Mismatch Unemployment*

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Abstract

We develop a framework where mismatch between vacancies and job seekers across sectors translates into higher unemployment by lowering the aggregate job-finding rate. We use this framework to measure the contribution of mismatch to the recent rise in U.S. unemployment by exploiting two sources of cross-sectional data on vacancies, JOLTS and HWOL, a new database covering the universe of online U.S. job advertisements. Mismatch across industries and occupations explains at most 1/3 of the total observed increase in the unemployment rate, whereas geographical mismatch plays no apparent role. The share of the rise in unemployment explained by occupational mismatch is increasing in the education level.

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1 Introduction

The U.S. unemployment rate rose from an average value of 4.6% in 2006 to its peak of 10% in October 2009, as the economy experienced the deepest downturn in the postwar period. Two years after its peak, the unemployment rate still hovered above 8%. This persistently high rate has sparked a vibrant debate among economists and policymakers. The main point of contention is the nature of these sluggish dynamics and, therefore, the appropriate policy response.

A deeper look at worker flows into and out of unemployment shows that, while the inflow rate has now returned to its pre-recession level, the job-finding rate is still half of what it was in 2006. Any credible theory accounting for the recent dynamics in unemployment must therefore operate through a long-lasting decline in the outflow rate. One such theory is that the recession has produced a severe sectoral mismatch between vacant jobs and unemployed workers: idle workers are seeking employment in sectors (occupations, industries, locations) different from those where the available jobs are. Such misalignment between the distribution of vacancies and unemployment across sectors of the economy would lower the aggregate job-finding rate.

The mismatch hypothesis is qualitatively consistent with three features of the Great Recession. First, over the past three years the U.S. Beveridge curve (i.e., the empirical relationship between aggregate unemployment and aggregate vacancies) has displayed a marked rightward movement indicating that, for a given level of vacancies, the current level of unemployment is higher than that implied by the historical data.[1] Put differently, aggregate matching efficiency has declined.[2] Second, around half of the job losses in this downturn were concentrated in construction and manufacturing.[3] To the extent that the unemployed in these battered sectors do not search for (or are not hired in) jobs in the sectors which

[1] See, among others, Elsby, Hobijn, and Şahin (2010), Hall (2010), Daly, Hobijn, Şahin, and Valletta (2011), Barlevy (2011), and Veracierto (2011). According to these studies, at the current level of vacancies, the pre-recession U.S. unemployment-vacancies relationship predicts an unemployment rate between 2 and 3 percentage points lower than its current value.

[2] According to Barlevy (2011) and Veracierto (2011), the size of this drop from its pre-recession level is between 15% and 25%, depending on the exact methodology used in the calculation.

[3] According to the Current Employment Statistics (CES), also known as the establishment survey, payroll employment declined by 7.4 million during the recession and construction and manufacturing sectors accounted for 54% of this decline.

largely weathered the storm (e.g., health care), mismatch would arise across occupations and industries. Third, house prices experienced a sharp fall, especially in certain regions (see e.g., Mian and Sufi, 2011). Homeowners who expect their local housing markets to recover may choose to forego job opportunities in other locations to avoid large capital losses from selling their house. Under this "house-lock"conjecture, mismatch between job opportunities and job seekers would arise mostly across locations.

In this paper, we develop a theoretical framework to conceptualize the notion of mismatch unemployment, and use this framework to measure how much of the recent rise in the U.S. unemployment rate is attributable to mismatch. We envision the economy as comprising a large number of distinct labor markets or sectors (e.g., segmented by industry, occupation, geography, or a combination of these attributes). Each labor market is frictional, i.e., its hiring process is governed by a matching function. To assess the existence of mismatch in the data, we ask whether, given the observed distribution of productive efficiency, matching efficiency, and vacancies across labor markets in the economy, unemployed workers are "misallocated, "i.e., they search in the wrong sectors. Answering this question requires comparing the actual allocation of unemployed workers across sectors to an ideal allocation. The ideal allocation that we choose as our benchmark is the one that would be selected by *a planner who faces no impediment in moving idle labor across sectors except for the within-market matching friction*. We show that optimality for this planner dictates that (productive and matching) efficiency-weighted vacancy-unemployment ratios be equated across sectors. By manipulating the planner's optimality condition, we construct a mismatch index that measures the fraction of hires lost every period because of misallocation of job seekers. Through this index, we can quantify how much lower the unemployment rate would be in the absence of mismatch. The difference between the observed unemployment rate and this counterfactual unemployment rate is *mismatch unemployment*.[4]

