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Although search-matching theory has come to dominate labor economics in recent years, few attempts have been made to compare the empirical relevance of search-matching theory to efficiency wage and bargaining theories, where employment is determined by labor demand. In this paper we formulate an empirical equation for net job creation, which encompasses search-matching theory and a standard labor demand model. Estimation on firm-level data yields support for the labor demand model, wages and product demand affect job creation, but we find no evidence that unemployed workers contribute to job creation, as predicted by search-matching theory.

Keywords: Job Creation, Involuntary Unemployment, Search-Matching, Labor Demand, Competitiveness.

JEL classification: E24, J23, J64.

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1. Introduction

Efficiency wage and bargaining theories predict wages to be above the market clearing level.[1] There is excess supply in the labor market, so firms can hire the workers they want. Unemployment is explained by too high wages and lack of demand. An increase in labor supply will increase employment only if wages fall, or there is some other factor that shifts labor demand.

In the last two decades, these demand-oriented theories have been challenged by search-matching theory, where unemployment arises because it takes time for workers and firms to find each other.[2] Without such frictions, there would be no unemployment. Search-matching theory assigns a minor role to the demand side of the labor market. Instead, supply creates its own demand: if labor supply increases, firms open more vacancies and vacancies are filled more quickly. Importantly, this happens even if wages do not adjust.[3]

While search-matching theory has come to dominate labor economics in recent years, few attempts have been made to compare the empirical relevance of search-matching theory and theories where employment is determined by labor demand. The purpose of this paper is to compare the explanatory power of these two paradigms for thinking about (un)employment. More specifically, we focus on the question whether search-matching theory helps to explain job creation. Do unemployed workers contribute to job creation, as predicted by search-matching theory? Does supply create its own demand?

All leading theories of the labor market imply that, in the long run, supply creates its own demand. If labor supply increases, this will eventually bring about more jobs. But labor market theories differ in their explanations of *how* this adjustment occurs and what drives medium-term variations in employment. Demand-oriented models point to wages and aggregate demand as key factors. Unemployed workers are available, waiting for work, but there are simply too few jobs to go around. In search-matching theory, unemployed workers are not just a passive 'reserve army' waiting for jobs, but their search activity contributes to

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[1] See e.g. Phelps (1968), Salop (1979), Shapiro and Stiglitz (1984), Oswald (1985), Akerlof and Yellen (1986), Blanchard and Summers (1986), Gottfries and Horn (1987), Layard, Nickell and Jackman (1991). Minimum wages is another reason why wages may be above the market clearing level.

[2] See e.g. Mortensen and Pissarides (1994) and Pissarides (2000).

[3] Suppose that the number of vacancies is determined by the zero profit condition $c = qJ(w)$ where c is the cost of keeping a vacancy J(w) is the value of a filled job, and q is the probability to fill a vacancy. Let the latter be determined by $q = m(U/V)^{\alpha}$. Then we can solve for vacancies: $V = (mJ(w)/c)^{1/\alpha} U$. For a given wage, the number of vacancies is *proportional* to unemployment, and so is the number of matches. Assuming a constant separation rate and using the flow equilibrium condition, it is easy to show that if frictions are eliminated, i. e. c goes to zero or α goes to infinity, unemployment will disappear.

matches being formed. This, in fact, is the essence of the matching function: hiring depends not only on the number of job openings, but also on unemployment.

The novel prediction from search-matching theory is that an increase in unemployment should bring about more job creation even without any adjustment of wages. To test this prediction, we formulate an empirical equation for net job creation, which encompasses both theories, and estimate it on firm-level data. The equation includes firm-specific measures of real wage cost per worker and product demand, as well as unemployment and vacancies in the local labor market area. The demand variable is constructed by weighing together international demand with domestic aggregate demand components using firm- and industry-specific weights.

Turning to estimation, a basic identification problem arises. Aggregate shocks, which affect employment in all firms, will affect wages and aggregate demand as well as unemployment and vacancies. To deal with this problem, we include time dummies to capture unobserved shocks that affect all firms. There could also be local shocks, which affect all firms, and hence vacancies and unemployment, in a local labor market area. We therefore instrument local unemployment and vacancies by demand and price indexes, which reflect the industry structure in the local labor market area. The sample period is Sweden in the 1990s, a period with large fluctuations in domestic and international demand, as well as in the exchange rate, which should help to identify the effects of supply and demand factors on net job creation.

The results provide strong support for demand-oriented theories of job creation. Wages and demand have statistically significant and quantitatively large effects on job creation. In contrast, unemployment does not have a significant effect on net job creation.[4] Nor do we see any evidence of congestion effects when there are many vacancies in the local labor market. Apparently, search-matching theory offers little value added when it comes to explaining job creation in this period.

The rest of the paper is organized as follows. In Section 2 we derive equations for net job creation from two different models: a labor demand model with adjustment costs, and a search-matching model. We also formulate an encompassing empirical specification. In Section 3 we present the data and discuss identification and estimation issues. The results are presented in Section 4 and the relation other empirical studies is discussed in Section 5.

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[4] There is a lot of evidence that an increase in unemployment will lead to wage moderation, and this will increase employment, but this effect would arise in any labor market model that we know of.

2. Theories of Job Creation and an Empirical Specification

Below we formulate two simple models of job creation: a labor demand model with adjustment costs and a search-matching model. The purpose is to clarify which factors determine job creation in each model and to highlight the differences between the two models. In both models, firms, indexed *i*, belong to different sectors and sell in different product markets, but hire in the same local labor market and take the wage as given.[5]

2.1 A Labor Demand Model with Adjustment Costs[6]

The wage is above the market clearing level and there are no search frictions, so firms can always hire the workers they want. The production function is $Q_{i,t} = N_{i,t}$, where $Q_{i,t}$ is production, and $N_{i,t}$ is the number of workers employed in firm *i*. Demand for the firm's product is $Q_{i,t} = D_{i,t} - \frac{1}{\eta} \frac{P_{i,t}}{P_{i,t}^C} + v_{i,t}$ where $D_{i,t}$ is a firm-specific demand-shifter, $P_{i,t}$ is the price set by firm *i*, $P_{i,t}^C$ is the average price level of the competitors of firm *i* in the relevant markets. $D_{i,t}$ and $P_{i,t}^C$ are indexed *i* because firms belong to different sectors and sell in different markets. $v_{i,t}$ is a firm-specific idiosyncratic i. i. d. demand shock. The shock is observed by the firm before it sets employment. It is costly for the firm to adjust its employment level, and the adjustment cost is given by $c P_{i,t}^c (N_{i,t} - N_{i,t-1})^2 / 2$.

