Mismatch Unemployment Across Industries in Spain

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Preliminary and Incomplete

Abstract

I measure the contribution of mismatch across industries to the rise in Spanish unemployment between 2006 and 2010. For this purpose, I apply the methodology developed in Sahin, Song, Topa, and Violante (2014). My calibration implies that mismatch across industries is strongly counter-cyclical. During the pre-recession period the fraction of hires lost because of an inefficient distribution of unemployed workers across industries was around 3%. On the contrary, in 2009 the fraction of hires lost grew to around 8%. In spite of this, mismatch across industries cannot explain a significant part of the total increase in unemployment during the Great Recession.

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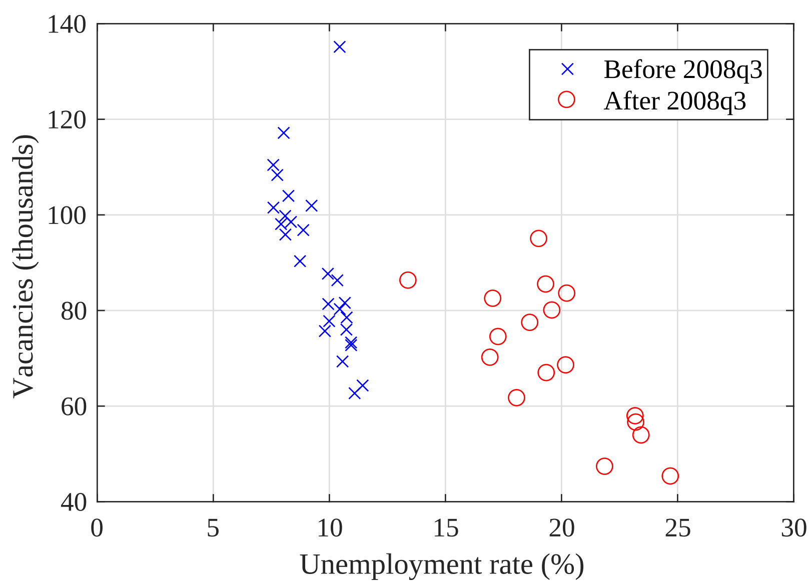
1 Introduction

From the beginning of 2007 to the third quarter of 2010, unemployment in Spain tripled from around 7-8% to 21%. Across industries, the increase was very asymmetric. While the unemployment rate in the transport sector grew from 6.2% to 14.2%, in the construction sector the increase was from 9.4% to 35%. This fact raised concerns that structural unemployment may shifted upwards and therefore explain the persistently high unemployment rates observed since 2010. One possible explanation is mismatch defined as "idle workers seeking employment in sectors different from those were the available jobs are" (Şahin, Song, Topa, & Violante, 2014). The goal of this paper is to quantify the increase in unemployment driven by mismatch across industries in the Spanish labor market.

Mismatch hypothesis is consistent with two important characteristics of the great Recession in Spain. Firstly, as shown in Figure 1, starting in 2008 the Spanish Beveridge curve has displayed a marked movement to the right meaning that aggregate matching efficiency has declined. Secondly, a large fraction of the job losses during the crisis came from the construction sector. As long as those workers do not look for a job in other sectors, mismatch across industries would increase.

FIGURE 1. BEVERIDGE CURVE IN SPAIN



Source: Encuesta de Poblacion Activa and Encuesta de Coyuntura Laboral (2002-2012)

In order to quantify the effect of industry level mismatch on aggregate unemployment, I rely on the methodology developed by Şahin et al. (2014) to the Spanish labor market. The theoretical framework divides the economy in different industries. Given the distribution on the unemployed, the methodology analyzes whether the unemployed are distributed inefficiently. The idea is to compare the actual distribution of the unemployed with the allocation a social planner would choose in case of facing no impediment in moving idle workers across industries. By manipulating the planner's optimal conditions, one can construct a mismatch index that measures the fraction of hires lost in every quarter because of misallocation of the unemployed across industries. Based on this index, I can compute the counterfactual unemployment rate that would exist in case of absence of mismatch. The difference between the observed unemployment rate and the counterfactual is what Şahin et al. (2014) call mismatch unemployment.

