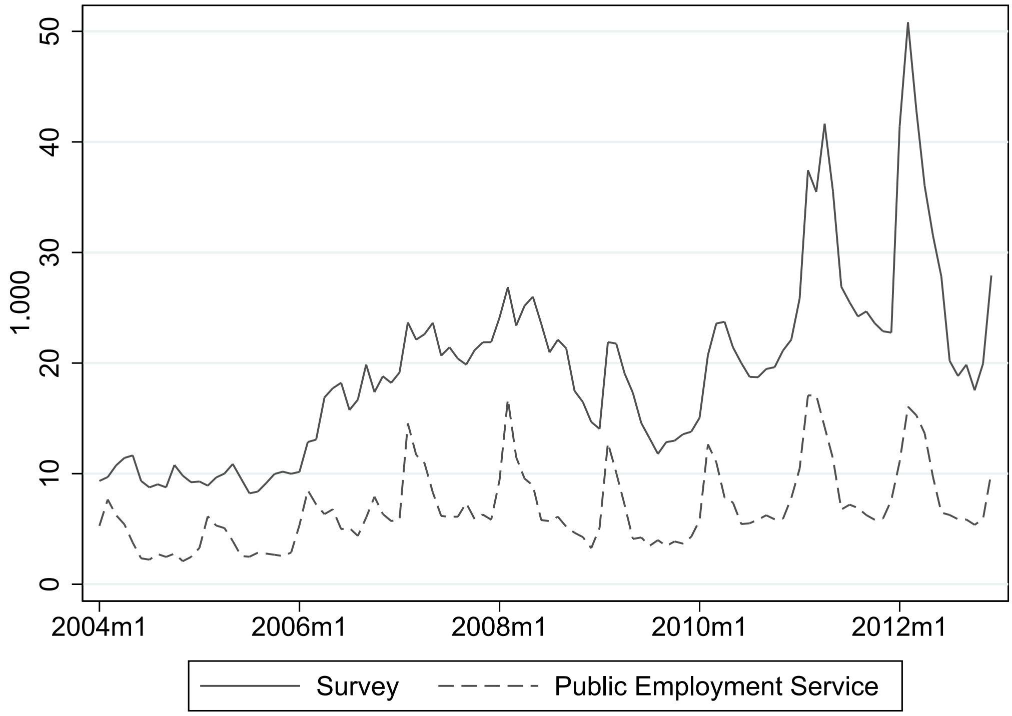
Hires

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* 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, the Institute for Evaluation of Labour Market and Education Policy (IFAU) 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 plant. From this data, I compute the number of monthly hires as the number of spells that starts in an establishment in a given month.

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



Notes: The figure shows the aggregate number of job openings in the survey and Public Employment Service, respectively. The sample of firms is restricted to those sampled in the *Job Vacancy Survey.* *Sources:* The Swedish Public Employment Service and Statistics Sweden.

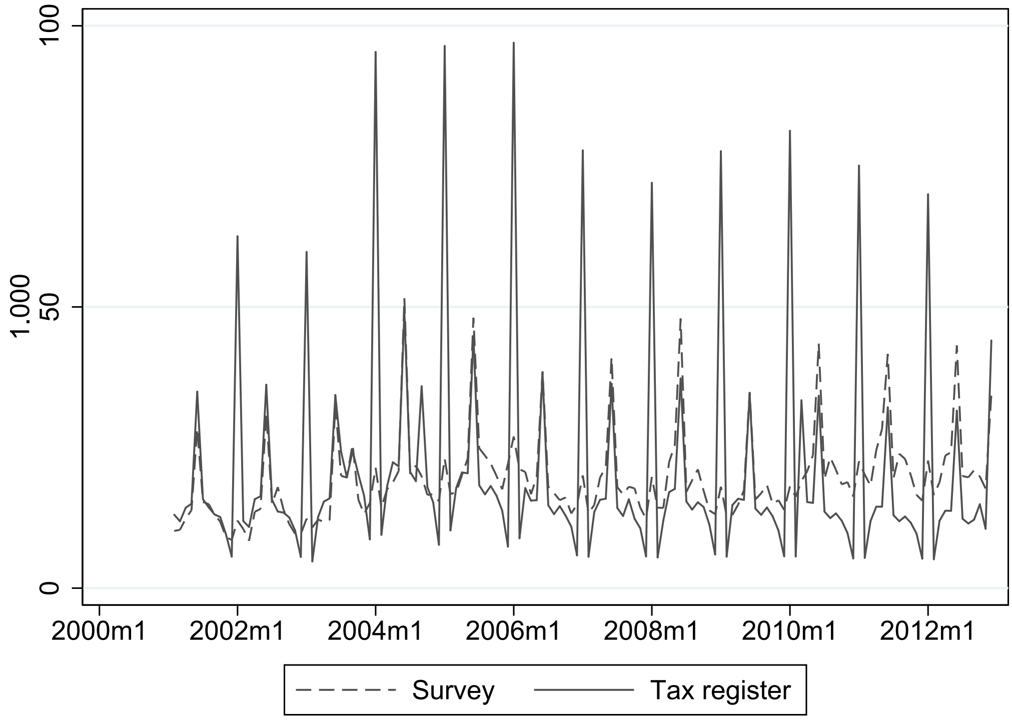
To discard repeated, or interrupted, spells I remove all spells where the individual has been employed in the last 12 months. Moreover, I restrict the sample to the plants also available in survey-based measure of hires in the given month.

