

Banco de México
Documentos de Investigación

Banco de México
Working Papers

N° 2014-08

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April 2014

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Can Matching Frictions Explain the Increase in Mexican Unemployment After 2008?*

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Abstract: We use a novel data set on firm vacancies and job seekers from a Mexican government job placement service to analyze whether changes in matching frictions can explain the large and persistent increase in Mexican unemployment after the 2008 global financial crisis. We find evidence of a statistically significant reduction in the efficiency of the matching function during the crisis. The estimated effect explains about 70 basis points of the 233 basis points observed increase in the unemployment rate. Hence, these results suggest that changes in matching frictions cannot explain most of the increase in unemployment.

Keywords: Matching function estimation; Unemployment; Vacancies.

JEL Classification: J63; J64; E24.

Resumen: Este trabajo utiliza una nueva fuente de datos sobre vacantes de empleo publicadas por empresas y de solicitantes de empleo proveniente de un servicio de vinculación laboral del gobierno mexicano para analizar si los cambios en las fricciones de contratación pueden explicar el importante y persistente incremento del desempleo en México después de la crisis financiera mundial de 2008. Se encuentra evidencia de una reducción estadísticamente significativa en la eficiencia de la función de matching durante la crisis. El efecto estimado explica alrededor de 70pb del aumento de 233pb observado en la tasa de desempleo. Así, este resultado sugiere que los cambios en las fricciones de contratación no pueden explicar la mayor parte del aumento en el desempleo.

Palabras Clave: Estimación de la función de matching; Desempleo; Vacantes.

*We would like to thank Alberto Torres, Ana María Aguilar, Laura Juárez, Santiago García-Verdú and the seminar and conference participants at Banco de México, the CEMLA Research Network meetings, the Labor Economics Summer School at Barcelona Graduate School of Economics and the LACEA-LAMES meetings in Mexico City for their comments and support. Daniel Casarín and Mario Oliva were very helpful in providing research assistance at early stages of the project. We are especially indebted to Marcelo Delajara, José Antonio Murillo and Jaime Rogerio Girón for their role in getting access to the data. All remaining errors are our own.

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1 Introduction

During the global financial crisis, unemployment levels in Mexico showed an increase not seen since the 1994 Tequila crisis. Although output recovered fairly quickly in both crises, after 2008 the response of the Mexican labor market has been sluggish and by 2013, unemployment had still not returned to pre-crisis levels.

Similar persistent increases in unemployment in developed countries have led to a research agenda that explores the possibility of structural changes in the labor market. For example, Daly et al. (2013) analyze the relationship between unemployment, GDP growth, total employment, hours worked and productivity in several developed countries¹ before and after the global financial crises. Concerns about structural changes in unemployment levels in the US have focused on the role of geographic and skill mismatches and the role of extended unemployment benefits in explaining recent jobless recoveries.²

In this context it is surprising that Mexico suffered from a similar atypical behavior in its unemployment rate, albeit of a lower magnitude and starting from a lower level, since the most common theories to explain structural unemployment shifts in the U.S. do not translate to the Mexican labor market. For example, the absence of any form of unemployment insurance precludes the role of government programs in explaining Mexican unemployment, and Mexico did not suffer from a housing boom, so geographical mobility has not been impeded by the “house-lock” conjecture. Given that Mexico operates at different segments of the value chain than the U.S., concerns about a long-term decline of manufacturing due to outsourcing cannot be invoked to explain Mexican unemployment.

Therefore, alternative theories must be invoked if one wishes to justify shifts in the Mexican labor market. Some potential candidates exist: the shock experienced in the U.S., Mexico’s main trading partner, might have forced a shift from manufac-

¹Germany, United Kingdom and United States.

²Although the question is not settled, several papers have found evidence against these hypothesis. In an influential paper, Lazear & Spletzer (2012) conclude that “Neither industrial nor demographic shifts nor a mismatch of skills with job vacancies is behind the increased rates of unemployment.” Barnichon & Figura (2011) find that neither dispersion in market tightness nor extended unemployment benefits can explain movements in the aggregate matching efficiency.

turing to services which could potentially have generated a skill mismatch. According to INEGI, employed personnel in manufacturing decreased approximately by 11.2%, between January 2007 and July 2009, although from July 2009 to October 2013 grew by 13.6%.³

A related but different concern is that the crisis significantly impacted migration flows from Mexico to the U.S. due to the contraction in the construction sector, traditionally an important source of employment for Mexican migrant workers. The net flow of migration reduced to almost zero since 2008.⁴ If returning migrants have a skill mismatch with respect to those demanded domestically, this supply shock could have potentially amplified matching frictions after 2008, but such a mismatch would be hard to justify if the reduction in net flows came mainly from potential migrants choosing to stay given the conditions abroad.

An important reference to order the discussion above is the job search literature (Blanchard & Diamond, 1989; Mortensen & Pissarides, 1999; Rogerson & Shimer, 2004) which has highlighted the importance of matching frictions in the hiring process to explain unemployment. Matching frictions are those factors that prevent firms that are actively seeking to fill job vacancies from hiring workers that are actively seeking a job at market clearing wages. Among the different frictions that may hinder the matching technology, we highlight the following: 1) Differences between the job skills of workers and the skills demanded by employers, as mentioned above, and, 2) Labor regulations affecting the hiring process, either because of legal obstacles to the entry of new workers or high firing costs that make employers averse to hiring employees which they are not sure are adequate to fill out their available job positions.

Despite recent legal reforms which aim to modernize the Mexican labor market, the difficulty to lay off workers is a relevant factor that affects the hiring process of firms, especially in the formal sector of the economy. According to the Doing Business report of 2013, prepared by the World Bank, the severance pay for redundancy dismissal in Mexico ranges from 14.6 to 30.0 times the weekly salary for a person who worked

³Instituto Nacional de Estadística y Geografía, the national statistics agency. In July 2009 employed personnel in manufacturing was at its lowest point.

⁴Pew Research Hispanic Trends Project.

for a year to ten years, respectively. The average severance payment for some Latin American countries (Brazil, Chile, Colombia and Peru) ranges from 3.0 to 20.1 times.

In this context, this paper analyzes if changes in matching frictions can explain the increase in Mexican unemployment after 2008. Although our data will not allow us to distinguish which of the theories above might be the source of the changes in frictions, we will contribute to the debate by quantifying the magnitude of the change and seeing if it can potentially explain the size of the shift in the unemployment level.

To measure the level of frictions, we analyze a novel data set from a government job placement service in Mexico administered by the Ministry of Labor.⁵ This data set is the only source we are aware of that contains information on job vacancies in Mexico. It also contains information on job seekers and placements executed through the system. By observing the demand and supply of labor separately, the data allows us to assess whether changes in matching frictions are responsible for the sustained increase in unemployment after 2008.

Using this data set, we estimate the matching function, the reduced-form relation between unemployment, vacancies, and new hires. Our parameter estimates are consistent with those reported in the literature for developed economies: the matching function exhibits constant returns to scale and a relative coefficient of about one half for vacancies with respect to unemployment (Blanchard & Diamond (1989) and Petrongolo & Pissarides (2001)).

We also find evidence of a reduction in the efficiency of the matching function during the 2008 crisis. The estimated effect explains 70bp of the 233bp increase in the unemployment rate, so we conclude that an alternative explanation is required to explain most of the movement in unemployment.