Our measurement exercise requires disaggregated data on unemployment and vacancies. The standard micro data sources for unemployment and vacancies are, respectively, the Cur-

[4] Our focus is on mismatch unemployment intended as unemployed searching in the "wrong" sector. A separate literature uses the term "mismatch" to denote the existence of employed individuals working on the "wrong" job—meaning a sub-optimal joint distribution of worker skills and firm's capital. See, for example, Eeckhout and Kircher (2011).

rent Population Survey (CPS) and the Job Openings and Labor Turnover Survey (JOLTS). Unfortunately, JOLTS only allows disaggregation of vacancies by 2-digit industries and very broad geographical area (4 Census regions).[5] In this paper, we introduce a new source of micro data, the Conference Board's Help Wanted OnLine (HWOL) database, designed to collect the universe of online job advertisements in the U.S. economy. Through this novel data set, we are able perform our empirical analysis at the 2- and 3-digit occupational level, at a more detailed geographical level (states and counties), and even by defining labor markets as a combination of occupation and location.[6]

Our empirical analysis yields the following main results. We find no significant role for geographical mismatch across U.S. states or counties. Mismatch at the 2-digit industry and 2- and 3-digit occupation level increased markedly during the recession, but declined throughout 2010, an indication of a cyclical pattern in mismatch. A similar, but milder, hump shape in mismatch is observed around the 2001 recession. We calculate that an additional four percent of monthly hires were lost during the Great Recession because of the misallocation of vacancies and job seekers across occupations and industries. As a result, our counterfactual analysis indicates that mismatch unemployment at the 2-digit industry level can account for 0.75 percentage points out of the 5.4 percentage point total increase in the U.S. unemployment rate from 2006 to October 2009. At the 3-digit occupation level, the contribution of mismatch unemployment rises just beyond one and a half percentage points. When we compute occupational mismatch separately for different education groups, we find its contribution to the observed increase in the unemployment rate is almost twice as large for college graduates than for high-school dropouts.

In an extension of the baseline analysis, we allow the misallocation of unemployed workers across sectors to also affect the vacancy creation decisions of firms: the presence of job-seekers in declining sectors makes it easier to fill jobs in those sectors and, therefore, distorts firms' incentives in the direction of, inefficiently, creating vacancies in the wrong markets. We show that this channel depresses aggregate vacancy creation relative to the planner's

[5]Note that industry classification in the JOLTS is slightly different than the 2-digit NAICS classification. See Table B1 for a complete list of industries in the JOLTS.

[6]The HWOL micro data would allow an even more disaggregated analysis. The binding constraint is determined by the small sample of unemployed workers in the monthly CPS.

solution, giving a further boost to mismatch unemployment. When this additional force is factored into our counterfactuals, the contribution of mismatch to the observed rise in the unemployment rate grows by a maximum of two thirds of a percentage point. We therefore conclude that, at the analyzed level of disaggregation, mismatch can explain at most 1/3 of the recent rise in the U.S. unemployment rate since 2006.

We now return briefly on the nature of our measurement exercise. Formalizing mismatch unemployment as "distance from a benchmark allocation" follows, in essence, the same insights of the vast literature on misallocation and productivity (Lagos, 2006; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Jones, 2011; Moll, 2011) and of that on wedges (Chari, Kehoe, McGrattan, 2007). Our implementation has two distinctive features. First, we do not need to solve for equilibrium allocations (and, hence, make specific assumptions about firms' and workers' behavior, their information set, price determination, etc.) We simply take the empirical joint distribution of unemployment and vacancies across sectors as the equilibrium outcome.[7] Second, we construct the counterfactual distribution (in absence of mismatch) from a simple planner's problem which can be solved analytically.