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 plant for simplicity may report spells as lasting for entire years instead of the correct duration in months.

Plant and firm background variables

From the survey data in the *Short-Term Employment Statistics* and the register data in the *Swedish Firm Register*, both administered by Statistics Sweden, I furthermore have access to background information on each plant and firm. In particular, this background information contains information on the number of employees and industry of each plant, while turnover and value-added is available on the firm level from the Firm Register. A summary of these variables is presented in Table 7 in the Appendix.

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 plants is restricted to those sampled in the *Short-Term Employment Statistics*.
Sources: Institute for Evaluation of Labour Market and Education Policy and Statistics Sweden.

Data selection

In Section 3, I relate the number of vacancies in the *Job Vacancy Survey* to the number of subsequent hires on the plant level. The reason I use the survey data, rather than the register data, is that the former broadly is considered more reliable due to the selection problems in the register data from the Public Employment Service. For hires I rely on the register data from the tax authorities. However, 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.[2]

[2] I do not 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 months as vacancies are measured.

3 Relationship between vacancies and hires on the plant-level

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 within construction where the yield is 1.37 hires per vacancies, while it is highest within manufacturing where the rate is 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 only hire 0.3 workers per vacancy, the plants in the decile with most employees hire 4.02 workers per vacancy. This result contracts the findings from the United States, where the vacancy yield is found to be *decreasing* in plant size (Moscarini and Postel-Vinay, 2016; Davis et al., 2013). Across turnover, measured on the firm level, a similar pattern is seen: plants in firms with larger turnover have a higher vacancy yield.

There are a number of potential explanations behind this 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 an employer's probability of filling a job is increasing in the size of the social network. To the extent that larger plants have larger social networks this can potentially go some way in explaining why the vacancy yield is increasing in plant size. Second, plants may rely on one vacancy to hire more than one worker. If a plant is attempting to hire workers with a homogenous skill set, 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, where the required skill set of workers is more homogenous.

Next, I show how the 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 one additional vacancy predicts less and less hiring.

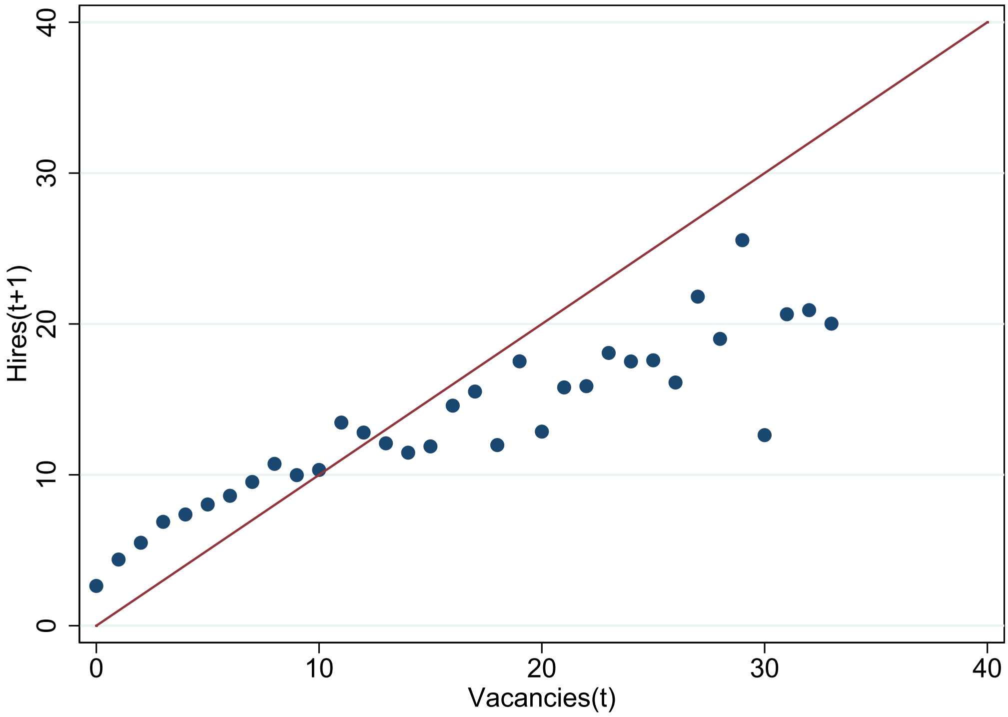
In addition many hires happen in plants, which did not report any vacancies. Figure 4 shows the share of all hires that are made in plants that did not report any vacancies in the preceding month. This share varies in the interval 40 % - 50 %, and falls to 30