Our work is related to Barnichon & Figura (2011) who decompose the cyclical movements in the aggregate efficiency of the matching function into changes due to composition and dispersion effects. Composition effects occur because workers with lower idiosyncratic matching efficiencies increase their share of the unemployed during recessions. For example, typically during recession there is an increase in the share

⁵Secretaría de Trabajo y Previsión Social (STPS).

of long-term unemployed which also have lower matching efficiency. Dispersion occurs because of variance in the market tightness between separate labor markets that shows up as a loss of efficiency in the aggregate data. Such dispersion would be consistent with concerns of mismatch. From their empirical estimations, the authors conclude that dispersion explains relatively little of the cyclical movements compared to the composition effects. In a related work, Sahin et al. (2012) find that “mismatch across industries and occupations explains at most one-third of the total observed increase in the unemployment rate” while “geographical mismatch plays no apparent role”.

In spite of the fact that throughout the paper we focus on real frictions and do not analyze the response of wages, it is necessary to note that an important concern from a central bank’s perspective is the role of nominal wage rigidities in introducing frictions in the labor market. This is particularly relevant in the new macroeconomic environment of the Mexican economy, where the double digit inflation observed in the 1990s gave way to a very different behavior since the 2000s. For example, although GDP in 2009 dropped 4.7% at an annual rate, core inflation decreased only 1.3 p.p. (from 5.5% to 4.2%). This contrasts with the experience of 1995 during the Tequila crisis, where GDP declined 5.8%, while core inflation spiked from 7.7% in 1994 to 50.6% at the end of 1995.

The rest of this paper is organized as follows. Section 2 reviews the main characteristics of the data we use. In section 3 we present our measure of labor market tightness in Mexico and relate it to some important macroeconomic variables through the cycle. Section 4 introduces our specification for the matching function and provides our estimation results. In section 5 we analyze if changes in matching frictions can explain the increase in Mexican unemployment after 2008. Section 6 concludes.

2 The Data

Since we employ a novel data set, it is worth reviewing its main characteristics in detail. One important hindrance to develop empirical studies of matching frictions in developing countries is the lack of data on job vacancies. In this work, we analyze a new data set that comes from *Bolsa de Trabajo* (BT) which is a government-run free employment service under the supervision of the Ministry of Labor. The data set includes monthly observations for vacancies, job applications and hirings through the system from January 1993 to April 2013 for each of Mexico's 31 federal states and its Federal District (Table 1 reports some summary statistics). This source of information allows us to analyze the job matching process in a well-defined segment of the Mexican labor market.

The *Bolsa* handles large volumes of job seekers and vacancies in about 160 branches throughout Mexico. The main aim of BT is to link job seekers with job openings that are appropriate to their profile. A job seeker is a person who has registered with BT during a month to apply for a job. Although job seekers are not necessarily unemployed we will treat them as such.

The system is run by state-level authorities and the information is collected by the federal government. The service works under quite specific terms. Job seekers have to fill out in person a detailed form with their qualifications and interests. If they are still looking for a job after one year they have to begin the process again. BT offers job seekers guidance and feedback on the availability of current vacancies to find an appropriate fit.

On the other side of the market, firms post vacancies and are also required to fill out a detailed form when registering them, including the exact number of vacancies and type of employee wanted. Every two weeks firms report if their vacancies are still open. Firms are not required to register their vacancies in person: BT offers the option to register it through a BT agent. These procedures render vacancies a specific meaning with a well-defined lifespan.

At the final stage of the process, BT sends job seekers to interview with employers

which decide to hire them or not. No fees are charged for any of these services, but firms are required to disclose whether a hiring was successful.

BT has strict criteria to ensure there is no redundancy in their administrative records. They have procedures to prevent a worker from registering more than once in the system and require that firms post a separate vacancy for each unique employment position. If a firm is recruiting several workers for the same position it registers a separate vacancy for each of them in the system.

A concern on the scope of our data is that all BT branches are located in the main urban areas of each state. A casual inspection of the posted vacancies shows that the majority of them are urban jobs, for example, secretaries, plant managers, electricians or plumbers. Given the transient nature of many rural jobs, it is hard to imagine that a rural employer would use job postings to fill out its vacancies. Because of this we interpret our data set as representative of urban jobs and will hereafter mostly compare our predictions with the urban series from the national employment surveys. In particular, we use the *Encuesta Nacional de Empleo Urbano* (ENEU) from 1993 to 2004 and the urban series of its successor, the *Encuesta Nacional de Ocupación y Empleo* (ENOE) from 2005 to 2012. This is somewhat convenient because the urban employment series are the longest available for the Mexican labor market. For the period in which the ENOE becomes available, 2005-2013, urban workers represent, on average, 80% of all employed workers, while the urban unemployed represent, on average, 88% of the unemployed population.

Another concern with our data is that it might be skewed towards the formal sector, since firms are asked that the vacancies they post comply with all labor regulations. This could in principle alter the representativeness of the data, since informality is especially prevalent in the Mexican labor market, accounting for approximately 60% of the employed population,⁶ yet it is unclear how the BT can guarantee that firms comply. Because of this, currently we have decided not to analyze the relationship of

⁶INEGI has two different measures for informality the *Tasa de ocupación en el sector informal*, which is around 28%, and the *Tasa de Informalidad Laboral*, which is around 59%. The first measure includes workers in informal firms as well as the self-employed, while the second measure includes all those workers in the informal sector as well as the workers in the formal sector who do not receive the benefits required by law.

our data with the (unobserved) formality status of its job placements.

It is important to understand that the BT is not in itself a major player in the Mexican labor market. For example, when we compare the hirings from the system with the gross flows from unemployment to employment reported in the national employment surveys we find that hirings through the Bolsa are on average 6.4 times smaller than the total gross flows.⁷ Instead, we take our data to be a good proxy for the general conditions of the Mexican labor market through the cycle subject to the caveats previously mentioned: it is biased towards urban and formal employment.

Finally, it is worth mentioning that the Ministry of Labor offers an independent parallel employment service called “Portal de Empleo” that forms matches between workers and jobs through an online site. This service is relatively new, starting in March 2002. Because of this, we observe an exponential growth in the data as it became more popular, which stabilized in recent years (Figure 1b).

Figure 1a: Employment series in "Bolsa de Trabajo" (Thousands, s.a.)

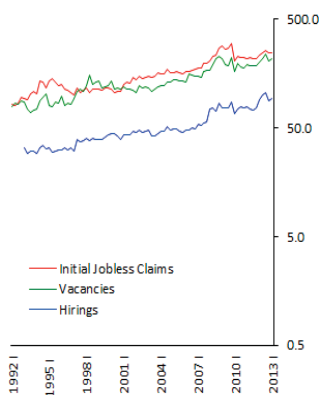
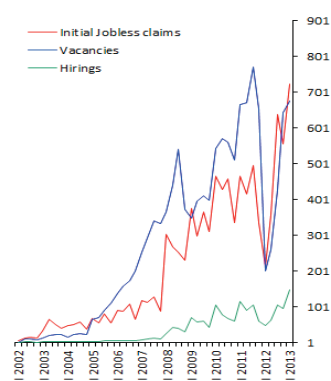


Figure 1b: Employment series in "Portal de Empleo" (Thousands)



Source: Mexican Ministry of Labor.