The profit maximization problem facing firm *i* is:

Kommentar [MC1]: Inte så snygg sidbrytning

$$
\max \quad E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} \frac{1}{P_{i,\tau}^C} \left[(P_{i,\tau} - W_{i,\tau}) N_{i,\tau} - \frac{c P_{i,\tau}^C}{2} (N_{i,\tau} - N_{i,\tau-1})^2 \right]
$$

$$
s.t. \ N_{i,\tau} = D_{i,\tau} - \frac{1}{\eta} \frac{P_{i,\tau}}{P_{i,\tau}^C} + v_{i,\tau}.
$$

(1)

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[5] We do not model wage setting but we think of the wage as being predetermined because of union contracts and nominal wage rigidity. Forslund, Gottfries and Westermark (2006) find a very high degree of nominal wage rigidity in all four Nordic countries. What is needed, however, is that the wage does not depend on the employment decision. In the empirical implementation, we instrument for the wage to take account of possible simultaneity.

[6] Models of this type are analyzed by Sargent (1979), Nickell (1986), Hamermesh (1993), and others. It is presented here to simplify the comparison with the search-matching model.

where the wage in firm i is denoted $W_{i,t}$.[7] The first order condition for the optimal employment level in period t is a second-order difference equation from which we can derive the following equation for net job creation (see the *Appendix*):

$$\Delta N_{i,t} = \frac{\lambda_1}{c} \sum_{\tau=t}^{\infty} \left(\frac{1}{\lambda_2}\right)^{\tau-t} E_t \left(\eta(D_{i,\tau} + v_{i,\tau}) - \frac{W_{i,\tau}}{P_{i,\tau}^C} \right) - (1-\lambda_1)N_{i,t-1}, \tag{2}$$

where λ_1 and λ_2 are functions of the parameters β, η and c; $0 < \lambda_1 < 1$ and $\lambda_2 > 1$. Job growth in firm i is determined by demand and wage cost deflated by an index of competitors' prices. In the following, we denote the latter variable "real wage cost" or "competitiveness." Employment in the previous period enters as a state variable.

2.2 A Search-Matching Model

In the textbook search-matching model firms are identical and hire at most one worker. In reality, firms belong to different production sectors and sell in different markets, and most of them hire many workers. To derive an employment equation that can be implemented empirically, we consider a search-matching model with multi-employee firms facing different wages and prices. The model is a large-firm version of the standard search-matching model (e.g. Pissarides, 2000), except that we assume vacancy costs to be quadratic. This assumption is made to avoid the extreme – and counterfactual - implication that all vacancies are opened by the most profitable firm.

Workers and firms are situated in local labor markets and they cannot move between markets. In each local labor market there is a large number of price-taking firms. Again, firms in a local labor market belong to different production sectors and sell in different markets, so they face different competitors' prices, $P_{i,t}^C$. Job destruction varies stochastically across firms. The timing of events is as follows:

(i)   At the start of a period, firms choose the number of vacancies to open. Firm i opens $V_{i,t}$ vacancies, and incurs total vacancy costs given by $P_{i,t}^C c V_{i,t}^2 / 2$.

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[7] To simplify the model, we assume that the adjustment cost is proportional to the competitors' price and the firm also deflates future profits by this price. With more realistic assumptions, we would have more relative prices entering the decision rule, but these effects would be hard to estimate empirically.

(ii)   Matching of previously unemployed workers $(U_{n,t-1})$ and total vacancies $(V_{n,t})$ takes place in the local labor market, indexed n. The matching process between vacancies and unemployment is described by a conventional constant-returns matching function: $M_{n,t} = U_{n,t-1}^{\alpha} V_{n,t}^{1-\alpha}$ where $M_{n,t}$ is the total number of matches in period t. Hence the probability of filling a vacancy is

$$q_{n,t} = M_{n,t} / V_{n,t} = (U_{n,t-1} / V_{n,t})^{\alpha}.$$

(iii)   A firm-specific separation shock is realized. Total separations in firm i are given by $(\lambda + \xi_{i,t})N_{i,t}$ where the shock, $\xi_{i,t}$, is i.i.d with mean zero.

(iv)   Production takes place.

Firm i chooses vacancies so as to solve the following profit maximization problem:

$$\max \ E_t \sum_{\tau=t}^{\infty} \beta^{\tau-t} \frac{1}{P_{i,\tau}^C} \left[(P_{i,\tau}^C - W_{i,\tau})N_{i,\tau} - \frac{P_{i,\tau}^C}{2} V_{i,\tau}^2 \right]$$

(3)

$$s.t. \ N_{i,\tau} = q_{n,\tau}V_{i,\tau} + (1 - \lambda - \xi_{i,\tau})N_{i,\tau}$$

At the optimum, the marginal cost of opening one more vacancy should be equal to the marginal benefit of opening a vacancy:[8]

$$cV_{i,t} = q_{n,t} \sum_{\tau=t}^{\infty} \left[\beta^{\tau-t}(1-\lambda)^{\tau-t} E_t \left(1 - \frac{W_{i,\tau}}{P_{i,\tau}^C} \right) \right].$$

(4)

Using the constraint in (3) and the expression for q_t we can express net job creation in firm i as:

$$\Delta N_{i,t} = \frac{1}{c}\left(\frac{U_{n,t-1}}{V_{n,t}}\right)^{2\alpha}\left(\sum_{\tau=t}^{\infty}\left[\beta^{\tau-t}(1-\lambda)^{\tau-t}E_t\left(1-\frac{W_{i,\tau}}{P_{i,\tau}^C}\right)\right]\right) - (\lambda + \xi_{i,t})N_{i,t-1}.$$

(5)

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[8] Alternatively, this condition can be derived by substituting for vacancies in the objective function, maximizing with respect to expected employment, and iterating on the resulting difference equation (see the *Appendix*).