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 hires. Due to observations with zero vacancies, the vacancy yield is not equal to the hiring rate divided by vacancy rate. Public sector has been dropped in tabulation by turnover.
Source: Own calculations from Statistics Sweden

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

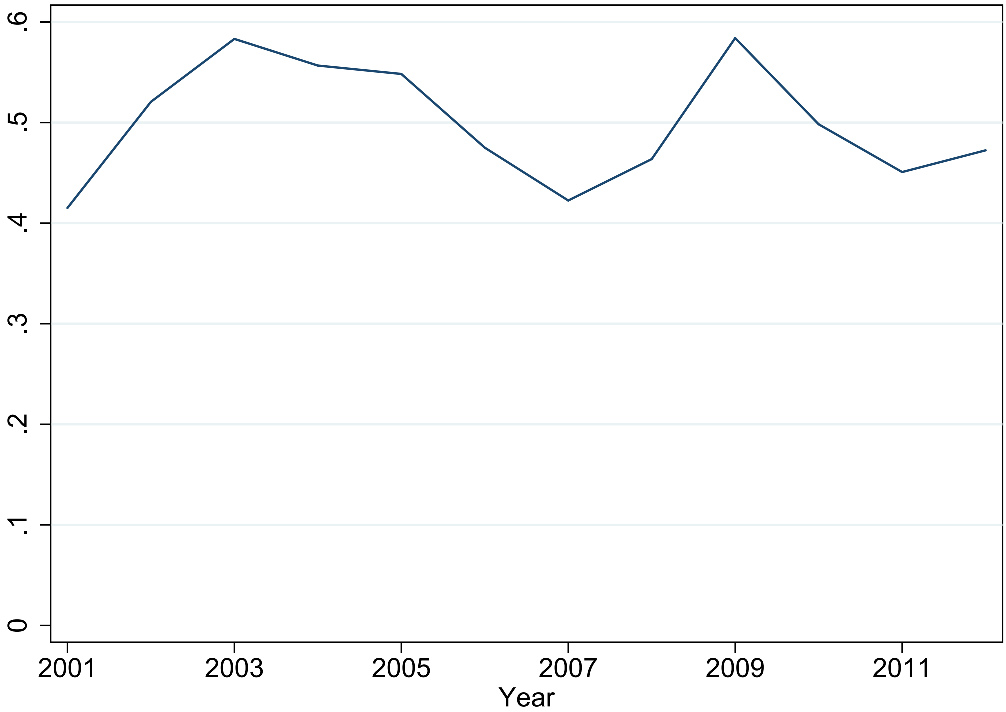


Notes: The figure shows the average number of hires (y-axis) for each number of vacancies in the previous month (x-axis). The solid line denotes the 45-degree line.
Source: Own calculation on data from Statistics Sweden.

% - 40 % if counting the share of hires that are made without any vacancies in the two preceding months. Some of these hires can be accounted by hiring out of other channels than vacancies, but some of the hires might also be explained by time-aggregation issues. Indeed, since I 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 total job-openings in the economy. Moreover, the large share of hiring in plants without preceding vacancies also suggests that vacancies are incomplete as measure of job-openings.

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



Source: Own calculations on data from Statistics Sweden.

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 textbook search and matching model aggregate hiring is determined by the matching of unemployed workers (U) and job-openings (V). This matching is done 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 can then be written as

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

Here the number of hires in plant j at time t is a function of (1) the tightness on the aggregate labor market[3] and (2) number of job-openings posted by the plant.

Two predictions follow from equation (1). First, the number of hires made by plant j at time t is linear in the number of job-openings posted by the plant. The coefficient on job-openings is inversely related to labor market tightness, such that a tighter labor market predicts fewer hires per job-opening. Second, we should only see hiring in plants

[3]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*.

where the number of job-openings is positive. As explained above these predictions appear to be at odds with the data. In the estimations below, I will address this by allowing for a non-linear relationship between vacancies and hires, and in Section 4 I will investigate how much of the hiring without vacancies that can be accounted for by time-aggregation.

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 9 in the Appendix). 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 in Section 4.

To identify (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 in equation (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 a γ of unity.

Identifying (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. 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 0.03, when removing the time-fixed effects.

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

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered on the firm level.
Source: Own calculations on data from Statistics Sweden

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

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Source: Own calculations on data from Statistics Sweden.