The key strength of these two features combined is that finer disaggregation in the available micro data poses no threat to the feasibility of the exercise. The approach we propose is robust and easily implementable, even with a high number of labor markets, and multiple sources of heterogeneity, idiosyncratic shocks, and aggregate fluctuations. The limit is that one cannot separately quantify the, possibly many, sources behind misallocation, as this would require specifying and numerically solving a complex structural equilibrium model. Factors explaining the discrepancy between the empirical and planner's distribution of unemployment across sectors include moving (e.g., retraining or migration) costs, relative wage rigidity, or certain government policies that may hamper the reallocation of idle labor from shrinking to expanding sectors. Since moving costs are characteristics of the physical environment that would also feature in a planner's problem, while our benchmark planner's allocation is derived under costless between-sector mobility, our calculations on the role of mismatch are an upper bound.[8] In light of this remark, the finding that mismatch accounts

[7]The extension to endogenous vacancy requires a minimal set of, mostly standard, assumptions that are discussed in Section 7.

[8]In the measurement exercise, when needed, we also make choices that preserve this upper-bound nature of

for at most 1/3 of the rise in U.S. unemployment appears even more compelling.

The model underlying our measurement exercise is a multi-sector version of the standard aggregate search/matching model (Pissarides, 2000). This stands in contrast to the model of Shimer (2007), who proposed an alternative environment to measure mismatch between firms and workers across labor markets. The crucial difference between the two models is the notion of a vacancy or, equivalently, at which point of the meeting process vacancies are measured. In the matching model, firms desiring to expand post vacancies: a vacancy is a manifestation of a firm's *effort to hire*. In Shimer's model, firms unsuccessful in meeting workers are left with idle jobs: a vacancy is therefore a manifestation of a firm's *failure to hire*. Both notions are theoretically correct. Since both models are parameterized using the same micro-data on vacancies, the key question is whether existing job-openings data from JOLTS and HWOL are more likely to represent firms' hiring effort or hiring failure. The short duration of job openings in JOLTS (2-4 weeks according to Davis, Faberman, and Haltiwanger, 2010) seems somewhat more consistent with the former view, but better data is needed to shed light on this critical point.

The notion of vacancy we adopt is common to the entire search/matching approach to the study of unemployment. Within this class, the closest paper to ours is Jackman and Roper (1987): in a static matching model with many sectors, they show that distributing unemployment across sectors so that sectoral labor-market tightnesses are equalized maximizes aggregate hires, and they propose the use of mismatch indexes to summarize deviations from this allocation.[9] At that time, economists were struggling to understand why high unemployment was so persistent in many European countries.[10] Padoa-Schioppa (1991) contains a number

the calculation.

[9]This idea goes back, at least, to Mincer (1966, page 126) who writes: "To detect the existence, degree, and changes in structural unemployment, (U, V) maps may be constructed for disaggregations of the economy in the cross-section, by various categories, such as industry, location, occupation, and any other classification of interest. For example, each location is represented by a point in the (U, V) map, and a scatter diagram showing such information for all labor markets may show a clear positive correlation. This would indicate that unemployment is largely nonstructural with respect to location, that is to say, that adjustments require movements within local areas rather than the more difficult movements between areas. In contrast, a negative relation in the scatter would indicate the presence of a structural problem. The scatters may, of course, show identifiable combinations of patterns. Observations of changes in these cross sectional patterns over time will show rotations and shifts, providing highly suggestive leads for diagnoses of the changing structure of labor supplies and demands."

[10]The conjecture was that the oil shocks of the 1970s and the concurrent shift from manufacturing to services

of empirical studies for various countries and concludes that mismatch was not an important explanation of the dynamics of European unemployment in the 1980s.[11] Our paper contributes to reviving this old literature by extending it in several directions: (i) we develop a dynamic, stochastic, environment with numerous sources of heterogeneity, (ii) we explain how to construct counterfactual measures of unemployment, absent mismatch, (iii) we incorporate the effect of misallocation on vacancy creation, and (iv) we perform our measurement at a much more disaggregated level, thanks to new micro data.

Beyond the present paper, a small but rapidly growing literature attempts to quantify whether mismatch played a substantive role in the Great Recession. Examples, which we discuss in some detail in the paper, are Barnichon and Figura (2011), Dickens (2010), Herz and van Rens (2011), and Jaimovich and Siu (2012).

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework. Section 3 derives the mismatch indexes and explains how we compute our counterfactuals. Section 4 describes the data. Section 5 performs the empirical analysis. In section 6 we verify the robustness of our results to measurement errors in unemployment and vacancy counts. Section 7 analyzes the case in which mismatch also affects vacancy creation. Section 8 concludes. Appendix A contains the proofs of our theoretical results and Appendix B contains more detail about the data and our measurement exercise.