As in the labor demand model, job creation in a firm depends on the firm's real wage cost. Furthermore, it increases with the level of unemployment for two reasons: high unemployment makes it easier to find workers and the firm also opens more vacancies. Job creation should decrease with the total number of vacancies in the local labor market because of congestion. It is harder for firm *i* to find workers when there are many vacancies in the local labor market. Again, the previous level of employment is a state variable.

2.3. An Encompassing Empirical Specification

Comparing the equations for job creation derived from our two models we see that real wage cost and the previous level of employment play a role in both. The key difference is that according to the labor demand model, demand is important for firms' hiring decisions, while the search-matching model emphasizes labor supply. Unemployed workers contribute to job creation in the search-matching model. Since we want to investigate the relative importance these various factors, our baseline empirical specification encompasses both models:

$$\Delta \ln N_{i,t} = \alpha_i + \beta_1(\ln W_{i,t} - \ln P_{i,t}^C) + \beta_2 \ln D_{i,t} + \beta_3 \ln U_{n,t-1} + \beta_4 \ln V_{n,t} + \beta_5 \ln N_{i,t-1} + \varepsilon_{i,t}. \quad (6)$$

In the theoretical models above, employment depends on weighted averages of current and expected future real wage costs and demand. Since we have a rather short panel, we simply use current values and include extra lags if necessary in the empirical specification.[9] Productivity growth is captured by time dummies.

Both models predict $\beta_1 < 0$ and $-1 < \beta_5 < 0$. According to the labor demand model $\beta_2 > 0$ and $\beta_3 = \beta_4 = 0$, while the search-matching model implies $\beta_2 = 0$, $\beta_3 > 0$ and $\beta_4 < 0$. We should note, however, that these differences arise because we made different assumptions in the two models about product *and* labor markets. In the labor demand model, the product market was assumed to be imperfectly competitive and there were no matching frictions in the labor market. In the search-matching model, the product market was assumed to be perfectly competitive and there were frictions in the labor market. These are the typical combinations considered in the literature. Most of the modern bargaining literature treats the product market as imperfectly competitive; it is the firm's market power which creates the surplus, over

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[9] The period in the models is shorter than one year, which is the frequency of the data. Ideally we would like to have data on higher frequency, but given the high persistence in the explanatory variables, it is very unlikely that such data would lead to qualitatively different results.

which firms and insiders/unions bargain.[10] Almost all search-matching models treat product markets as perfectly competitive, downplaying the role of demand factors.[11]

There are other combinations, however, e.g. efficiency wage models with perfect competition in the product market (Shapiro and Stiglitz (1984)) and search-matching models with imperfect competition in the product market (Ebell and Haefke (2004)). Thus we can have $\beta_2 > 0$ in a search-matching model and we should be aware that β_2 sheds light on the nature of product market competition rather than matching frictions. The real test of whether search-matching theory offers any value added lies in testing whether coefficients β_3 and β_4 are significantly different from zero, with the signs predicted by search-matching theory.

3. Data and Estimation

Firm specific variables are taken from a firm-level dataset provided by Statistics Sweden and administered by Sveriges Riksbank. This dataset contains annual information for the years 1990-2000 on all Swedish *industrial firms* with 20 or more employees and a sample of smaller firms. The database is constructed by merging information from several sources: Registry Based Labor Market Statistics (RAMS), Survey Based Statistics for Industrial Plants (Industristatistiken) and Survey Based Statistics for Firms (Finansstatistiken 1990-1996, Företagsstatistiken 1997-2000). Since we want to identify the labor market area where the firm is situated, we consider only firms with a single plant, which do not move during the sample period. To construct our demand index we use the export share of the firm, and this is available only for firms with 50 employees or more.[12] We use only data for firms for which we have all the relevant information and these constraints limit the sample, leaving us with a sample of 461 ongoing firms. The following variables are included in the equation:

Employment $N_{i,t}$ is the average number of workers employed in firm *i* in year *t*.

Real wage cost is $\ln W_{i,t} - \ln P_{i,t}^C$ where $W_{i,t}$ is the firms' total labor cost per employee (including wage and e.g. collective fees). A firm-specific competitor price for firm *i* in industry *j* is calculated as $\ln P_{i,t}^C = (1 - \delta_i) \ln P_{j,t}^D + \delta_i \ln P_{j,t}^{IC}$, where δ_i is the average export share over the sample period for firm *i* and $P_{j,t}^D$ is the industry-level producer price index for the domestic market (i. e. domestic deliveries plus imports, SNI92 two-digit industry

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[10]See e.g. Calmfors and Driffill (1988), Layard, Nickell and Jackman (1991).
[11] E.g. Pissarides (2000) does not consider the case where there is imperfect competition in the goods market.
[12] An alternative would be to use the export share for the industry but this is less appealing because export shares vary substantially between firms within an industry.

classification). The international competitors' price is calculated as

$\ln P_{j,t}^{IC} = \sum_m \omega_{j,m}(\ln E_{m,t} + \ln P_{j,m,t}^F)$, where $\omega_{j,m}$ is the average share of industry j's exports

that went to country m during 1990-1994 ($j \in \{31, 32,..,38\}$, SNI69 industry classification).

These shares are computed using the available trade data for the classification of goods

(varusni69) matching the SNI69 industry (production) classification. The countries, indexed

m, are Sweden's 13 main trading partners.[13] The competitor product price in foreign

currency, $P_{j,m,t}^F$, is the implicit value-added deflator for industry j in country m taken from the

OECD industrial database STAN. $E_{m,t}$ is the exchange rate (SEK per country m's currency)

taken from the OECD Annual National Accounts.

The *demand* variable for firm i in sector j is constructed as

$\ln D_{i,t} = (1-\delta_i)[\phi_j^C \ln C_t + \phi_j^I \ln I_t + (1-\phi_j^C - \phi_j^I)\ln Y_t] + \delta_i D_{j,t}^I$, where δ_i is again the firm's

average export share, ϕ_j^C is the industry specific share of output going to final consumption in

total domestic use, ϕ_j^I is the corresponding share going to investment and $1-\phi_j^C - \phi_j^I$ is the

corresponding share used as intermediate goods (SNI92 two-digit industry classification).