Can measure of job-openings be improved?

The findings in Table 2 and 3 above show that the relationship between vacancies and hires on the plant level is weak and non-linear. Moreover, the descriptive statistics in Table 1 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 in (3) is an augmented version of that in equation (1). Whereas job-openings in equation (1) were measured as posted vacancies only, job-openings in (3) are measured by the function $F\left[V(j,t-1),\mathbf{x}(t-1)\right]$, in which job-openings is allowed to be a function of where 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 modeled as a time-fixed effect in the regressions.

Equation (3) is estimated using ordinary least squares as well as using non-linear least squares in column 2-5 of Table 2 and 3. From column 2 to 5, I gradually allow job-openings to be a function of more plant and firm 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. To ensure this is not the case, I redo the estimations where the sample is restricted to the subset where all variables are available (Table 10 in the Appendix). 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, 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 vacancies and plant size in the following form

$$F(V(j,t),size(j,t)) = V(j,t-1)^{a} size(j,t-1)^{b} \tag{4}$$

outperformed the traditional vacancy in its ability to predict hiring on the plant level. In equation (4) a is effectively zero and b is estimated to be in the interval $0.4-0.91$. 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 any 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 hiring in a given plant: (1) what are the aggregate conditions on the labor market[4], (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 in the middle of 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 in the middle of 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 depletion rate[5] and θ_t is the inflow of new 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 filled nor depleted, plus the inflow of new vacancies.

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

[5]That is, the daily rate by which vacancies are taken of the market without having been filled.

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 right-handside 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 right-handside 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.

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.[6] As a robustness check 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 5 shows the calibrated time-series for f_t and θ_t. The calibrated monthly inflow of new vacancies is on average 0.6% of the labor force and varies in the interval $0.2 - 0.8\%$. The daily fill-rate of vacancies is on average 2.5%, which corresponds to an average duration of 40 days, and varies in the interval $1 - 3.5\%$.

Using the calibrated model I can 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.

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

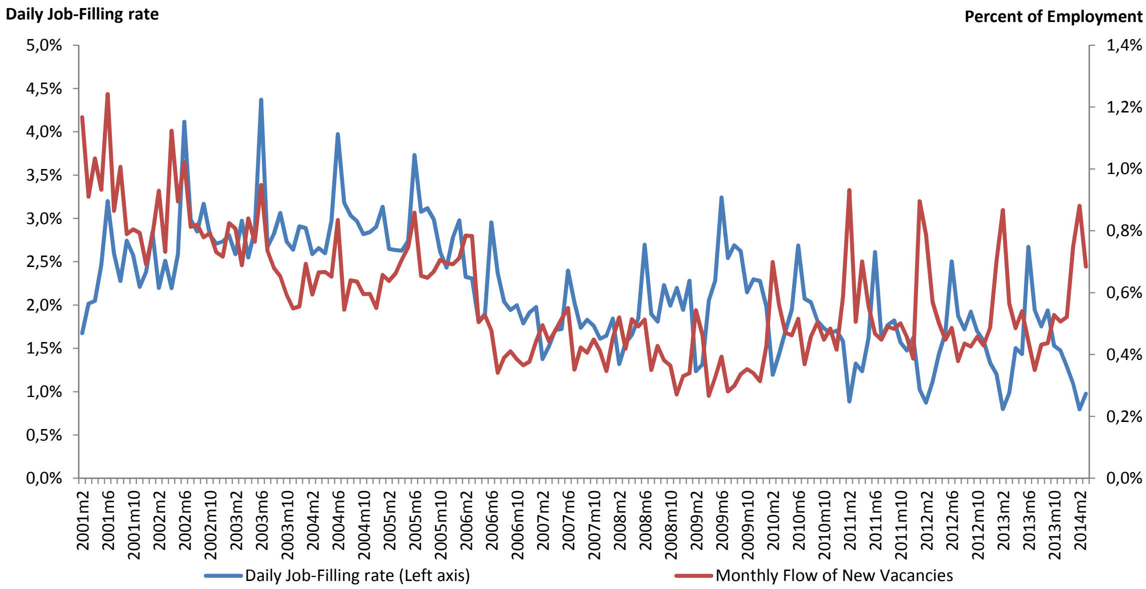
Second, I compute hires in each month corrected for the number of hires that are predicted to be associated with newly created vacancies.