2 Environment and planner problem

We begin by describing our benchmark economic environment and deriving the planner's optimal allocation rule of unemployed workers across sectors—the crucial building block of our theoretical analysis. In Section 2.2, we carry out a number of extensions and demonstrate that the benchmark planner's allocation rule generalizes in a very intuitive way. Throughout these derivations, we maintain the assumption that the evolution of the vacancy distribution

induced structural transformations in the labor market that permanently modified the skill and geographical map of labor demand. From the scattered data available at the time, there was also some evidence of shifts in the Beveridge curve for some countries.

[11] Subsequent explanations of European unemployment based on the interaction between technological changes and rigid labor market institutions were more successful quantitatively (e.g., Ljungqvist and Sargent, 1998; Mortensen and Pissarides, 1999; Hornstein, Krusell and Violante, 2007).

is exogenous. We relax this assumption in Section 7.

2.1 Benchmark environment

Time is discrete. The economy is comprised of a large number I of distinct labor markets (sectors) indexed by i. New production opportunities, corresponding to job vacancies (v_i), arise exogenously across sectors.[12] The economy is populated by a measure one of risk-neutral individuals who can be either employed in sector i (e_i) or unemployed and searching in sector i (u_i). Therefore, $\sum_{i=1}^{I}(e_i+u_i)=1$. On-the-job search is ruled out, and an unemployed worker, in any given period, can search for vacancies in one sector only.

Labor markets are frictional: new matches, or hires, (h_i) between unemployed workers (u_i) and vacancies (v_i) in market i are determined by the matching function $\Phi \cdot \phi_i \cdot m(u_i, v_i)$, with m strictly increasing and strictly concave in both arguments and homogeneous of degree one in (u_i, v_i). The term $\Phi \cdot \phi_i$ measures matching efficiency (i.e., the level of fundamental frictions) in sector i, with Φ denoting the aggregate component and ϕ_i the idiosyncratic sectoral-level component. The number of vacancies and matching efficiency are the only two sources of heterogeneity across sectors in our baseline model.

All existing matches produce Z units of output in every sector. Matches are destroyed exogenously at rate Δ, also common across sectors. Aggregate shocks Z, Δ and Φ, and the vector of vacancies $\mathbf{v}=\{v_i\}$ are drawn from conditional distribution functions $\Gamma_{Z,\Delta,\Phi}(Z', \Delta', \Phi'; Z, \Delta, \Phi)$ and $\Gamma_{\mathbf{v}}(\mathbf{v}'; \mathbf{v}, Z', \Delta', \Phi')$. The notation shows that we allow for autocorrelation in $\{Z, \Delta, \Phi, \mathbf{v}\}$, and for correlation between vacancies and all the aggregate shocks. The sector-specific matching efficiencies ϕ_i are independent across sectors and are drawn from $\Gamma_\phi(\phi'; \phi)$, where $\phi=\{\phi_i\}$. The vector $\{Z, \Delta, \Phi, \mathbf{v}, \phi\}$ takes strictly positive values.

Within each period, events unfold as follows. At the beginning of the period, the aggregate shocks (Z, Δ, Φ), vacancies $\mathbf{v}$, and matching efficiencies ϕ are observed. At this stage, the distribution of active matches $\mathbf{e}=\{e_1, \ldots, e_I\}$ across markets (and hence the total number of unemployed workers u) is also given. Next, unemployed workers choose a labor market i without any impediment to labor mobility. Once the unemployed workers

[12] We explain in Section 7 that assuming that vacancies are exogenous is equivalent to a model where the job creation margin is endogenous, and the elasticity of the cost of creating vacancies is infinitely large.

are allocated, the matching process takes place and $h_i = \Phi\phi_i m(u_i, v_i)$ new hires are made in each market. Production occurs in the e_i (pre-existing) plus h_i (new) matches. Finally, a fraction Δ of matches are destroyed exogenously in each market i, determining next period's employment distribution $\{e_i'\}$ and stock of unemployed workers u'.

Planner's solution In Appendix A.1 we prove that the planner's optimal rule for the allocation of unemployed workers across sectors in this economy can be written as

$$\phi_1 m_{u_1}\left(\frac{v_1}{u_1^*}\right) = \ldots = \phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right) = \ldots = \phi_I m_{u_I}\left(\frac{v_I}{u_I^*}\right), \tag{1}$$

where we have used the "*" to denote the planner's allocation. This condition states that the planner allocates more job seekers to labor markets with more vacancies and higher matching efficiency.