These shares are computed as the average value from the 1995 and 2000 Input-Output tables

provided by Statistics Sweden. Y, C, and I are all aggregate variables. Y_t is a volume index of

industrial production, C_t is real private consumption and I_t is real private sector gross fixed

investment. The international demand component is calculated as $\ln D_{j,t}^I = \sum_m \omega_{j,m} \ln Y_{j,m,t}$,

where $Y_{j,m,t}$ is real value-added for industry j in country m taken from the OECD industrial

database STAN and used as proxy for industry demand; the weights are defined above.

Unemployment $U_{n,t}$ is defined as the total number of unemployed workers in the

local labor market area n and is provided by Swedish Labour Market Board (AMS). Local

labor market areas consist of one or more municipalities and are constructed by Statistics

Sweden using commuting patterns. We use the 1993 definition with 109 labor market areas.

According to Johansson and Persson (2000), 80-90 percent of hired workers come from the

local labor market area.

Vacancies $V_{n,t}$ in the local labor market area are constructed using monthly vacancy

data from the Swedish Labour Market Board (AMS), which measures the number of unfilled

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[13] That is, Germany, France, Italy, the Netherlands, Belgium, UK, Denmark, USA, Canada, Japan, Norway, Finland and Austria. These countries absorb about 80 percent of Sweden's exports.

vacancies at the start of the month in each local labor market area. We take the average over the year as our measure of vacancies.

For *productivity* we constructed a firm-specific productivity trend as $\tau_i T_t$ where $\tau_i = (\ln(Y_{i,2000} / N_{i,2000}) - \ln(Y_{i,1990} / N_{i,1990}))$, $Y_{i,t}$ is the firm's real sales and T_t is a linear time trend.

Table 1 shows how firms in the sample are distributed across industries. We also see that export shares and the composition of demand vary considerably across industries. *Figure 1* illustrates the severity of the Swedish recession, with investment and consumption falling substantially in 1992-1993. *Figure 2* shows that the large depreciation of the currency in 1992-1993 had a substantial effect on real wage cost (competitiveness) in the machine industry, with a 64 percent export share, but did not much affect the food industry, with an 11 percent export share. *Figure 3* shows that there is considerable co movement of unemployment rates across local labor markets, but also a non negligible cross-sectional variation. Vacancies appear to be more disperse across local labor markets (*Figure 4*).

By regressing our variables on time dummies, we can find out how much of the variation that is cross sectional. Time dummies explain 14 percent of the change in real wage costs, 83 percent of the change in demand, 86 percent of changes in regional unemployment rates, and 30 percent of changes in vacancies. Thus, about the same fraction of the variation is cross-sectional for unemployment changes as for demand changes.

Can we plausibly identify the effects we are interested in? The main problem is that shocks, which affect employment in many firms, may affect wages and aggregate demand as well as unemployment and vacancies in the local labor market area. The shock $\varepsilon_{i,t}$ in equation (6) may have aggregate, industry-specific, and local components. We include time dummies which absorb the effects of aggregate shocks. Industry-specific shocks are dealt with by not relying on industry-specific time series data to construct demand indices but constructing this variable from aggregate data as described above.[14] The industry price, which is used to calculate the real wage cost, is instrumented using suitably chosen lags (see discussion below). To deal with simultaneity arising from local shocks, we instrument local unemployment and vacancies by demand and (lags of) competitors' price indexes which reflect the industry structure in the local labor market area.

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[14] We assume that unobserved *world-wide* industry shocks are unimportant.

A *demand* variable for the local labor market n is constructed as

$\ln D_{n,t} = \sum_j \kappa_{j,n} \ln D_{j,t}$ where the weights $\kappa_{j,n}$ reflect the local labor market's industry

composition (SNI92 two-digit industry classification). These weights are constructed by using

RAMS data on the number of employees in each sector (by local labor market SNI92 two-

digit industry classification). Industry demand is calculated as

$\ln D_{j,t} = (1-\delta_j)[\phi_j^C \ln C_t + \phi_j^I \ln I_t + (1-\phi_j^C - \phi_j^I)\ln Y_t] + \delta_j D_{j,t}^I$ where δ_j is now the industry's

average export share.

Local competitors' price is constructed analogously as $\ln P_{n,t}^C = \sum_j \kappa_{j,n} \ln P_{j,t}^C$

where $\ln P_{j,t}^C = (1-\delta_j)\ln P_{j,t}^D + \delta_j \ln P_{j,t}^{IC}$.

By using instruments for vacancies, we also deal with the problem of measurement

errors in vacancy data. As is well known, many job openings are not officially registered, so

vacancies are a relatively poor measure of the number of job openings.

Wage data may also suffer from measurement problems because of composition

effects and variation in hours. Also, wages and prices may be simultaneously determined. We

therefore use lagged values of the real wage cost variable, $\ln W_{i,t} - \ln P_{i,t}^C$, as instruments for

the real wage cost.

Since our empirical specification includes lagged dependent variables as well as

fixed effects, we use an Arellano-Bond (1991) estimator.[15] Thus, fixed effects are eliminated

by taking first differences. This procedure introduces an MA(1) process in the residual

$(\Delta \varepsilon_{i,t})$, so that the first difference of the lagged dependent variable and the residual are

correlated. But provided that $\varepsilon_{i,t}$ is not serially correlated, we can use (suitably chosen) lags

of the dependent variable as instruments.

As is generally the case for an asymptotically efficient GMM estimator, the

instrument set grows with the number of time periods. However, as the lag order increases,

lags become less informative as instruments. To avoid including irrelevant instruments, it is

sensible not to include the full history of lags. We do not use instruments further back than

five years relative to the variable that is to be instrumented. The results are not sensitive to

including the full history of lags, however. Taking account of all the considerations above, we

chose the instrument set listed in *Table 2*.

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[15] We have also tried using the System-GMM estimator suggested by Blundell and Bond (1998). However, the Hansen test indicates that the data does not square well with the restrictions imposed on the initial conditions process.