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

To compute $v_{t,ultimo}$ and $h_{t,corrected}$ in (9) and (10) I use values of f_t and θ_t calibrated

[6] 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 5: Daily Job-Filling Rates and Flow of New Vacancies, 2001-2012



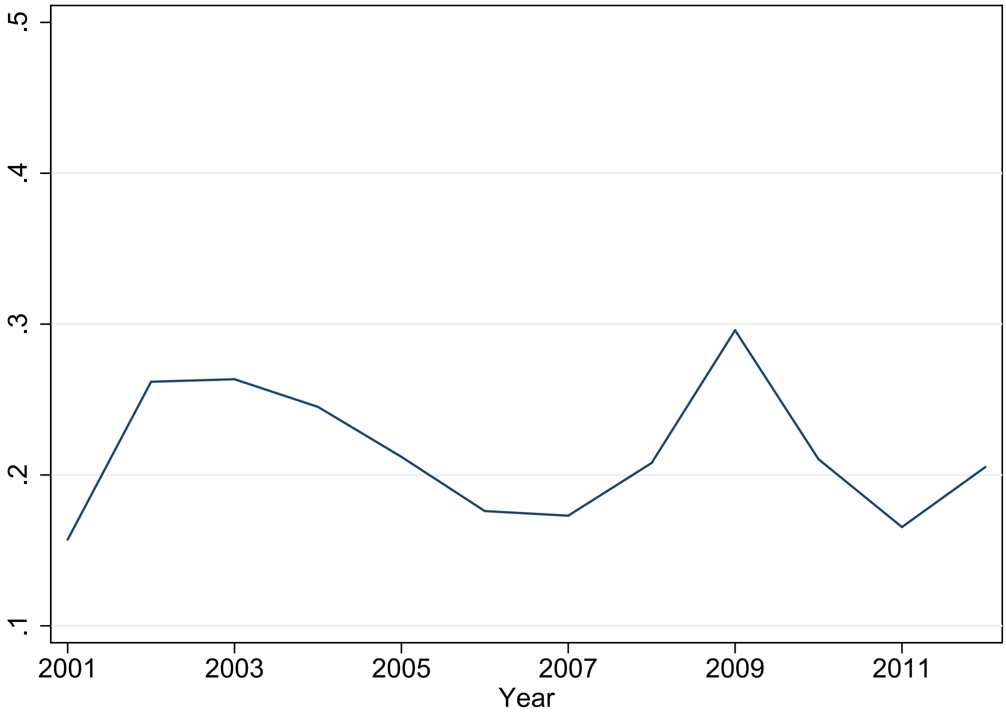
Source: Own calculations on data from Statistics Sweden.

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 relevant industry.

Having computed $v_{t,ultimo}$ and $h_{t,corrected}$ I can now redo the analysis from Section 3. In Table 4 and 5, 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 estimated 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 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.

Having accounted for time-aggregation, I revisit the issue of hiring without preceding vacancies. In Figure 4, I showed that the share of hires without vacancies in the preceding month varied in the interval 50-60 %. In Figure 6, I redo this exercise having accounted for time-aggregation. Here the share of hiring without vacancies in the preceding month varies in the interval 16 % to 26 %. This suggests that time-aggregation can account for some, but not all, of the observed hiring without preceding vacancies.

Figure 6: Share of all hires without vacancies in the preceding month, corrected for time-aggregation, 2001-2012



Note: Figure depicts share of $h_{t,corrected}$ rounded value of $v_{t-1,ultimo}$ being above one.
Source: Own calculation on data from Statistics Sweden.

Additional robustness checks

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

First, one might question the choice of relating vacancies in one month to hires in the next month only. Especially, when contrasting the evidence on vacancy durations from the Public Employment Service from Figure 9 with the calibrated fill rates in Figure 5. 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 *average number of hires over the two next months*. This analysis is presented in Table 8 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 do have 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 9 in the Appendix, and do also not overturn the results from Table 2 and 3.

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered on the firm level. Hires: hiring in month $t + 1$ corrected for hires associated with newly created vacancies. Vacancies: Vacancies computed at the end of month t.
Source: Own calculations on data from Statistics Sweden

Table 5: Plant level hiring regression, corrected for time-aggregation, 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)	0.60***	0.13***	0.14***	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
Plant size (t)		0.56***	0.55***	0.93***	1.00***
		(0.01)	(0.01)	(0.01)	(0.03)
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	0.047	0.059	0.060	0.145	0.060

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.
Source: Own calculations on data from Statistics Sweden

5 Aggregate implications

The findings above potentially have 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 matching functions estimated on aggregate data for unemployment, job-openings and job-finding rates. 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 yields

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

In Table 6, 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 the 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. In column 3, I use the number of plants with a positive number of vacancies weighted by their size. The purpose of these alternative measures is, in a very simple manner, to account for the distributional issues of vacancies that I have found above. Notice that I for simplicity weigh plants *linearly* with their size, rather than with a concave function as size as suggested by the results in Section 3.

Interestingly, the alternative measures of job-openings yield better fitting matching functions 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.