A disadvantage of the data from Portal is that there is no easy way to evaluate the quality of the data, since there are no controls to prevent a job seeker or a firm from filling more than one posting. The experience in other countries, especially in

⁷Because the ENEU/ENOE data suffer from a downward bias due to time-aggregation, this number overstates the relative size of BT.

developed ones, shows that the online vacancy publishing services have tended to displace traditional services. So far it is not clear that this has happened in Mexico and so we decided not include this information in our analysis.

3 Some macroeconomic facts of labor market tightness in Mexico.

The fact that we have data available for both the supply and demand side of the labor market allows us to study for the first time the relationship between some labor indicators commonly used in the job search literature and other macroeconomic variables in Mexico. The purpose of this section is twofold: first we present some macroeconomic facts of the Mexican labor market tightness and then we relate them with the literature (Shimer (2005), Rogerson & Shimer (2010)). We are especially interested in describing the behavior of labor market tightness during economic downturns, its correlation with the output gap, productivity and wages.

Figure 2a presents two standard indicators for the Mexican labor market, the national unemployment rate and urban unemployment rate. Both indicators are highly correlated (0.97) and show a similar pattern during the 2008 crisis: a significant rise in unemployment in the first quarter of 2009 that has persistently remained at above crisis levels. The main advantage of using urban employment series is that they are the longest available for the Mexican labor market, making it possible to compare two periods of sharp economic downturns, the 1994 crisis and the 2008 crisis. As seen in the Figure 2a, during the 1994 crisis the peak in unemployment was even higher than in the current crisis. However, the recovery of economic activity led to a rapid decrease in the unemployment rate, which by the third quarter 1997 returned at a level similar to that observed in the pre-crisis period.

The behavior described above can be also seen in other labor market indicators. For example, Figure 2b shows the underemployment rate,⁸ which reflects the under-

⁸*Población Subocupada*: Persons in underemployment are all those who worked or had a job during the reference week but were willing and available to work for more hours than their job currently permits. This is the definition used by the International Labour Organization (ILO).

tilization of the productive capacity of the employed population. The lack of unemployment insurance in Mexico forces a share of the unemployed workers to move to part-time jobs. This induces unemployment figures for Mexico to be relatively low by international standards, making indicators such as underemployment rate particularly informative to understand the country's labor dynamics.

We construct a series for labor market tightness for each state as the ratio between the number of vacancies posted by firms, $v_{j,t}$, and the stock of unemployed, $u_{j,t}$, in each period t in each state j : $\theta_{j,t} \equiv \frac{v_{j,t}}{u_{j,t}}$. As mentioned above, BT contains information for each of Mexico's 31 federal states and its Federal District. We treat each state as a single labor market with the exception of the Metropolitan Area of Mexico City (MAMC), which includes the State of Mexico and the Federal District. This issue will be thoroughly discussed in the next section.

Figure 2a: Unemployment Rate and Urban Unemployment Rate

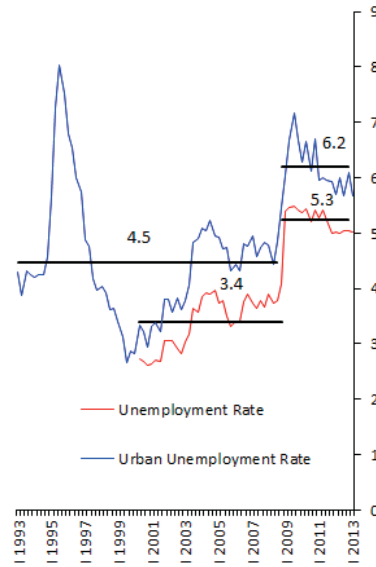
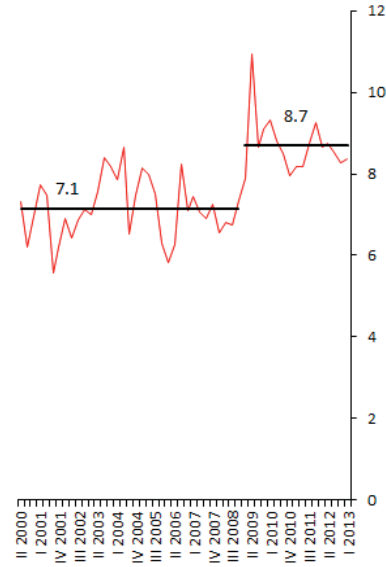


Figure 2b: Under-employment Rate



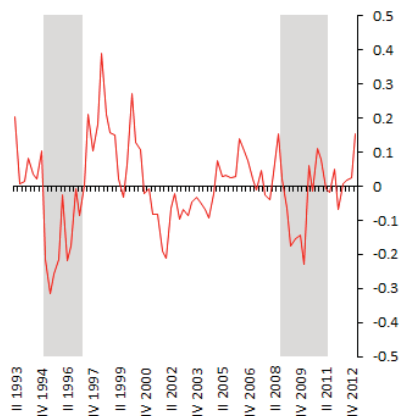
The numbers represent the average for 1993-2008 and 2009-2012, respectively. Source: Mexican Ministry of Labor.

We define the aggregate labor market tightness as the weighted average of the market tightness in each state using the size of its labor force, $LF_{j,t}$, as weights. Thus, our measure of market tightness is

$$\theta_t = \sum_j \frac{LF_{j,t}}{\sum_k LF_{k,t}} \theta_{j,t}$$

Figure 3 presents the quarterly labor market tightness in logs as deviations from an HP trend with a smoothing parameter equal to 1600. There we can see that the Mexican labor market tightened substantially from the third quarter of 1995 to the second quarter of 2001. This tightening was accompanied by a steady decline in the urban unemployment rate from a peak of 8.0 percent in the third quarter of 1995 to 3.4 percent in 2001. Figure 3 shows that market tightness decreased significantly during 2009 while recovered to pre-crisis levels by 2010 but the unemployment rate did not (see Figure 2a). There could be two explanations for this: either the efficiency of the matching function decreased or there was an increase in the firing rate (the rate at which workers leave jobs). Although our estimations below do find evidence of a decline in matching efficiency, we will show that the magnitude is not enough to explain the size of the increase in unemployment.

Figure 3: Labor Market Tightness
(Deviations from trend)



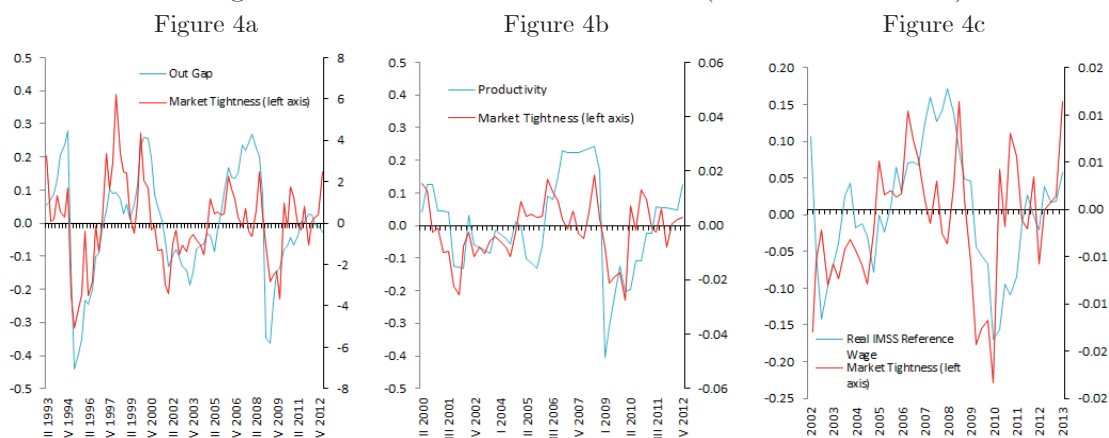
Note: Shaded areas represent cyclical downturns.