4. Results

When we estimate equation (6) as it stands, the AR(2)-test indicates that we have a problem with second-order serial dependence in the residuals. Our stylized theoretical models may not fully capture the dynamic adjustment, or there may be some omitted variables. By including two additional lags of employment in the regressions we are able to remove any signs of serial dependence in the residual.[16] The Hansen test does not reject the joint hypothesis that the model is correctly specified and that the instruments are valid. Examining the relevance of the instrument set, we find that the partial R^2:s are 0.56 for unemployment, 0.32 for vacancies, and 0.08 for real wage cost.[17] Thus, we should keep in mind that the relevance of the instrument set is somewhat low for the real wage cost.

Table 2 shows the results. Column I shows the results for a pure labor demand model. This model is supported by the data. Real wage cost and demand have the expected effects on job creation and both coefficients are highly significant. Since both variables are relatively crude proxies for the true costs and demand, the estimated coefficients are likely to understate the importance of these factors.[18]

In contrast, the search-matching model in Column II is not consistent with the data: unemployment and vacancies have insignificant effects on job creation. Column III shows the results for the encompassing model. These results only confirm the results for the labor demand model. Thus we find no evidence that unemployed workers contribute to matches being formed. When we model employment changes in individual firms, we do not gain any explanatory power by including the variables suggested by search-matching theory.[19]

Our theoretical models have relatively simple dynamics. To allow for more complicated dynamics, we estimate the model including one additional lag on real wage cost, demand, unemployment and vacancies. As seen in Column IV in *Table 2*, the only lag that is significant is lagged demand. The coefficient is almost as large as the contemporary effect, but with opposite sign, implying an essentially immediate effect of a demand shock on employment. One interpretation of this result is that customer relations are important in the

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[16] We cannot eliminate the serial dependence mentioned above by adding lags of any other explanatory variable than employment.

[17] The relevance statistics are calculated using a static instrument set.

[18] According to the theoretical models, the correct variables would be weighted averages of current and expected future demand and real-wage costs, demand is measured using industry rather than firm-level export composition, wage data does not take account of variation in hours etc.

[19] Obviously, unemployment and vacancies depend on demand and wages, but this is a problem only if the correlation is so high that there is a multicollinearity problem. The highly significant coefficients for the latter variables suggest that this is not the case.

product market. Customer market theory offers a natural explanation why demand effects are immediate but price effects take time.[20]

To test whether our results are sensitive to our choice of estimation method, we also estimate the model by OLS using a within transformation to handle fixed effects. Column V in *Table 2* shows the results. Wages and demand have significant effects, but the coefficients are somewhat smaller compared to the GMM estimates. This may be due to measurement errors for wages, in which case *all* the coefficients in the regression will be biased.

One possible objection against the results in *Table 2* is that some firms may cater mainly to the local labor market. If so, local-demand and competitiveness variables $\ln D_{n,t}$ and $\ln P_{n,t}^{C}$ are invalid instruments because they actually belong in the equation. Suppose that some firms in the local labor market area are hit by negative shocks and local unemployment increases. If firm i is a sub-contractor, or caters to the employees of those firms, it will also reduce employment. If the true coefficient for unemployment is positive, this will bias the coefficient towards zero. One way to check whether such local interdependencies affect the results is to limit the analysis to firms with a substantial export share. Such firms should be less dependent on local demand conditions, so the estimated coefficient on local unemployment should be less biased. Estimating equations for firms with substantial export shares, e. g. 25 or 50 percent, we still do not find any significantly positive effect of local unemployment on net job creation.

5. Comparisons with Other Results

An earlier paper that tries to distinguish empirically between search and labor demand models is Burgess (1993). His paper is, in spirit, similar to ours and he claims support for the search-matching model. The results are hard to compare, however, because his specification is fundamentally different from ours. First, he uses aggregate data and estimates a time series model with a large number of explanatory variables. Second, he argues that the key

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[20] Following Gottfries (2002), let a firm's customer stock x be determined by $x_{i,t} = (1-\lambda) x_{i,t-1} - \lambda \eta \left(p_{i,t} - p_{i,t}^{c} \right)$, where, η is the long run elasticity, and λ is the speed of adjustment of the customer stock. All variables are logs. Suppose further that each customer buys $\exp(\sigma d_t)$ units and there is constant returns to scale so the log of employment equals production: $n_{i,t} = x_{i,t} + \sigma d_t$. Let the price be set according to $p_{i,t} - p_{i,t}^{c} = a_w \left(w_{i,t} - p_{i,t}^{c} \right)$. Then we can easily derive the following equation for employment: $\Delta n_{i,t} = -\lambda \eta a_w \left(w_{i,t} - p_{i,t}^{c} \right) + \sigma d_{i,t} - \sigma(1-\lambda) d_{i,t-1} - \lambda n_{i,t-1}$. Gottfries (2002, Table 1) estimated $\eta = 2.88$, $a_w = 0.37$, and λ corresponding to 0.28 on a yearly frequency. These results are qualitatively in line with the results in Column IV.

implication of search-matching is that hiring costs depend on the state of the labor market. A slack labor market will reduce hiring costs and speed up the adjustment towards the desired level of employment. Thus he tests for interaction effects between labor market tightness and the gap between desired and actual employment. This is reasonable when the desired employment adjustment is positive (hiring) but makes little sense when the desired employment change is negative. Also, it different from the standard search matching model, where labor market slack, by itself, makes it more profitable to open vacancies.

Another related literature is concerned with the labor-market impact of immigration. Card (1990) and others exploit geographical differences in immigration and find small effects of immigration on wages and job opportunities for natives in local labor markets. Taken at face value, such results suggest that supply does indeed create its own demand. But an increase in immigration obviously increases both supply and demand in the local labor market. Further, as emphasized by Borjas (2003), there is a serious simultaneity problem because immigrants are attracted to regions where there are many jobs. In our view, these results are not directly comparable to ours, which are primarily concerned with cyclical fluctuations.