These findings have potentially important implications for how we should think about the recent developments on the labor market. Figure 7 shows the time-serie for labor market tightness[7] 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 almost equally tight before and after the Great Recession. This is however not the case when using the alternative measure to gauge labor market

[7]Measured as job-openings per unemployed worker

Table 6: Estimated aggregate matching function, Sweden, 2001Q1-2012Q4

	(1) log(jfr)[1]	(2) log(jfr)[1]	(3) log(jfr)[1]
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

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (1) jfr: Job-finding rate
Source: Own calculations on data from Statistics Sweden.

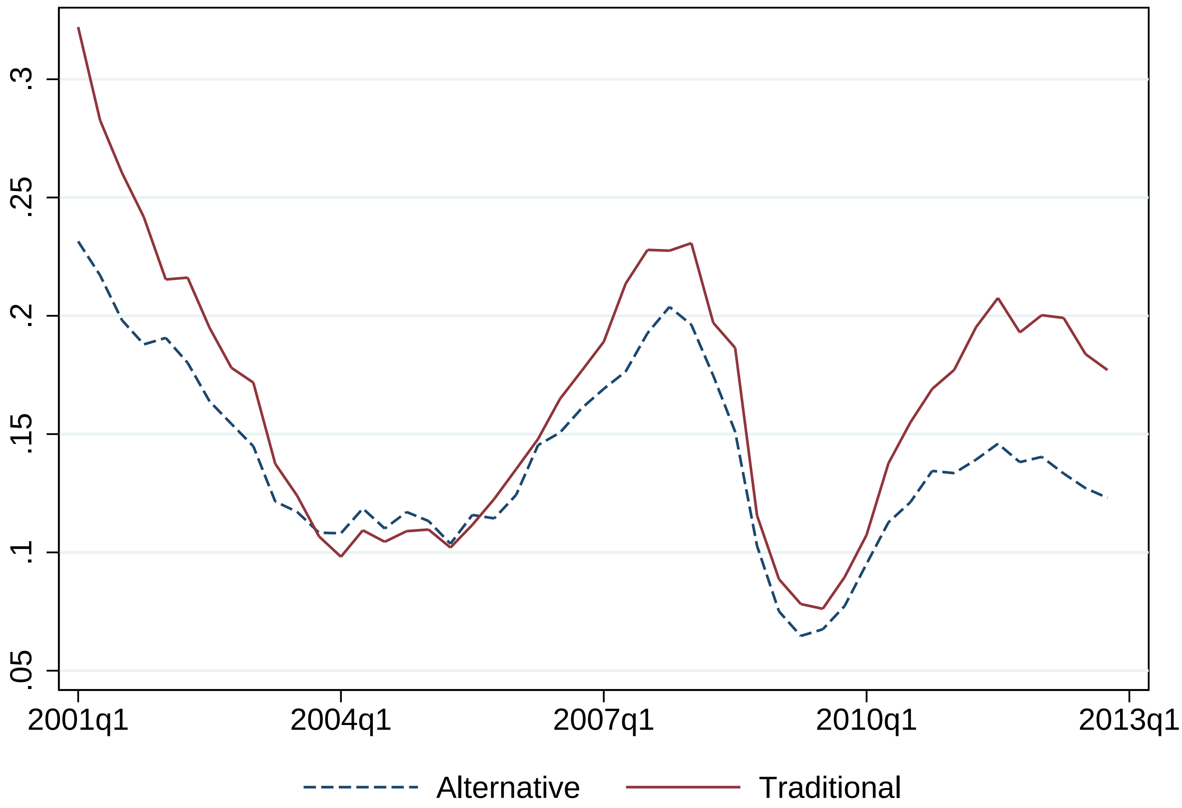
tightness. Here the Swedish labor market was substantially less tight after the Great Recession.

The difference in 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 yield 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 was during the 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 8). In line with what have been hypothesized about the case of the United States, some Swedish economists and policymakers have argued that the shift can have been caused by a gradually declining matching efficiency on the labor market (Sveriges Riksbank, 2012; Haakanson, 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 8). 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.