Source: Own calculations with data from INEGI and Mexican Ministry of Labor.

Next, we relate our measure of θ to three fundamental variables of the Mexican economy: the output gap, labor productivity and real wages. The results are consistent with those found in the literature. Table 2 summarizes the detrended time series of our measure of market tightness, output gap, labor productivity and wages. All variables are reported in logs as deviations from an HP trend.

In Figure 4a we show the output gap and our measure of labor market tightness. Both series are positively correlated with each other (0.66). Thus, recessions are associated with times when unemployment is higher relative to the posted vacancies; whereas in expansions the demand of labor is large relative to the supply, giving rise to a tighter labor market.

Figure 4: Co-movement in Macro Variables (Deviations from trend)



Notes: Seasonally adjusted market labor tightness, θ , built from BT data. The time series of the output gap and labor productivity are constructed by Banco de México from INEGI statistics. The time series for the real IMSS reference wage is constructed with data from INEGI. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

Figure 4b shows that the correlation between contemporaneously measured labor tightness and labor productivity is 0.50. Shimer (2005) finds a similar correlation of 0.40 between labor productivity, measured as real output per worker in the nonfarm business sector and the v/u ratio. All else constant, an increase in labor productivity makes vacancies relatively cheap, whereas unemployment becomes relatively expensive, giving rise to a tightening in the labor market. Despite the success of the Mortensen-Pissarides search and matching model (Mortensen and Pissarides (1994), Pissarides (1985, 2000)) to explain many facts about unemployment and gross flows it has been

argued (Shimer (2005)) that the model cannot explain the cyclical behavior of labor market variables (e.g. vacancies and unemployment) in response to measured productivity shocks consistent with the data. The correlation between contemporaneously measured labor market tightness and productivity is closed to 1 in those models. For instance Shimer (2005) and Hagedorn and Manovskii (2008) use different versions of the standard search and matching models and found a correlation of 0.999 and 0.967, respectively. This is much larger than what we observe in our data.

Finally, Figure 4c shows the co-movement between θ and the IMSS reference wage in inflation-adjusted pesos. The contemporaneous correlation between these two variables is 0.29, while the four lag correlation between them rises to 0.55; the latter suggests that θ is a good predictor of real wage growth. Hence, a tightening of the labor market is associated with an increase in real wages paid to the employees four quarters ahead. If the number of vacancies increases relative to the number of unemployed, a job seeker may expect to find a vacant relatively more quickly than a firm may expect to find an unemployed worker. Thus, the firm may offer higher wages, with a lag, in order to improve its hiring probability.

3.1 The empirical specifications and some preliminary analysis

As is standard in the literature, we model the total number of new hires as a Cobb-Douglas function of vacancies and unemployment:

$$U_{j,t}H_{j,t} = A_{j,t}V_{j,t}^{\alpha_v}U_{j,t}^{\alpha_u} \quad (1)$$

Where $j=1, \dots, N$ denotes the state-level cross-sectional dimension and $t=1, \dots, T$ the time series dimension; $H_{j,t}$ denotes the monthly hiring probability, the percentage of unemployed workers that find a job during period t , $U_{j,t}$ times $H_{j,t}$ denotes the number of hires during period t , while $V_{j,t}$ and $U_{j,t}$ denote the number of vacancies and unemployed, respectively. As in Kano and Ohta (2005), $A_{j,t}$ denotes region-specific

and time-varying matching efficiency, which we model in the following way:

$$A_{j,t} = e^{\alpha + \mu_j + \lambda t + \varepsilon_{j,t}} \quad (2)$$

Where μ_j denotes time-invariant regional attribute for j , λ stands for a state-invariant time attribute for t , and $\varepsilon_{j,t}$ is a random shock for state j at period t . We consider each state to be a separate labor market with one exception: since most of the BT offices in the State of Mexico are in municipalities of the Metropolitan Area of Mexico City (MAMC), we integrate the data with the series for the Federal District into a single labor market. This criterion is consistent with the definition for the main metropolitan areas used in national labor surveys, which includes only those municipalities that belong to the same state, with the exception of the MAMC.

At this point, it is worth mentioning that there are some peculiarities with the data coming from MAMC. As shown in Figure 5b, all series, the flow of initial jobless claims, vacancies and hirings, show a significant drop during the first quarter of 2010. This suggests the presence of a methodological change rather than a fundamental change in the market activity. Since the MAMC represents a large share of the labor market, this decline is reflected at the national level. Figure 5a shows that the discrete drop is observed in all of our series although Figure 5b shows it occurred in an approximately proportional matter. Nevertheless, this measurement problem may be biasing our results towards finding losses in the efficiency of the matching process; therefore, as a robustness check, we will repeat our analysis excluding the MAMC. As shown in Figure 5c, once we eliminate the MAMC from our data we can no longer observe the decline in the first quarter of 2010.

Figure 5a: Unemployment,
Vacancies and Hirings
(Thousands, s.a.)

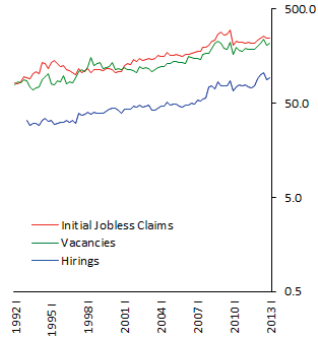


Figure 5b: Unemployment,
Vacancies and Hirings in MAMC
(Thousands, s.a.)

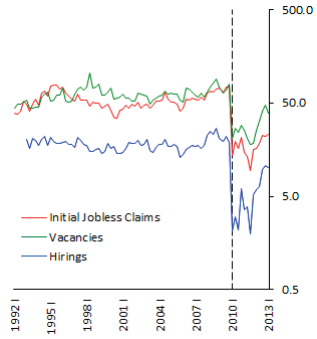
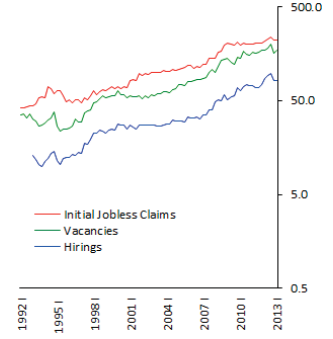


Figure 5c: Unemployment,
Vacancies and Hirings excluding
MAMC (Thousands, s.a.)



Notes: All series are seasonally adjusted and built from BT data.
Source: Mexican Ministry of Labor.