A large number of studies have estimated "matching functions" and found a positive effect of unemployment on hiring (see Petrongolo and Pissarides (2001) for an overview). Blanchard and Diamond (1989), for example, estimate a matching function and conclude that "employment is not simply determined by demand" (p.4). Does the empirical success of the matching function contradict our findings? In our view it does not because an estimated matching function says very little about *how* employment adjustment actually comes about. Most labor market theories imply that unemployment tends to revert to some natural rate, so hiring tends to be high when unemployment is high. In a regression of hiring on unemployment we should expect a positive coefficient – independently of which is the correct theory of the labor market. If we include vacancies in the regression, the coefficient on unemployment should fall but remain positive because vacancies are a very imperfect measure of actual job openings. Thus, every labor market theory predicts positive coefficients in a regression of hiring on unemployment and vacancies. Most theories would also imply constant returns to scale: hiring is twice as high in a labor market that is twice as big. So an estimated matching function does not say much about the importance of search frictions in the labor market.[21]

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[21] Since we do not have vacancy data for individual firms, we cannot replicate matching-function estimates using this dataset.

To separate different labor market theories, we need to know whether employment adjustment occurs because wages fall when unemployment is high, because of changes in aggregate demand and exchange rates, or because search by unemployed workers in itself contributes to more jobs being filled. We tried to separate these factors and we found clear effects of wages and demand.[22] There was no evidence that unemployment has a *direct* effect on job creation.[23]

We should note, however, that the Swedish labor market was very weak in the 1990s. Open unemployment went up to 8 percent, with another 5 percent in labor market programs. Matching problems may be more important in a tight labor market and to investigate this is an interesting avenue for future research. Still, our results suggest that more attention to the demand side is needed if search-matching models are to be useful for modeling medium term employment dynamics.

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[22] Blanchard and Diamond (1989) motivate the omission of wages from the estimated matching function by assuming that "wages play no allocational role in individual matches, merely dividing rents between firms and workers". Our results indicate an important allocative role of wages. Gottfries (1992), Oswald (1993), Holden (1994), Gottfries-Sjöström (1999) and Eriksson-Gottfries (2005) provide arguments why wages are rigid and play an allocative role.

[23] There is also a recent literature that investigates whether the search-matching model is capable of generating the observed cyclical fluctuations in unemployment and vacancies. Shimer (2005) finds that the standard search-matching model with continuously renegotiated wages cannot explain such variation. If wages are assumed to be sticky, the fit of the model improves significantly (Shimer (2004)). However, this literature is concerned with wage setting rather than the importance of search-frictions in the labor market.

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Appendix. Derivation of the Job Creation Equations

The Labor Demand Model:

This derivation follows Sargent (1979) closely. Using the constraint to eliminate $P_{i,\tau}$ in the objective function and taking the first-order condition for period t we get:

$$E_t\left\{\eta(D_{i,t} - 2N_{i,t} + v_{i,t}) - \frac{W_{i,t}}{P_{i,t}^C} - c(N_{i,t} - N_{i,t-1}) + \beta c(N_{i,t+1} - N_{i,t})\right\} = 0$$

By the law of iterated expectations, this holds if we take expectations at time t for future periods. Since this is linear we can solve the problem as if future variables were known with certainty. Using lag operators, this can be rewritten as:

$$\beta\left[1 + \frac{\phi}{\beta}L + \frac{1}{\beta}L^2\right]N_{i,t+1} = -\frac{\eta}{c}(D_{i,t} + v_{i,t}) + \frac{1}{c}\frac{W_{i,t}}{P_{i,t}^C}.$$

where $\phi = -\left[1 + \beta + 2\eta/c\right]$. The expression within the brackets can be factorized:

$$\beta\left[(1 - \lambda_1 L)(1 - \lambda_2 L)\right]N_{i,t+1} = -\frac{\eta}{c}(D_{i,t} + v_{i,t}) + \frac{1}{c}\frac{W_{i,t}}{P_{i,t}^C},$$

where λ_1 and λ_2 are functions of β, η and c. This can be rewritten as:

$$N_{i,t+1} = \lambda_1 N_{i,t} + \frac{\lambda_1}{c}\sum_{\tau=t}^{\infty}\left(\frac{1}{\lambda_2}\right)^{\tau-t}\left(\eta(D_{i,\tau+1} + v_{i,\tau+1}) - \frac{W_{i,\tau+1}}{P_{i,\tau+1}^C}\right).$$

One can show that the same expression holds for period t.

The Search-Matching Model

Using the constraint to eliminate $V_{i,\tau}$ in the objective function and maximizing with respect to planned employment to get the following first-order condition for period τ :

$$E_\tau \left\{ (1 - \frac{W_{i,\tau}}{P_{i,\tau}^C}) - c \left(\frac{N_{i,\tau} - (1 - \lambda - \xi_{i,\tau})N_{i,\tau-1}}{q_{n,\tau}^2} \right) + (1 - \lambda)\beta c \left(\frac{N_{i,\tau+1} - (1 - \lambda - \xi_{i,\tau+1})N_{i,\tau}}{q_{n,\tau+1}^2} \right) \right\} = 0.$$

Using the same conditions for subsequent periods and the law of iterated expectations we can derive planned employment in period *t*:

$$E_t(N_{i,t}) = \frac{q_{n,t}^2}{c} \sum_{\tau=t}^\infty \left[\beta^{\tau-t} (1 - \lambda - \xi_{i,\tau})^{\tau-t} E_t \left(\frac{P_{i,\tau}^C - W_{i,\tau}}{P_{i,\tau}^C} \right) \right] + (1 - \lambda)N_{i,t-1}$$

Table 1. Industry Distribution of Firms in the Sample. Average Export Share and Share Used for Consumption, Investment and Intermediate Goods for each Industry

Industry (SNI92)	Number of firms	Average export share	Consumption	Investment	Intermediate
15	22	0.11	0.58	0	0.42
16	0	0.06	1	0	0
17	15	0.63	0.28	0	0.72
18	7	0.79	0.89	0	0.11
19	4	0.73	0.39	0	0.61
20	44	0.52	0.02	0	0.98
21	22	0.65	0.03	0	0.97
22	18	0.04	0.16	0	0.84
23	3	0.50	0.40	0	0.60
24	19	0.69	0.28	0	0.72
25	26	0.52	0.07	0	0.93
26	5	0.30	0.03	0	0.97
27	17	0.54	0.01	0	0.99
28	68	0.28	0.02	0.14	0.84
29	92	0.64	0.02	0.40	0.58
30	4	0.74	0.04	0.80	0.16
31	9	0.70	0.06	0.17	0.77
32	7	0.78	0.04	0.35	0.61
33	12	0.62	0.02	0.49	0.49
34	28	0.66	0.28	0.20	0.52
35	9	0.69	0.12	0	0.88
36	29	0.46	0.38	0.20	0.42
37	1	0	0	0	1