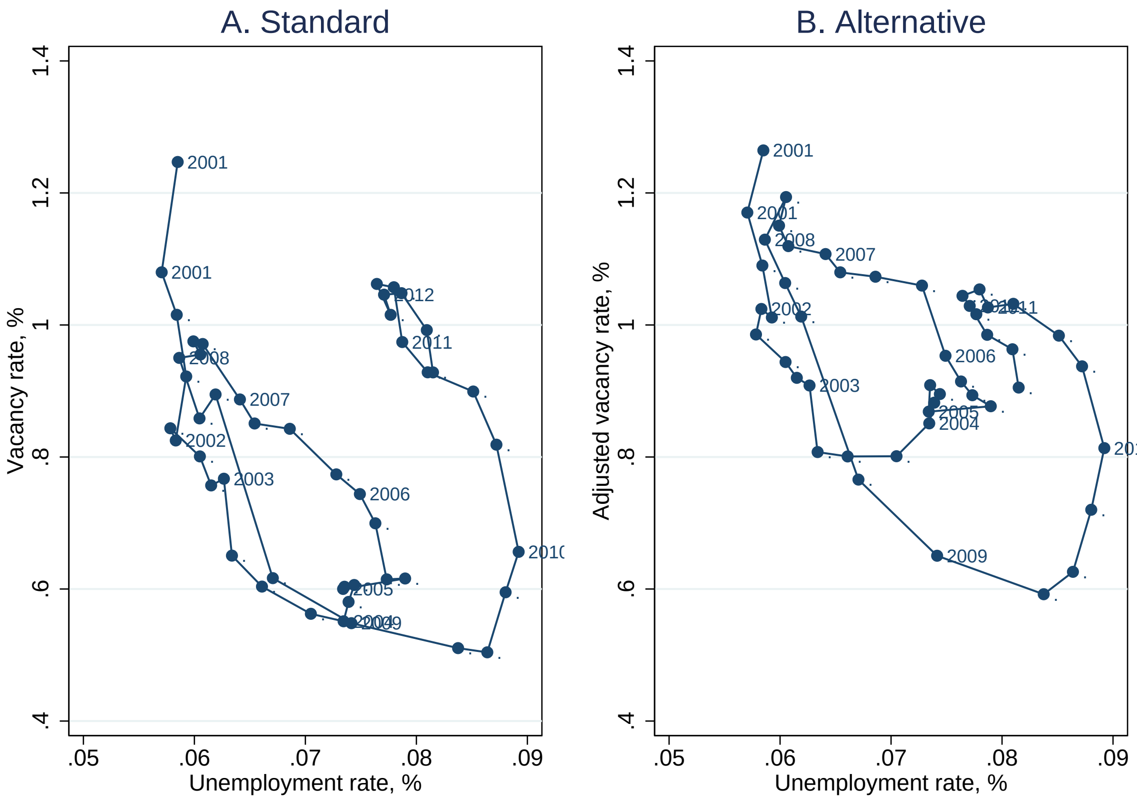
In sum, my findings suggest that part of the recent movements in the Swedish Beveridge curve can be explained by measurement issues. Vacancies quickly bounced back after the crisis, but less so in larger plants where the vacancy yield is highest. This may have made the Swedish labor market look tighter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

Figure 7: Labour market tightness



Notes: The figure shows labor market tightness defined as the stock of job-openings divided by the stock of unemployed. The traditional measure uses vacancy as measure of job-openings. The alternative uses the sum of plants with any vacancies weighted by size.
Source: Own calculation on data from Statistics Sweden.

Figure 8: Beveridge curves



Notes: In panel A the Beveridge curve is drawn using the standard vacancy measure for job-openings. In panel B the sum of plants with any vacancies weighted by size is used as measure for job-openings. *Source:* Own calculation on data from Statistics Sweden.

6 Conclusion

In modern macroeconomic models job-openings are a key concept. To measure job-openings in the data the literature relies on vacancy data. Such data is either measured in surveys or in register data. Yet so far we know very little about how job-vacancies relate to actual hiring on the micro level. Insofar that job vacancies capture the concept of job-openings well, we should expect to see a tight relationship between vacancies and subsequent hires.

This paper is one of the first to study this relationship on the plant level. It does so using a novel Swedish dataset. Using this dataset, I show that the relationship between job-vacancies and subsequent hires is weak and concave. That is, one additional vacancy on the plant level predicts less and less hiring. I also show that the number of hires per vacancies (the *vacancy yield*) varies in the cross-section of plants. In particular it is increasing in plant size. Moreover, plants hire many more workers than they post vacancies. I take these findings as evidence of vacancies being a poor measure of actual job-openings in the economy.

I also show that it is possible to construct a better measure of job-openings. By allowing job-openings to depend not only on vacancies, but also on plant size, I show that it is possible to improve the ability to predict hiring on the plant-level by up to 40 %.

Building on these findings from the plant-level, I then construct an alternative measure of job-openings in the aggregate. Motivated by the concave relationship between vacancies and hires, and the fact that the vacancy yield is increasing in plant size, I propose *the sum of plants with a positive number of vacancies weighted by size* as an alternative measure of job-openings in the economy. Interestingly, this measure also yields a better fitting aggregate matching function than the traditional vacancy measure.

This alternative measure for job-openings provides a new perspective on the apparent outward shift in the Beveridge curve after the Great Recession. Using the alternative measure for job-openings to analyze the recent developments on the Swedish labor market, the labor market appears less tight after the Great Recession and the outwards shift in the Beveridge curve was not as pronounced. *Ceteris paribus* this lends less support to the hypothesis that matching efficiency has decreased after the crisis.