Preliminary results show a strong counter-cyclical pattern of mismatch. The fraction of hires lost because of an inefficient distribution of unemployed workers across industries grew from around 3% between 2002 to 20007 to 8% in the first quarter of 2009. In spite the fact that mismatch across industries worsened during the crisis, it cannot explain a significant fraction of the observed increase in unemployment rates from 2006 to 2010. My quantitative results imply that mismatch unemployment can account for around 1 percentage point of the observed unemployment in 2010.

2 Literature Review

The historically high unemployment rates in Spain constitute one of the most important problems of the Spanish economy and key for understanding differences in income with other OECD countries. The expansion of 1995-2006, however, drew attention away from unemployment. The Great Recession has again shifted the focus towards the reasons behind the abundance of Spanish jobless.

One important factor that led to increases in unemployment was the housing bust following the housing boom. The significant expansion of credit and the immigration inflow attracted by the construction sector supported employment growth during the boom. When the crisis hit, there was a large missallocation of resources linked to past accumulation in highly unproductive sectors (García-Santana, Moral-Benito, Pijoan-Mas, & Ramos, 2016). Furthermore, as shown in Bentolila, Dolado, and Jimeno (2012) using a sample of 16 OECD countries, there is a strong and positive correlation between housing price growth rate in 2000-2007 and the increase in unemployment rate in 2007-2009. A potential explanation for this correlation is that unemployed workers, once employed in the construction sector, were not looking for jobs in other industries. My results imply, however, that this channel cannot explain a substantial increase in the unemployment rate. In line with this result Bentolila, García-Pérez, and Jansen (2017) find that unemployed workers from the construction sector did not have more difficulties finding a job than similar workers from other sectors.

In contrast to mismatch hypothesis, there also exists important institutional reasons for the persistently high unemployment rates during recessions. Indeed, Bentolila, Dolado, and Jimeno (2012) also show that the negative relation between housing inflation and employment growth also holds when the construction industry is excluded. More precisely, they point towards an inefficient institutional framework of the Spanish labor market which prevents wages and hours work to adjust when negative aggregate shocks hit the economy. As a result, Spanish firms accommodate a lower aggregate demand by firing more workers. Furthermore, Costain, Jimeno, and Thomas (2010) and Bentolila, Cahuc, Dolado, and Le Barbanchon (2012) find that the coexistence in the Spanish labor market of "temporary" contracts with low firing costs and "permanent" contracts with high firing costs raises importantly the volatility of the unemployment rate. This mechanism would also explain massive inflows into unemployment during the crisis.

In recent work, Boscá, Doménech, Ferri, and García (2017) investigate the aggregate effects of the decrease in the matching efficiency shown in Figure 1. The authors find that the decrease in the matching efficiency during the Great Recession is responsible of a around a third of the observed drop in employment. In contrast to this work, the authors do not consider the reasons behind the marked right shift of the Spanish Beveridge curve. In this paper, I explore to which extent the decrease in the matching efficiency driven by worsening mismatch across industries can explain the observed increase in unemployment. Even though mismatch is found to be strongly counter-cyclical, it cannot explain a significant fraction of the observed increase in unemployment.

Across countries, Şahin et al. (2014) and Patterson, Şahin, Topa, and Violante (2016) using sectoral data at the 3-digit level find that mismatch cannot either explain a large fraction of the observed increase in unemployment during the Great Recession for the US and the UK, respectively. Given that I can only construct a consistent database for the period 2002-2010 with 9 industries and that the mismatch index is increasing in the number of sectors, a more disaggregated database would be needed for comparing the role of mismatch across countries.

3 Summary of the Theoretical Framework

In the economy there are I distinct frictional industries. Hires (h) in each labor market are determined by the matching function $h_{it} = \Phi_t m(u_{it}, v_{it})$. The term Φ_t captures changes in the aggregate component of the matching efficiency. m is the matching function strictly increasing and strictly concave in both arguments: u_{it}, number of unemployed searching in industry i and v_{it}, number of vacancies in industry i. Vacancies arise exogenously across labor markets. The agents can either be employed (e) or unemployed (u). The unemployed can search for a job in only one labor market at a time. There is no on-the-job search and all existing matches are subject to exogenous, aggregate separation shocks Δ. All the workers produce Z units of output in every sector. The number of vacancies is the only sources of heterogeneity across sectors.