2.2 Generalizations

We develop two generalizations of our benchmark model where productivities and destruction rates are heterogeneous across sectors. First, we allow for sector-specific shocks that are uncorrelated across sectors and independent of the aggregate shock (in the spirit of Lilien, 1982). Second, we lay out an alternative model of sectoral cycles where sectoral productivity fluctuations are driven by the aggregate shock because different sectors have different elasticities to this common factor (in the spirit of Abraham and Katz, 1986). Throughout these two extensions, we also allow the planner to choose the size of the labor force subject to paying a fixed cost of search for each job-seeker in the unemployment pool, but we keep worker separations exogenous. Finally, we allow the planner to choose whether to endogenously dissolve some existing matches and show that, under some conditions, it never chooses to do so. All the derivations for these extensions are contained in Appendix A.2-A.4.

2.2.1 Heterogeneous productivities and job destructions

Let labor productivity in sector i be given by $Z \cdot z_i$, where each component z_i is strictly positive, i.i.d. across sectors and independent of Z. Similarly, denote the idiosyncratic component of the exogenous destruction rate in sector i as δ_i. Then, the survival probability of a match is $(1-\Delta)(1-\delta_i)$. It is convenient to proceed under the assumption that

$\{Z, 1-\Delta, z_i, 1-\delta_i\}$ all follow independent unit root processes, which amounts to simple restrictions on the conditional distributions $\Gamma_{Z,\Delta,\Phi}, \Gamma_z$, and Γ_δ.[13] Appendix A.2 proves that the planner's optimal allocation rule of unemployed workers equates

$$\frac{z_i}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)}\phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right) \tag{2}$$

across markets. This rule establishes that the higher vacancies, matching efficiency, and expected discounted productive efficiency in market i, the more unemployed workers the planner wants searching in that market. In particular, expected output of an unemployed worker in sector i is discounted differently by the planner in different sectors because of the heterogeneity in the expected duration of matches.

2.2.2 Heterogeneous sensitivities to the aggregate shock

In a classic paper disputing Lilien's (1982) sectoral-shift theory of unemployment, Abraham and Katz (1986) argue that, empirically, sectoral employment movements appear to be driven by aggregate shocks with different sectors having different sensitivities to the aggregate cycle. Here we show how the planner's allocation rule (2) changes under this alternative interpretation of the source of sectoral labor demand shifts.

Let productivity in sector i be $z_i = \exp\left(\zeta_i\right) Z^{\eta_i}$ where ζ_i is a parameter rescaling the average productivity of the sector relative to that of the aggregate economy Z, and η_i is a parameter measuring the elasticity of sectoral productivity to the aggregate shock Z. Let $\log Z$ follow a unit root process with innovation ϵ distributed as $N\left(-\sigma_\epsilon/2, \sigma_\epsilon\right)$. In Appendix A.3, we show that the planner will allocate unemployed workers to equalize

$$\frac{\exp\left(\zeta_i\right) Z^{\eta_i}}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}\phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right) \tag{3}$$

across sectors. The new term in the denominator captures that the drift in future productivity in sector i varies proportionately with η_i because of the log-normality assumption. In essence, this sectoral drift changes the effective rate at which the planner discounts the future.

[13] We can allow the vector $x = \{Z, 1-\Delta, z_i, 1-\delta_i\}$ to have the more general linear conditional mean function of the type $\mathbb{E}\left[x'\right] = \rho_x x$. However, the derivations are more convoluted, and we do not make use of this more general assumption in the empirical analysis.

Understanding the nature of sectoral fluctuations goes beyond the scope of this paper. The main lesson of this generalization is that our approach is valid under alternative views of what drives sectoral fluctuations: different views lead to different measurements of the sectoral component of productivity in the planner's allocation rule.

2.2.3 Endogenous separations

Consider the environment of Section 2.2.1 and allow the planner to move workers employed in sector i into unemployment or out of the labor force at the end of the period, before choosing the size of the labor force for next period. In Appendix A.4 we demonstrate that, if the planner always has enough individuals to pull into (out of) unemployment from (into) out of the labor force, it will never choose to separate workers who are already matched and producing. The planner's allocation rule remains exactly as in equation (2) and all separations are due to exogenous match destructions.