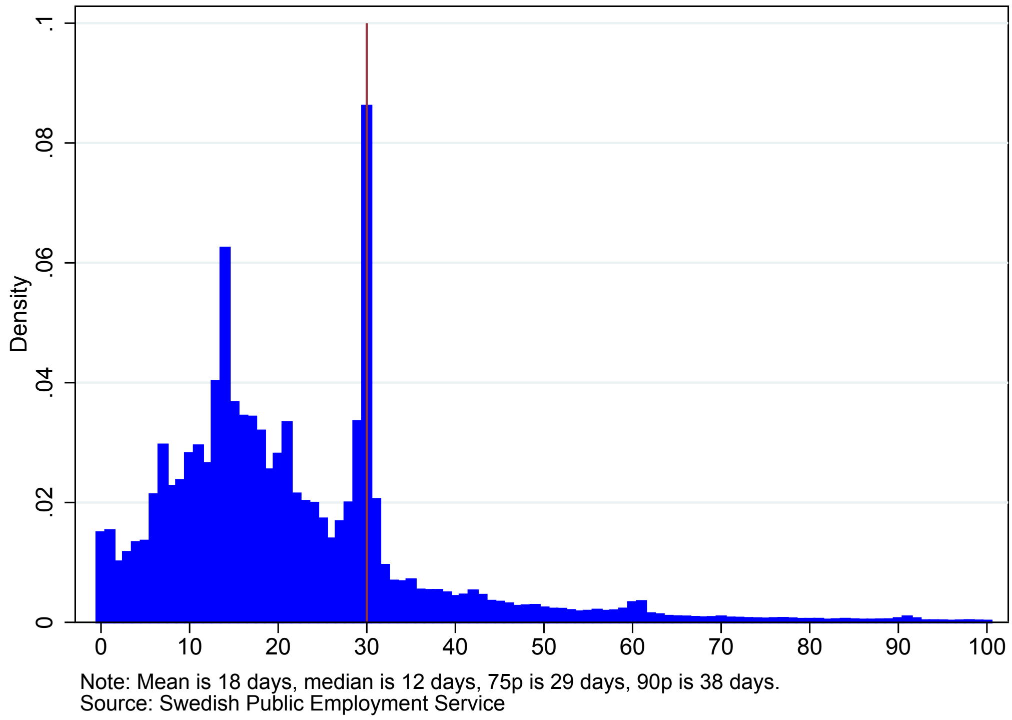
Overall, my findings suggest that more work is needed on how to best measure job-openings in the economy. A substantial amount of hiring happens without preceding vacancies, and approximately 40 % of all vacancies registered at the Public Employment Service do not have a counterpart in the survey data on vacancies. This points to a reliability problem in our vacancy data. Understanding why hiring happens without being picked up in our vacancy survey is a first step towards designing better measures of job-openings.

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 9: 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.

Table 8: Plant level hiring regression, average hires in next two months, ordinary least squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires	Hires	Hires	Hires	Hires
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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered on the firm level. Hires: The average number of hires in month $t + 1$ and $t + 2$.
Source: Own calculations on data from Statistics Sweden

Table 9: Plant level hiring regression, average hires and vacancies during a year, ordinary least squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires(t)	Hires(t)	Hires(t)	Hires(t)	Hires(t)
Vacancies(t)	0.209***	0.00486	0.00537*	0.00400	0.00266
	(0.00350)	(0.00302)	(0.00304)	(0.00353)	(0.00354)
Plant size(t)		0.420***	0.419***	0.466***	0.469***
		(0.00296)	(0.00308)	(0.00499)	(0.00501)
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	41298	41237	41237	27038	27038
Adjusted R^2	0.263	0.541	0.541	0.434	0.435
AIC	95989.2	76323.5	76322.1	48289.6	48239.9

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered on the firm level. Hires/vacancies: The average number of monthly hires/vacancies in year t. Sample is all plants with more than 3 observations per year.
Source: Own calculations on data from Statistics Sweden

Table 10: Plant level hiring regression, constant sample, ordinary least squares, 2001-2012

	(1)	(2)	(3)	(4)	(5)
	Hires(t)	Hires(t)	Hires(t)	Hires(t)	Hires(t)
Vacancies(t)	0.193***	0.00226	0.00710	0.00430	0.00170
	(0.0135)	(0.00974)	(0.00980)	(0.00956)	(0.00947)
Plant size(t)		0.452***	0.442***	0.489***	0.496***
		(0.0137)	(0.0137)	(0.0194)	(0.0196)
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	79097	79097	79097	79097	79097
Adjusted R^2	0.210	0.366	0.370	0.373	0.374
AIC	223941.9	206532.1	205969.5	205583.9	205425.5

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered on the firm level. Sample is all plants with more than 3 observations per year.
Source: Own calculations on data from Statistics Sweden

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