Since our specification uses the stock of unemployed workers as an explanatory variable, it is necessary to build it from the flow data of the initial applications of job seekers. To do this we calculate the average duration of unemployment in Mexico reported in the national employment surveys. Table 3 summarizes this. To construct our stock variable, we build a weighted six-month moving average where the weights are proportional to the average number of unemployed workers who have been searching for a job for different lengths as reported in ENOE. For example, we consider all job seekers that enroll in BT to be unemployed throughout the month in which they enrolled but we only assume that a fraction equal to 0.31 ($=17.7/56.7$) of those that enrolled in the previous month remain actively unemployed (Table 3). Although by truncating the window we disregard workers with long term unemployment spells, our six-month window covers 95% of all unemployed workers.⁹

Taking logarithms of Eq. (1) we have:

$$\log(H_{j,t}) = a + \mu_j + \lambda t + \alpha_v \log(V_{j,t}) + (\alpha_u - 1) \log(U_{j,t}) + \varepsilon_{j,t} \quad (3)$$

Since we are interested in estimating potential changes in matching efficiency during economic downturns, we will add dummy variables for both the 1994 crisis and the 2008

⁹For robustness, we tried using a 9 month moving average. Our results do not change, but we had to drop too many observations close to the 1994 Tequila crisis.

crisis. The crisis periods were selected to match with periods where the monthly Global Indicator of Economic Activity (IGAE) was below its potential.¹⁰

$$\log(H_{j,t}) = a + \mu_j + \lambda t + \alpha_v \log(V_{j,t}) + (\alpha_u - 1) \log(U_{j,t}) + \beta_{94} I_{95-97} + \beta_{08} I_{08-11} + \varepsilon_{j,t} \quad (4)$$

In all our regressions, our main coefficient of interest will be β_{94} and β_{08} , which estimate deviations from the average efficiency of the matching process during economic downturns. In Section 4 we will use our predicted values for the hiring probability with and without the dummy crisis to analyze whether the size of the estimated effect can explain the increase in unemployment during the crisis. With an abuse of language, we will say the predicted values with the crises dummies have matching frictions.

As a benchmark, we first estimate Eq. (4) through pooled OLS ignoring the individual effects (μ_j) and controlling for possible heteroscedasticity by using robust standard errors. The pooled OLS estimates in the first column of Table 4 show that the elasticity on unemployment is 0.65, whereas the point estimate for the elasticity on vacancies is 0.32. Consistent with the results for other countries, the function exhibits constant returns to scale (CRS), which we will impose in the rest of our regressions. This changes our regression as follows:

$$\log(H_{j,t}) = a + \mu_j + \lambda t + \alpha_v \log(\theta_{j,t}) + \beta_{94} I_{95-97} + \beta_{08} I_{08-11} + \varepsilon_{j,t} \quad (5)$$

Where $\theta_{j,t}$ is our state-level measure of market tightness. Column 2 of Table 4 estimates our basic specification under the CRS assumption. The elasticity of hires to vacancies is around one third, which is smaller than the estimated coefficient for other countries.

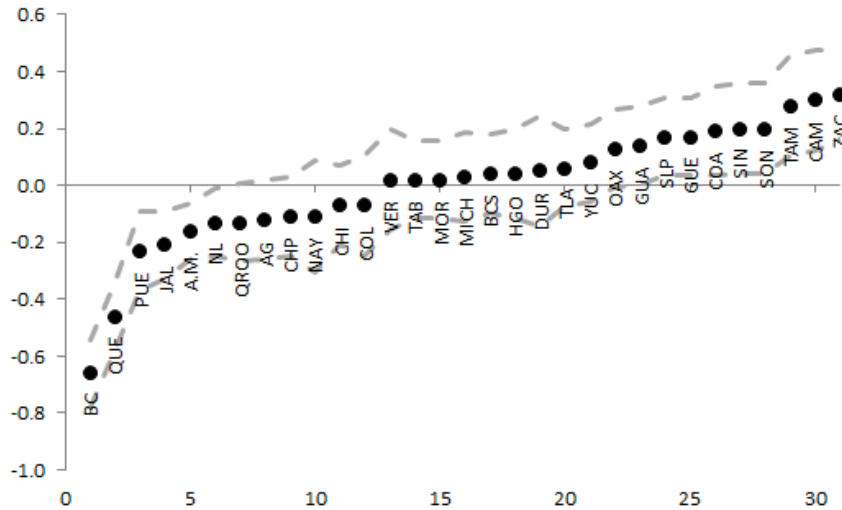
Up to this point, we have only taken into account the average efficiency of the matching process without regard to persistent variations in the efficiency of the process across states. To incorporate this, our third regression repeats the exercise in

¹⁰Here we measure our monthly potential output using an HP filter with a parameter equal to 14,400.

column 2 including state fixed effects. The main difference between this regression and the one in the second column is the rise in the elasticity of vacancies from 0.32 to 0.46. This coefficient is closer to what has typically been found in the literature. We can reject the null hypothesis that the state fixed effects (μ_j) are jointly equal to zero (p-value<0.0001). Hence, there is evidence to reject the null hypothesis. Thus, it is important to consider in our estimation biases due to unobservable regional heterogeneity.

In Figure 6, we show the estimated fixed effects for our third specification. There seems to be a considerable variation across states. The majority of the estimates (19) exhibit a higher coefficient relative to the estimated average efficiency in the matching function (constant term), this implies that those states have a more efficient matching process, whilst the remaining 12 show a lower relative efficiency.

Figure 6: Fixed Effects for Regression 3 in Table 4



Source: Own calculations with data from Mexican Ministry of Labor.
Dashed lines represent confidence intervals.

The set of regressions 1-3 is potentially subject to an endogeneity problem due to reverse causality. Our theory of matching frictions assumes that increases in vacancies and the number of unemployed workers causes increases in the number of hirings. In the data, it might be the case that previous knowledge that a hire will take place causes workers to register as job seekers and firms to post vacancies.

To try and solve this problem, our next regression estimates (5) using instrumental variables, assuming CRS and maintaining the state fixed effects. As Blanchard and Diamond (1989), we use three lags for both vacancies and unemployment as instruments¹¹. Our hope is that lagged values of unemployment and vacancies are correlated with the current value of labor market tightness and not directly correlated with the current value of the hiring rate.

Borowczyk-Martins, Jolivet and Postel (2013) use an alternative specification that models matching productivity as an ARMA process. They then propose a systematic procedure to identify which lags should be used as instruments. Since using a flexible reduced-form estimation to model cyclicalities might bias our estimation against finding level changes during economic crises, we prefer to maintain our simpler specification while performing robustness checks on the lag selection for our instruments.

The equation for our first-stage of this regression¹² can be expressed as follows:

$$\log(\theta_{j,t}) = a + \mu_j + \lambda t + \beta_{94} I_{95-97} + \beta_{08} I_{08-11} + \sum_{i=1}^3 \pi_i L^i \log(U_{j,t}) + \sum_{i=1}^3 \rho_i L^i \log(V_{j,t}) + \zeta_{j,t} \quad (6)$$

Where π_i and ρ_i represent the coefficients for lags 1-3 for unemployment and vacancies, respectively and $\zeta_{j,t}$ the error term. The value of the F statistic is 235.4, which is above the heuristic value of 10, indicates that we do not have a weak-instruments problem. We also conducted the Anderson-Rubin and Stock-Wright tests and, in both cases, we rejected the null that the instruments are weak. Finally, we performed Hansen's J test, testing overidentifying restrictions, and we did not reject the null that the instruments are valid at a 5% confidence level. (The p-value is about 9%, see Table 7).