3 Mismatch index and counterfactual unemployment

We now use the planner's allocation rule to derive an index measuring the severity of labor market mismatch between unemployed workers and vacancies. From this point onward we must state an additional assumption, which is well supported by the data as we show below: the individual-market matching function $m(u_{it}, v_{it})$ is Cobb-Douglas, i.e.,

$$h_{it} = \Phi_t \phi_{it} v_{it}^{\alpha} u_{it}^{1-\alpha}, \tag{4}$$

where h_{it} are hires in sector i at date t, and $\alpha \in (0,1)$ is the vacancy share common across all sectors.[14] Next, we describe how to use these indexes to construct counterfactuals to measure how much of the recent rise in U.S. unemployment is due to mismatch.

3.1 Mismatch index

Our mismatch index measures the fraction of hires lost because of misallocation, or $(1 - h_t/h_t^*)$ where h_t denotes the observed aggregate hires and h_t^* the planner's hires.

[14]At this point we to abandon the recursive formulation and introduce time t explicitly.

Consider first the benchmark environment of Section 2.1. From (4), summing across markets, the aggregate number of new hires can be expressed as:

$$h_t = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \cdot \left[\sum_{i=1}^{I} \phi_{it} \left(\frac{v_{it}}{v_t} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \right]. \tag{5}$$

The optimality condition dictating how to allocate unemployed workers between market i and market j is:

$$\frac{v_{it}}{u_{it}^*} = \left(\frac{\phi_{jt}}{\phi_{it}} \right)^{\frac{1}{\alpha}} \cdot \frac{v_{jt}}{u_{jt}^*}. \tag{6}$$

The optimal number of hires that can be obtained by the planner allocating the u_t available unemployed workers across sectors is

$$h_t^* = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_{i=1}^{I} \phi_{it} \left(\frac{v_{it}}{v_t} \right)^{\alpha} \left(\frac{u_{it}^*}{u_t} \right)^{1-\alpha} \right]. \tag{7}$$

Substituting the optimality condition (6) in equation (7) , the optimal number of new hires becomes $h_t^* = \Phi_t \bar{\phi}_t v_t^{\alpha} u_t^{1-\alpha}$, where $\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t} \right) \right]^{\alpha}$, a CES aggregator of the sector-level matching efficiencies weighted by their vacancy share. Therefore, we obtain an expression for the mismatch index

$$\mathcal{M}_{\phi t} = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_{it}}{\bar{\phi}_t} \right) \left(\frac{v_{it}}{v_t} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha}. \tag{8}$$

$\mathcal{M}_{\phi t}$ measures the fraction of hires lost in period t because of misallocation. This index answers the question: if the planner had u_t available unemployed workers and used its optimal allocation rule, how many additional jobs would it be able to create? These additional hires are generated because, 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, which we will call the "direct effect" of mismatch. It is useful to note that, in addition to this direct effect, u_t^* is in general lower than u_t which, for any given allocation rule, translates into a higher aggregate job-finding rate and more hires, which we will call the "feedback" effect. $\mathcal{M}_{\phi t}$ measures only the direct effect of mismatch on hires, but the counterfactual of Section 3.2 fully incorporates the feedback effect as well.

From (8) and (5) one can rewrite the aggregate matching function as

$$h_t = (1 - \mathcal{M}_{\phi t}) \cdot \bar{\phi}_t \cdot \Phi_t v_t^{\alpha} u_t^{1-\alpha} \tag{9}$$

which makes it clear that higher mismatch lowers the (measured) aggregate efficiency of the matching technology and reduces the aggregate job-finding rate because some unemployed workers search in the wrong sectors (those with few vacancies). The term $\bar{\phi}_t$ can also contribute to a reduction in aggregate matching efficiency when the vacancy shares of the sectors with high ϕ fall.[15]

In Appendix A.5, we show three useful properties of the index. First, $\mathcal{M}_{\phi t}$ is between zero (no mismatch) and one (maximal mismatch). Second, the index is invariant to "pure" aggregate shocks that shift the total number of vacancies and unemployed up or down, but leave the vacancy and unemployment shares across markets unchanged. Third, $\mathcal{M}_{\phi t}$ is increasing in the level of disaggregation. This last property suggests that every statement about the role of mismatch should be qualified with respect to the degree of sectoral disaggregation used.