The social planner maximizes the following problem:

$$
\begin{aligned}
V(\mathbf{e};\mathbf{v},Z,\Delta,\Phi) = \quad & \max_{\{u_i \geq 0\}} \sum_{i=1}^{I} Z(e_i+h_i) + \beta\mathbb{E}[V(\mathbf{e}';\mathbf{v}',Z',\Delta',\Phi')] \\
\text{subject to} \quad & \sum_{i=1}^{I}(e_i+h_i) = 1 \\
& h_i = \Phi m(u_i, v_i) \\
& e' = (1-\Delta)(e+h)
\end{aligned}
$$

The planner's solution yields the optimal rule for the allocation of unemployed workers across sectors:

$$
m_{u_1}\left(\frac{v_{1t}}{u^*_{1t}}\right) = \cdots = m_{u_i}\left(\frac{v_{it}}{u^*_{it}}\right) = \cdots = m_{u_I}\left(\frac{v_{It}}{u^*_{It}}\right), \tag{1}
$$

where m_{u_i} is the derivative of m with respect to u_i and where we have "*" to denote the planner's allocation. This allocation rule equates the finding rate across industries so that every unemployed worker has the same chance of getting a job irrespective of the sub-market. Therefore, the planner allocates more job seekers to labor markets with more vacancies till the job finding rates are equalized across industries.

3.1 Mismatch

Using the planner's optimal allocation rule in equation 1, Şahin et al. (2014) derive an index to measure the severity of the labor market mismatch between unemployed workers and vacancies. Assuming a well supported Cobb-Douglas matching function ($m(u_t, v_t)$) (Petrongolo & Pissarides, 2001), the number of hires in a given industry is given by:

$$
h_{it} = \Phi_t v_{it}^{\alpha} u_{it}^{1-\alpha}, \tag{2}
$$

where the vacancy share $\alpha \in (0,1)$ is common to all industries. Summing up across industries, we obtain the total number hires:

$$
h_t = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_{i=1}^{I}\left(\frac{v_{it}}{v_t}\right)^{\alpha}\left(\frac{u_{it}}{u_t}\right)^{1-\alpha}\right]. \tag{3}
$$

The optimal number of hires that the planner can make by allocating u_t unemployed is given by:

$$h_t^* = \Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}^*}{u_t} \right)^{1-\alpha} \right]. \tag{4}$$

Equation 1 that provides the rule for allocating unemployed workers, is written for the Cobb-Douglas case as:

$$\left(\frac{v_{it}}{u_{it}^*} \right)^\alpha = \left(\frac{v_{jt}}{u_{jt}^*} \right)^\alpha \tag{5}$$

I can express the total number of hires under the planner's conditions as:

$$h_t^* = \Phi_t v_t^\alpha u_t^{1-\alpha}. \tag{6}$$

Defining mismatch $\mathcal{M}$ as the index measuring the fractions of hires lost because of misallocation of unemployed workers, we compute $\mathcal{M}$ as:

$$\mathcal{M}_t = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \tag{7}$$

By better allocating the same number of unemployed, the planner can increase the aggregate job-finding rate and achieve more hires compared to the equilibrium. $\mathcal{M}_t$ measures the inefficiency in the allocation of unemployed workers in equilibrium which is always a number between 0 (no mismatch) and 1 (maximal mismatch).

3.2 Mismatch Unemployment

The mismatch index allows to construct a counterfactual level of unemployment i.e the unemployment level that would prevail in absence of mismatch. Unemployment rate in the decentralized and centralized economy are driven by:

$$u_{t+1} = u_t + s_t(1 - u_t) - f_t u_t \tag{8}$$

and

$$u^*_{t+1} = u^*_t + s_t(1 - u^*_t) - f^*_t u^*_t, \tag{9}$$

respectively. s_t represents the separation rate, f_t is actual job finding rate and f^*_t is the optimal finding rate in the centralized economy.