Table 2: Results

Dependent variable: $\Delta \ln N_{i,t}$

	I	II	III	IV	V
Estimation method	GMM	GMM	GMM	GMM	OLS
$\ln W_{i,t} - \ln P_{i,t}^C$	-0.270** (0.105)	-0.275** (0.105)	-0.263** (0.102)	-0.345** (0.109)	-0.178** (0.044)
$\ln W_{i,t-1} - \ln P_{i,t-1}^C$	-	-	-	0.125 (0.110)	-
$\ln D_{i,t}$	0.302** (0.098)		0.319** (0.101)	0.459** (0.160)	0.285** (0.059)
$\ln D_{i,t-1}$	-	-	-	-0.398* (0.159)	-
$\ln U_{n,t-1}$	-	-0.018 (0.059)	-0.012 (0.057)	-0.006 (0.060)	-0.039 (0.027)
$\ln U_{n,t-2}$	-	-	-	-0.031 (0.053)	-
$\ln V_{n,t}$	-	-0.015 (0.020)	-0.020 (0.019)	-0.023 (0.018)	-0.007 (0.008)
$\ln V_{n,t-1}$	-	-	-	0.012 (0.016)	-
$\ln N_{i,t-1}$	-0.264** (0.070)	-0.220** (0.067)	-0.269** (0.071)	-0.218** (0.083)	-0.211** (0.032)
$\ln N_{i,t-2}$	-0.063 (0.037)	-0.062 (0.037)	-0.060 (0.036)	-0.080* (0.039)	-0.071* (0.035)
$\ln N_{i,t-3}$	0.039 (0.030)	0.034 (0.031)	0.035 (0.030)	0.028 (0.028)	0.018 (0.024)
Productivity	0.006 (0.004)	0.007 (0.004)	0.006 (0.004)	0.005 (0.004)	0.006 (0.003)
Time Dummies	Yes	Yes	Yes	Yes	Yes
Period	1994-2000	1994-2000	1994-2000	1994-2000	1993-2000
Number of obs.	3227	3227	3227	3227	3688
AR(2) (P-value)	0.197	0.163	0.170	0.144	-
Hansen(P-value)	0.301	0.168	0.263	0.374	-

Note: The sample is 461 firms. ** and * denote significance at the 1 and 5 percent levels respectively. The estimation in columns I-IV is performed using the Arellano and Bond (1991) GMM estimator calculated with DPD 1.21 for Ox. The GMM-type instruments used are: $\ln N_{i,t-s}$ where s = 2, …,5, $\ln W_{i,t} - \ln P_{i,t}^C$ where s=2, …,5, $\ln P_{n,t-s}^C$ where s = 2, 3, …,6, $\ln D_{n,t-s}$ where s = 0, …,6. $\ln D_{i,t}$ is treated as exogenous and we treat the productivity trend as deterministic. Second-step coefficients with robust Windmeijer (2005) finite-sample corrected standard errors in parenthesis. AR (2) denotes the p-value for the test of second-order autocorrelation in the first differenced residuals. Hansen denotes the p-value of the joint test of the model specification and instrument validity. The estimation in column V is performed using the OLS within estimator and robust standard errors are in parentheses.

Figure 1: Changes in Demand Components
Change in Domestic Consumption, Investment and Production, and International Demand
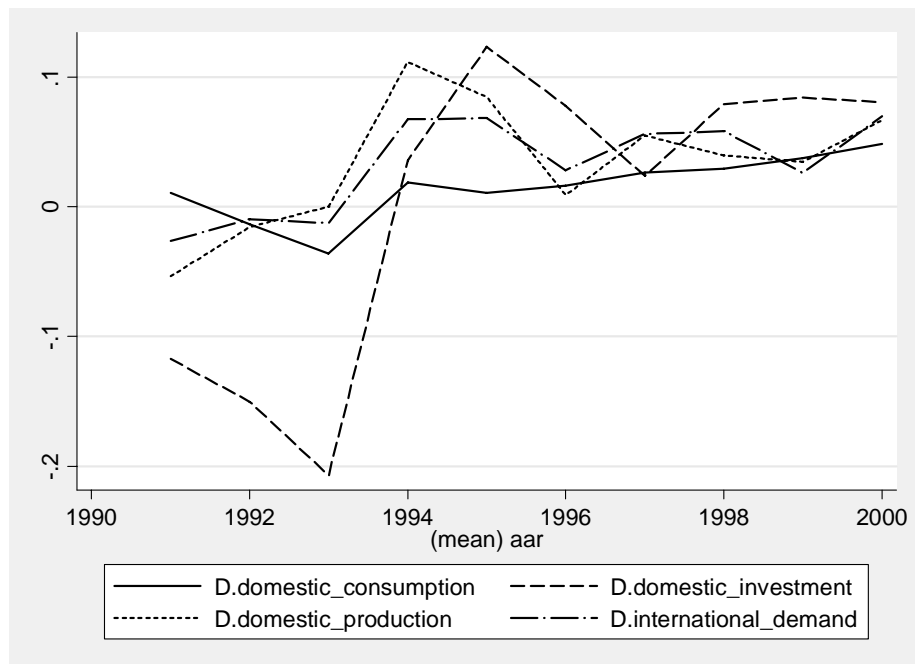(the latter is for sni69=38)