The results for the second-stage of this regression show an increase in the elasticity of vacancies with respect to the estimates in the third column, which is consistent with

¹¹To analyze whether there is a systematic difference, we estimate our instrumental variables regression varying the number of lags on both variables, from 1 to 6 lags, without finding a significant difference. As robustness check, we also estimate our regression using lagged values of market tightness as instruments and our results do not change.

¹²The results for the first-stage regression can be seen in Table 6.

the results found by Blanchard and Diamond (1989) once they use instruments. In our case, the coefficient changes from 0.46 to 0.50.

Although the coefficient for the linear time trend is not statistically significant in most specifications, it gives us additional information about the evolution of the matching process. Averaging the coefficient for the linear time trend across the specifications in Table 4, our estimation suggests that the efficiency of the matching process in Mexico increased 6.2% in ten years.¹³

Focusing on our main coefficients of interest, the dummy variables during the two crises, we consistently find in all regressions a statistically significant decrease in the efficiency of the matching process during both economic crises. For 1994, the estimated loss in the efficiency of the matching function is between 0.18 and 0.21 log points, while the efficiency loss during the 2008 crisis is between 0.11 and 0.13 pp. For each of our specifications we tested the null hypothesis that $\beta_{94}=\beta_{08}$, and for all our regressions we fail to reject the difference between both crises (see Table 4). Since our reduced-form estimation finds no difference in matching efficiency during 1994 relative to 2008 and the point estimate is larger for 1994, it is unlikely that this estimated loss in itself could be the explanation for the persistent increase in unemployment observed in latter crises, but not in the first.

Finally, we perform two different robustness checks for our estimations. First, we complement the analysis by allowing a more flexible functional form by estimating a constant elasticity of substitution function (CES) instead of a Cobb-Douglas specification. We estimated the CES function through nonlinear least squares. This changes our specification in the following way:

$$\log(H_{j,t}) = a + \mu_j + \lambda t + \frac{1}{\rho} \log(\gamma + (1 - \gamma)\theta_{j,t}^\rho) + \beta_{94}I_{95-97} + \beta_{08}I_{08-11} + \varepsilon_{j,t} \quad (7)$$

Where ρ represents the elasticity of substitution between vacancies and unemployment and γ the share parameter. The results for the regression are presented in Column 5 of Table 4. This estimated value of $\rho = -1.53$ suggests that the relationship between

¹³We performed this calculation as follows: $e^{(\bar{\lambda}\Delta t)} - 1$, where $\bar{\lambda}$ is the average of the coefficient of linear time trend across specifications and $\Delta t = 120$ or twelve months times ten years.

vacancies and unemployment is more complementary than the one implied by a Cobb-Douglas matching function. Despite this difference, our estimates for the changes in the matching efficiency during the crises periods (1994 and 2008) are practically the same as those obtained in previous specifications.

We were also concerned that the methodological change in the MAMC data could be biasing our results. To address this problem, we repeat all our regressions excluding the MAMC. The point estimates, shown in Table 5, are consistent with those found in exercises involving all states. This suggests that the large movement in the MAMC is not guiding our results.

4 Can matching frictions explain the change in unemployment after 2008?

To evaluate the implications of our estimations for the unemployment rate, we use the following well-known steady-state formula that relates unemployment rate with flow rates. Assume the size of the labor force remains constant. Let δ_t denote the firing rate: the rate at which employed workers become unemployed during period t which corresponds to a continuous time Poisson switching model. Likewise let h_t denote the hiring rate. If δ_t and h_t remain constant for a sufficient period, the system will converge to the following steady state unemployment rate:

$$u_t = \frac{\delta_t}{\delta_t + h_t}$$

As is common in the literature, we assume the system converges to the steady state fast enough so that gross flows give an accurate approximation to the actual unemployment rate. This formula will form our basis to evaluate whether changes in our estimated hiring rate can explain changes in the unemployment rate. Our functional form allows us to do counterfactual analysis on what the hiring rate should be in the absence of changes in matching frictions (changes in A_t) or under alternative paths for the observed market tightness (changes in θ_t).

But first we need an estimate of the firing rate δ_t . We build one using the urban series of the national employment surveys (ENEU and ENOE). From this data we can identify workers who were employed in period $t-1$, which happened to be unemployed in the next period. Thus, we defined the firing probability $D_{LS,t}$ as the number of people who changed their employment status from employed to unemployed between periods $t-1$ and t divided by the number of employed in $t-1$. The corresponding continuous time firing rate is given by $\delta_{LS,t} \equiv -\log(1 - D_{LS,t})$. Analogously, we construct the hiring rates and probabilities consistent with the gross flow of workers from unemployment to employment: $h_{LS,t}$ and $H_{LS,t}$ respectively.

A usual concern when working with discrete time data is the loss of labor transitions within periods, which can cause a significant bias in the transition probabilities. As argued by Shimer (2012), this time aggregation bias can be more severe for the firing rate than for the hiring rate, since a worker who loses his job is more likely to find a new one without experiencing a measured spell of unemployment. This is especially true for Mexico given the long sampling window in ENOE (3 months) and the relatively short unemployment spells (85% of respondents have a duration of unemployment of less than 3 months, see Table 3).

To address this issue, we use the methodology proposed by Shimer (2012) to correct for time aggregation bias in the firing rate. Our adjusted firing rate, δ_{SH} , is estimated numerically by solving the following formula:

$$u_{t+1} = (1 - e^{-h_{LS,t} - \delta_{SH,t}}) \frac{\delta_{SH,t}}{\delta_{SH,t} + h_{LS,t}} + e^{-h_{LS,t} - \delta_{SH,t}} u_t$$

Figure 7a shows the comparison between the firing rate estimated from the data available in the national labor surveys δ_{LS} and the firing rate we obtain using Shimer's methodology δ_{SH} . The first lesson we get from Figure 7a unless we correct for time aggregation bias, δ_{LS} significantly underestimates the firing rate in economy, as expected. Second, we observe that δ_{SH} is much more volatile than δ_{LS} . The latter becomes relevant at the end of the period where we see a high variation in the firing rate. Therefore, to construct the implied unemployment rate, we decided to smooth the continuous exit rate with a four quarter moving average.

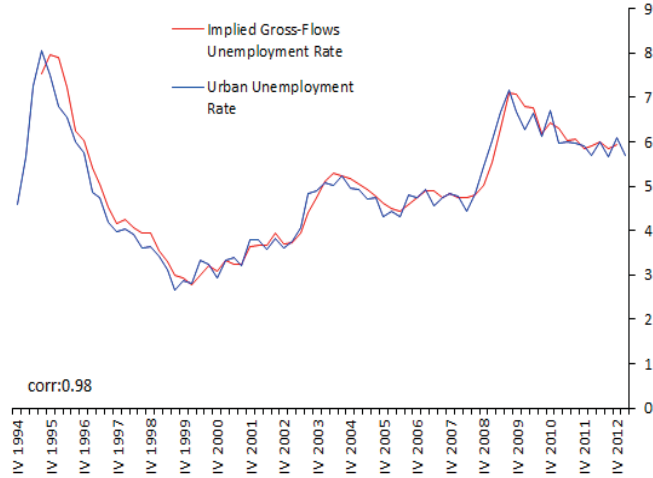
Figure 7a: Firing Rate from ENEU/ENOE Figure 7b: Hiring Rate from ENEU/ENOE



Source: Own calculations with data from INEGI.