From the definition of the mismatch index, I can write:

$$h_t = (1 - \mathcal{M}_t)h^*_t = (1 - \mathcal{M}_t)\Phi_t v^\alpha_t u^{1-\alpha}_t.$$

This expression shows that mismatch lowers the aggregate matching efficiency reducing the number of hires. Dividing both sides by the number of unemployed u and using equation 6, I obtain the job finding rate:

$$f_t = (1 - \mathcal{M}_t)\frac{h^*_t}{u_t} = (1 - \mathcal{M}_t)\Phi \left(\frac{v_t}{u_t}\right)^\alpha \tag{10}$$

On the other hand, the optimal job-finding rate is obtained from:

$$f^*_t = \frac{h^*_t}{u^*_t} = \frac{\Phi_t v^\alpha_t (u^*_t)^{1-\alpha}}{u^*_t} = \Phi_t \left(\frac{v_t}{u^*_t}\right)^\alpha.$$

Dividing and multiplying by u_t and using (11) we obtain:

$$f^*_t = f_t \cdot \underbrace{\frac{1}{1 - \mathcal{M}_t}}_{\text{Direct Effect}} \cdot \underbrace{\left(\frac{u_t}{u^*_t}\right)^\alpha}_{\text{Feedback}}. \tag{11}$$

There are two reasons which explain why the optimal finding rate is larger than the actual one. First, the "direct effect" captures the idea that, with a given number of unemployed, the planner would generate more hires because of a better allocation of the unemployed. Second, since the number of unemployed in the centralized economy is lower than the equilibrium, unemployed workers have more chances of filling a vacancy since they face less competitors("feedback effect"). Given an initial value for u^*_0, I am able to compute the counterfactual level of unemployment iterating forward on equation 9. The gap between u_t

and u^* is considered as mismatch unemployment.

The empirical method that Şahin et al. (2014) have developed allows me to analyze the relative importance of mismatch across industries. On the other hand, with this methodology I am not able to infer the causes of such mismatch. The analysis of Herz and Van Rens (2015) suggests that relative wage rigidity is more important than moving costs. In contrast, in this paper, since the allocation is derived under costless reallocation of unemployed workers, the analysis represents an upper bound on the role of mismatch.

4 Data

To compute the mismatch index $\mathcal{M}_t$, I need industry level data on vacancies, unemployment and the vacancy share of the matching function α. For this purpose, I rely on a broad industry classification which consists of 9 different sectors based on the spanish industry classification cnae-09: industry (cnae-09: 10-18), mining (cnae-09: 5-9, 19-25, 36-39), manufacturing (cnae-09: 26-33), construction (cnae-09: 41-43), accomodation (cnae-09: 45-47, 55-56), transportation (cnae-09: 49-53, 58-63), financial intermediation (cnae-09: 64-66, 68, 69-75, 77-82), public sector (cnae-09: 86-88), and other services (cnae-09: 90-93, 94-97, 99).

Vacancies—. Data on vacancies at the industry level come from the Encuesta de Coyuntura Laboral (ECL). The ECL was a survey conducted in Spain at the quarterly frequency and representative of the universe of workers except those in the agricultural sector and housekeeping.

Unemployment—. Data on unemployment at the industry level come from the Encuesta de Poblacion Activa (EPA). The EPA is a nationally representative sample. The unemployed are asked to report the last industry in which they worked in. The question is however in only asked to individuals who lost their jobs in the last 12 months. Therefore for the current version, I assume that individuals who spent more than 12 month unemployed, are distributed across industries as those with lower unemployment spells. This is clearly a limitation of the data that might imply an important underestimation of mismatch across industries as those unemployed workers with longer spells are probably the ones coming from most affected sectors. In future work, I plan to use administrative data from INEM for computing unemployment shares across industries using this data.

Hires—. For computing the vacancy share (α) and the aggregate matching efficiency (Φ_t), I need the job finding rate. This can be obtained using the rotating panel of the EPA. In the EPA, one sixth of the sample is renewed quarterly; hence, I am able to observe labor market outcomes of an individual for up to six quarters. Thus, I track the employment status of individuals who are unemployed at a given quarter and construct the job finding rate.