Figure 2: Changes in Real Wage Cost
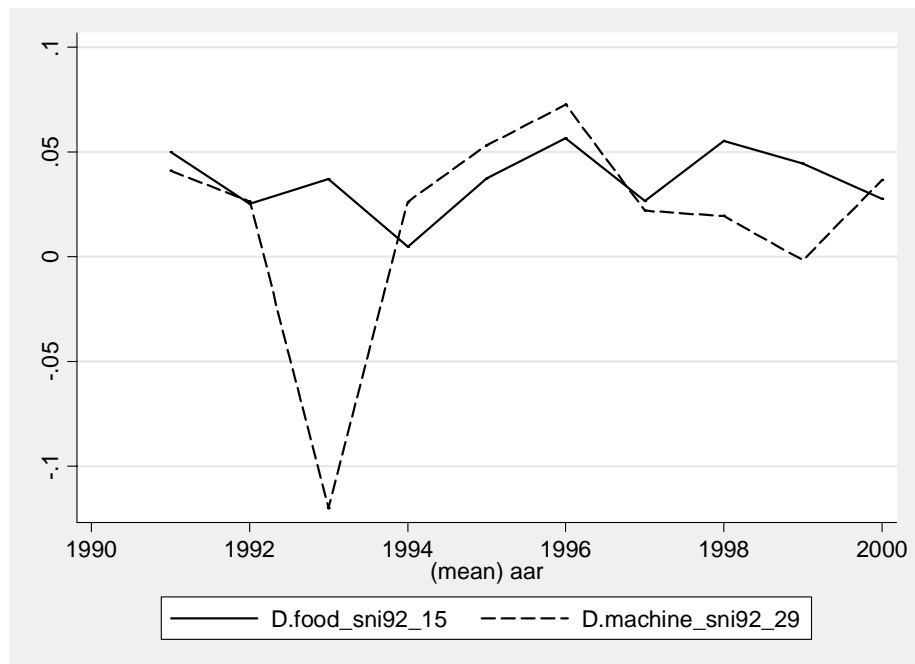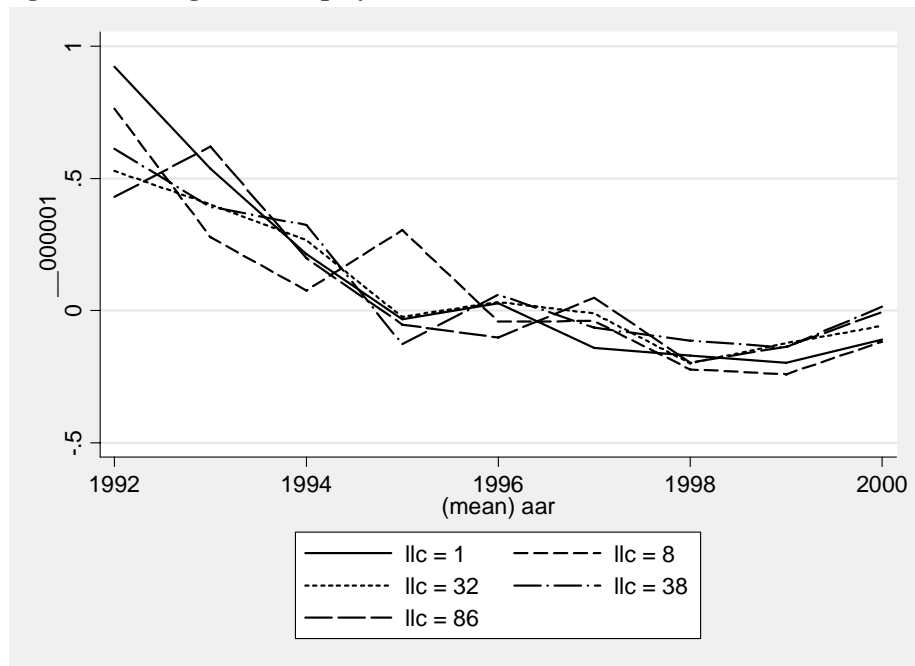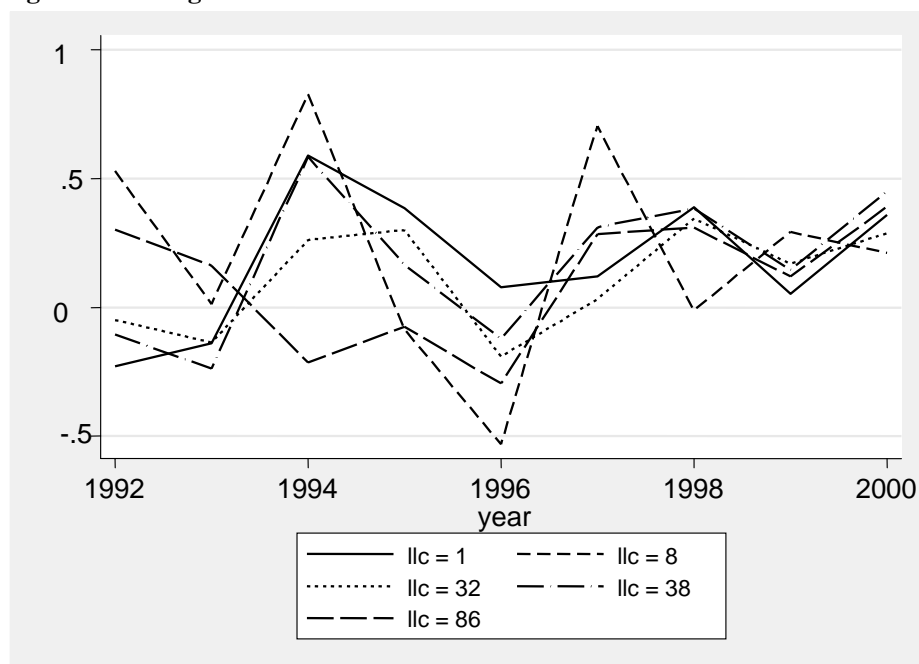Food (sni92=15) and Machine Industries (sni92=29)

Figure 3: Change in Unemployment for some Local Labor Markets

Note: The local labor market areas used for this illustration are Stockholm (llc=1), Gnosjö (llc=8), Malmö (llc=32), Göteborg (llc=38) and Örnsköldsvik (llc=86).

Figure 4: Change in Vacancies for some Local Labor Markets

Note: The local labor market areas used for this illustration are Stockholm (llc=1), Gnosjö (llc=8), Malmö (llc=32), Göteborg (llc=38) and Örnsköldsvik (llc=86).

22