Figure 8 shows the urban unemployment rate from the national labor surveys (ENEU and ENOE) and uses the gross flows from the same survey to calculate an implied unemployment rate. The correlation between the series is quite high (0.98) and the implied unemployment rate captures the big movements of the series during the booms and busts.

Figure 8: Urban Unemployment Rate vs. Implied Gross-Flows
Unemployment Rate



Source: Own calculations with data from INEGI.

To analyze the implications of our estimated matching frictions on the unemployment rate we replace the ENOE hiring probability with the predicted hiring probability of our estimations with and without crisis dummies. We will base all our analysis on the IV regression with state-level fixed effects reported in column 4 of Table 4.¹⁴

¹⁴Our regression is based on a state-level panel, so we need to aggregate the data to compare them with the national urban unemployment numbers. To do so we weigh the predicted hiring rate for each state by the size of its labor force as follows: $\hat{h}_t = \sum_j \frac{LF_{j,t}}{\sum_k LF_{k,t}} \hat{h}_{j,t}$.

Before proceeding, we must make the following clarification. Our estimates for the hiring probability (with and without) matching frictions are based on monthly observations. Therefore, it is necessary to perform a slight transformation to the data in order to make our predictions comparable with the national labor survey’s quarterly data. Once again, Shimer’s methodology provides a reasonable framework to perform this task. According to Shimer (2012) the hiring probability H_t is related to the continuous hiring rate h_t in the following way $h_t \equiv -\log(1 - H_t)$. From our predictions we construct a monthly hiring rate, which we average in order to obtain quarterly observations. The quarterly hiring probability is related to the quarterly hiring rate as follows: $H_{Q,t} \equiv 1 - e^{-h_t \Delta t}$, where Δt represents the change in frequency in monthly terms.

As can be seen in Figure 9a, our estimations yield a slightly lower hiring probability than the one we observe in ENOE, which translates into a slightly larger implied unemployment rate. The correlation between the ENOE hiring probability and our predicted hiring probability with and without matching frictions is positive: 0.30 and 0.45, respectively. In this regard, the regression with frictions has a better fit.

Figure 9a: Observed Hiring Rate in ENOE vs. Predicted Hiring Rate

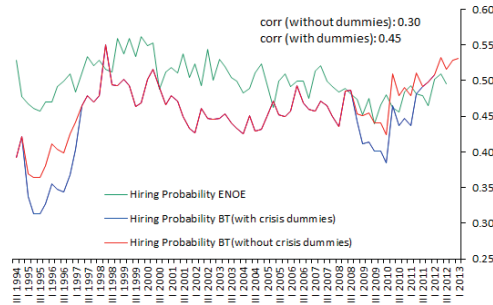
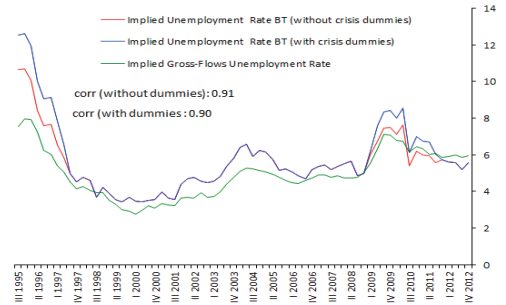


Figure 9b: Predicted Gross-Flows and implied Unemployment Rates



Source: Own calculations with data from INEGI and STPS.

In spite of this, the difference between the implied unemployment rates does not seem to be economically significant. Figure 10b shows that the average difference in the implied unemployment with and without matching frictions is 70 bp, which is less than one third of the 233bp increase in the implied unemployment rate based on ENOE flow data from Q3-2008 (before the crisis) to Q2-2009 (the peak of the crisis).

Figure 10: Predicted implied unemployment rate with and without matching frictions

Figure 10a: Tequila crisis

(1995 III-1997 I)

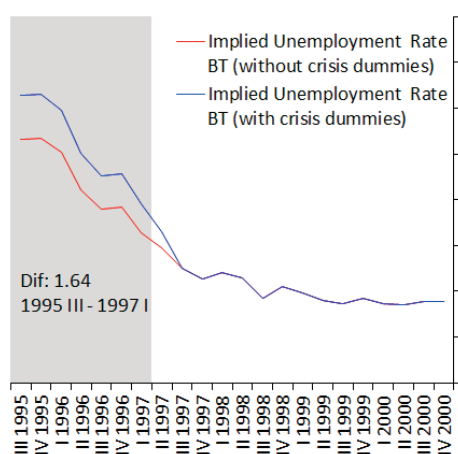
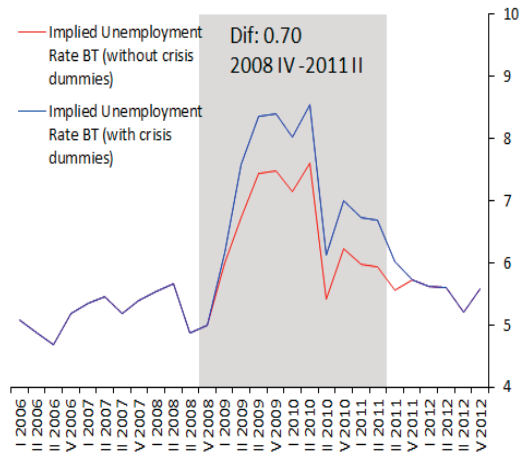


Figure 10b: Global Financial crisis

(2008 IV-2011 II)



Note: Shaded areas represent cyclical downturns. Source: Own calculations with data from INEGI.

There are other reasons to believe that matching frictions are not responsible for the persistent increase in unemployment after 2008. The estimated increase in unemployment due to matching frictions is smaller than the estimated increase in 1994 (164bp on average). Since the unemployment rate recovered after the 1994 crisis, it is hard to argue that a statistically significant increase in matching frictions in the 2008 crisis by itself captures a structural change in the Mexican labor market.

Also, it is important to note that the implied unemployment rate with and without matching frictions exhibits a notorious decreasing trend towards the end of the sample that we do not observe in the actual unemployment rate. Indeed, both our predicted series had almost recovered to pre-crisis levels by Q1 2013.

This is consistent with the fact that our measured market tightness returns to pre-crisis levels since 2010 and even reaches higher levels toward the end of the sample (Figure 3). This should not be surprising, since market tightness in our data is procyclical and economic activity recovered around this time. Therefore the observed pattern in our predicted unemployment rate is consistent with our original puzzle: why has unemployment remained so high even when economic activity has recovered? Our results indicate that we need an alternative explanation that goes beyond changes in matching frictions.

5 Conclusion

In this paper we study the role played by matching frictions in explaining the behavior in unemployment in Mexico after 2008. To do so, we estimate the potential loss of efficiency of the matching function during two similar crises that involved large drops in GDP: the 1994 Tequila crisis and the 2008 Global Financial crisis.