4.1 Matching functions

To compute aggregate matching efficiency and vacancy share, I estimate constant-returns to scale matching functions. In particular, I follow Borowczyk-Martins, Jolivet, and Postel-Vinay (2013) in dealing with the well known endogeneity issues in matching function estimation. More precisely, I decompose matching efficiency Φ_t into a time polynomial and an unobserved error component. Rewriting equation 2 in logs, we obtain:

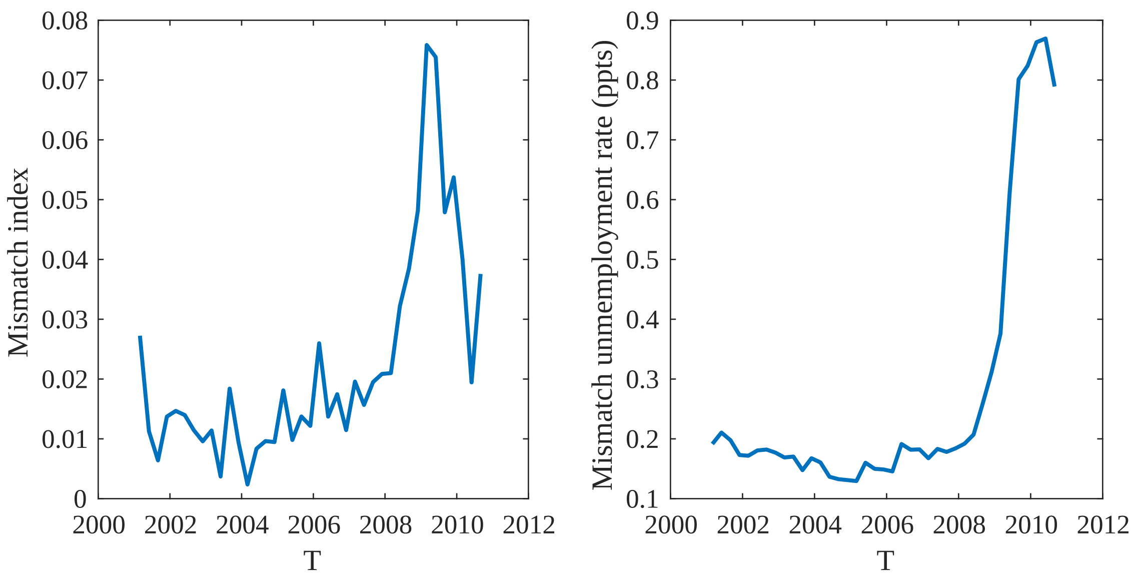
$$ln(f_t) = \mu_0 + \mu_1 t + \mu_2 t^2 + \alpha\theta_t + \epsilon_t, \tag{12}$$

where $\theta_t = ln(\frac{v_t}{u_t})$ and $\boldsymbol{\mu}$ are coefficients of the time polynomial. Assuming a moving average representation of ϵ implies that lags of θ_t beyond order 2 are valid instruments for $(\theta_t, \ldots, \theta_{t-min\{p,q\}})$ and for $(f_{t-1}, \ldots, f_{t-min\{p,q\}})$. Using the second lag of θ_t as instrument, I find a vacancy share of 0.36 with a 95 percent confidence interval between 0.23 and 0.48. Estimates of the matching efficiency imply an increase of it between 2000 and 2008 and a decrease afterwards.

5 Results

The left panel of figure 2 plots the mismatch index $\mathcal{M}_t$ across the nine industries. The figure shows that, before the last recession (in mid-2006), the fraction of hires lost because of misallocation of unemployed workers across industries ranged from 0.2 to 3 percent per quarter. In the first quarter of 2009, it had increased to 8 percent per quarter. It has since then dropped and increased back again during the last quarter of 2010. This indicates a strong countercyclical pattern of mismatch.

Figure 2. Mismatch index ($\mathcal{M}_t$) by industry (left panel) and the corresponding mismatch unemployment rates (right panel)



The right panel of figure 2 plots mismatch unemployment -the difference between the actual and the counterfactual unemployment rates — at the industry level for the 2001–2011 period, computed as described in Section 3.2. It shows that in 2010, mismatch unemployment across 9 different industries can explain at most 1 percentage point of the actual unemployment (20%).

6 Conclusions

In this paper I apply the methodology developed by Şahin et al. (2014) to compute the increase in unemployment driven by mismatch across industries. Even though mismatch unemployment increased by 5 times, it cannot explain an important fraction of the observed increase in unemployment during the crisis. Other channels seem therefore necessary to explain why unemployment rates increased so strongly in Spain during the crisis while GDP losses were relatively close to other OECD countries. Institutional factors seem therefore to play a central role in explaining Spanish persistently high unemployment rates during recessions.

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