We are able to measure matching frictions for the first time in Mexico because we had access to a novel data on job vacancies and hirings through a government job placement service: Bolsa de Trabajo, which is under the supervision of the Ministry of Labor. These data are more concentrated on urban jobs so we compare our results to the urban series in the national employment surveys. In principle the data should also be a subset of the formal sector in the economy, but we cannot observe this directly. By observing the demand and supply of labor separately, the data allows us to assess whether changes in matching frictions are responsible for the sustained increase in unemployment after 2008.

We find evidence of a statistically significant reduction in the efficiency of the matching function after 2008. The estimated effect explains about 70bp of the 233bp observed increase in the urban unemployment rate from 4.85 in the third quarter of 2008 to 7.17 in the third quarter of 2009. We also find that the estimated loss in the matching efficiency during 1994 is higher than in 2008, so increases in matching frictions might be a recurring occurrence during large crises in Mexico. Our results suggest that changes in matching frictions cannot explain most of the increase in unemployment after 2008.

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6 Summary Tables and Regressions

Table 1: Summary Statistics, Monthly Data, 1993-2013

	Hirings	Initial Jobless Claims	Vacancies
Average (Thousands)	51.2	157.1	133.4
Standard Deviation (Thousands)	19.3	54.3	43.7
Variance in Time	0.48	0.42	0.39
Variance across States	0.52	0.58	0.61

Source: Mexican Ministry of Labor.

Table 2: Summary Statistics, Quarterly Data, 1993-2012.

	Market Tightness (θ)	Output Gap	Labor Productivity ^{1/}	Real IMSS Reference Wage ^{2/}
Standard Deviation	0.13	2.64	0.02	0.01
Quarterly autocorrelation	0.65	0.85	0.75	0.82
Correlation of θ with	1	0.66	0.51	0.29
Maximum correlation with θ_{t+i}		0.66(i=0)	0.51 (i=0)	0.55 (i=-4)

1/ Due to the lack of available information, we used the 2000-2012 period.

2/ Due to the lack of available information, we used the 2002-2012 period.

Notes: Seasonally adjusted labor market tightness built from STPS data. The time series of the output gap and labor productivity are constructed by Banco de México from INEGI statistics. The time series for the real IMSS reference wage is constructed with data from INEGI. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

Table 3: Average Duration of Unemployment. (ENOE)

Duration	Average	Weights
Less than	2005 I -2012 I	
1 month	56.71%	1.00
2 months	17.67%	0.31
3 months	10.39%	0.18
4 months	4.93%	0.09
5 months	2.61%	0.05
6 months	1.88%	0.03
7 months	1.32%	0.02
8 months	0.83%	0.01
9 months	0.41%	0.01

Note: To calculate the average, we considered the following years, where the information was available: 2005-I, 2006-I, 2007-II, 2008-II, 2009-I, 2010-I, 2011-I, 2012-I. Source: Own calculations with information from ENOE.

Table 4: Main Regression: Dependent Variable Placements through BT (logs)

	(1)	(2)	(3)	(4)	(5)
	OLS without	OLS with	OLS with	IV with	CES with
	CRS	CRS	CRS & FE	CRS & FE	FE
Unemployment ($\alpha_u - 1$)	-0.35***				
(logs)	(0.08)				
Vacancies (α_v)	0.32***	0.32***	0.46***	0.50***	
(logs)	(0.07)	(0.07)	(0.05)	(0.07)	
1994 crisis	-0.21***	-0.21***	-0.18***	-0.18***	-0.15***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.02)
2008 crisis	-0.13**	-0.13**	-0.12**	-0.11**	-0.12***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.01)
Linear Time Trend	0.07*	0.06	0.04	0.03	0.02**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)
ρ					-1.55***
					(0.13)
γ					0.85***
					(0.02)
Constant	-1.39***	-1.57***	-1.43***		-1.65***
	(0.22)	(0.11)	(0.07)		(0.03)
Observations	7,406	7,406	7,406	7,310	7,406
R-squared	0.193	0.190	0.258	0.255	0.378
$H_0: \beta_{94} - \beta_{08} = 0$	Not Reject	Not Reject	Not Reject	Not Reject	Not Reject

Clustered standard errors in parentheses (for col. 1, 2 and 3). Col. 4 uses clustered standard errors and corrects for heteroskedasticity. Col. 5 uses the conventionally derived variance estimator for nonlinear models fit using Gauss-Newton regression. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Regression excluding Metropolitan Area of Mexico City: Dependent Variable Placements through BT (logs)

	(1) OLS without CRS	(2) OLS with CRS	(3) OLS with CRS & FE	(4) IV with CRS & FE	(5) CES with FE
Unemployment ($\alpha_u - 1$) (logs)	-0.36*** (0.07)				
Vacancies (α_v) (logs)	0.32*** (0.07)	0.32*** (0.07)	0.46*** (0.05)	0.50*** (0.07)	
1994 crisis	-0.21*** (0.06)	-0.21*** (0.06)	-0.18*** (0.06)	-0.18*** (0.06)	-0.16*** (0.02)
2008 crisis	-0.12** (0.06)	-0.12** (0.06)	-0.11** (0.05)	-0.11** (0.05)	-0.11*** (0.02)
Linear Time Trend	0.08* (0.04)	0.06 (0.04)	0.04 (0.04)	0.03 (0.04)	0.02*** (0.01)
ρ					-1.53*** (0.14)
γ					0.85*** (0.02)
Constant	-1.34*** (0.23)	-1.57*** (0.12)	-1.43*** (0.08)		-2.11*** (0.03)
Observations	7,167	7,167	7,167	7,074	7,167
R-squared	0.192	0.189	0.260	0.256	
H ₀ : $\beta_{94} - \beta_{08} = 0$	Not Reject	Not Reject	Not Reject	Not Reject	Reject

Clustered standard errors in parentheses (for col. 1, 2 and 3). Col. 4 uses clustered standard errors and corrects for heteroskedasticity. Col. 5 uses the conventionally derived variance estimator for nonlinear models fit using Gauss-Newton regression. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: IV with CRS and FE: First-Stage Regression

Variable	(1) IV with CRS & FE Market Tightness (logs)
1994 crisis	-0.05*** (0.01)
2008 crisis	-0.01*** (0.02)
Linear Time Trend	0.05*** (0.01)
Unemployment (logs)	
L1.	-0.76*** (0.04)
L2.	-0.11* (0.05)
L3.	0.02 (0.04)
Vacancies (logs)	
L1.	0.45*** (0.02)
L2.	0.20*** (0.02)
L3.	0.14*** (0.02)
Observations	7310

Clustered standard errors in parentheses. Also corrects for heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Weak Instruments and Overidentification Tests

Global Significance in First-Stage Regression				
Statistic	Value	p-value	H ₀	Result
F	235.4	0.000	All $\beta_i = 0$	Reject
Weak-Instrument Tests				
Anderson-Rubin F	20.03	0.000	The coefficients of the endogenous regressors in the structural equation are jointly equal to zero	Reject
Anderson-Rubin Chi-squared	124.50	0.000		Reject
Stock-Wright S statistic	24.73	0.000		Reject
Overidentification Test				
Hansen J Chi-squared	9.44	0.09	Instruments are uncorrelated with the error term, and excluded instruments are correctly excluded	Fail to Reject

Note: All tests were computed by the xtivreg2 command in Stata.