Consider now the economy of Section 2.2.1, where labor markets also differ in their level of productive efficiency. It is useful to define "overall market efficiency" as $x_{it} \equiv \phi_{it} z_{it} / \left[1 - \beta \left(1 - \Delta_t\right) \left(1 - \delta_{it}\right)\right]$.[16] Following the same steps, we arrive at the index

$$\mathcal{M}_{xt} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_i}{\bar{\phi}_t^x}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}, \tag{10}$$

where

$$\bar{\phi}_t^x = \sum_{i=1}^{I} \phi_{it} \left(\frac{x_{it}}{\bar{x}_t}\right)^{\frac{1-\alpha}{\alpha}} \left(\frac{v_{it}}{v_t}\right), \text{ with } \bar{x}_t = \left[\sum_{i=1}^{I} x_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}. \tag{11}$$

$\bar{\phi}_t^x$ is an aggregator of the market-level overall efficiencies weighted by their vacancy share.

In the absence of heterogeneity with respect to matching efficiency, productivity, or job destruction, the index becomes $\mathcal{M}_t = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}$. In what follows, we will also use the notation $(\mathcal{M}_{zt}, \mathcal{M}_{\delta t})$ to denote mismatch indexes for an economy where the only source of heterogeneity is productivity and job destruction rates, respectively.

[15] Barnichon and Figura (2011) show that the variance of labor market tightness across sectors, suggestive of mismatch between unemployment and vacancies, can also be analytically related to aggregate matching efficiency and, hence, can be a source of variation in the job-finding rate.

[16] To construct a mismatch index for the economy of Section 2.2.2, it suffices substituting $z_{it} / \left[1 - \beta \left(1 - \Delta_t\right) \left(1 - \delta_{it}\right)\right]$ with the term $\exp\left(\zeta_i\right) Z_t^{\eta_i} / \left[1 - \beta \left(1 - \Delta_t\right) \left(1 - \delta_{it}\right) \left(\exp\left(\eta_i \left(\eta_i - 1\right) \frac{\sigma_\varepsilon}{2}\right)\right)\right]$ in all the derivations below.

3.2 Mismatch unemployment

This misallocation index allows us to construct the counterfactual unemployment rate, u_t^*, in the absence of mismatch. The actual aggregate job-finding rate in the economy at date t can be written as

$$f_t = \frac{h_t}{u_t} = (1 - \mathcal{M}_{xt})\,\bar{\phi}_{xt}\Phi_t \left(\frac{v_t}{u_t}\right)^{\alpha}.$$

Let u_t^* be counterfactual unemployment under the planner's allocation rule. The optimal number of hires at date t when u_t^* unemployed workers are available to be allocated across sectors is $\bar{\phi}_{xt}\Phi_t v_t^{\alpha}(u_t^*)^{1-\alpha}$. Therefore, the optimal job-finding rate (in absence of mismatch) is

$$f_t^* = \bar{\phi}_{xt}\Phi_t \left(\frac{v_t}{u_t^*}\right)^{\alpha} = f_t \cdot \underbrace{\frac{1}{(1 - \mathcal{M}_{xt})}}_{\text{Direct Effect}} \cdot \underbrace{\left(\frac{u_t}{u_t^*}\right)^{\alpha}}_{\text{Feedback}} \tag{12}$$

There are two sources of discrepancy between counterfactual and actual job-finding rate. The first term in (12) captures the fact that a planner with u_t available job-seekers to move across sectors would achieve a better allocation and a higher job-finding rate. This effect, which we call the "direct" misallocation effect, is summarized by the mismatch index, as explained. The second term captures a "feedback" effect of misallocation: no mismatch means lower unemployment $(u_t^* < u_t)$ which, in turn, increases the probability of meeting a vacancy for job-seekers. This feedback effect explains why, even if after a period of higher than average mismatch $\mathcal{M}_{xt}$ returns to its average, mismatch unemployment can remain above average for some time, as it takes time for the additional unemployed to be reabsorbed—a pattern we see in our empirical analysis.

Given an initial value for u_0^*, the dynamics of the counterfactual unemployment rate can be obtained by iterating forward on equation

$$u_{t+1}^* = s_t + (1 - s_t - f_t^*)\,u_t^*, \tag{13}$$

where s_t is the separation rate. Our strategy takes the sequences for separation rates $\{s_t\}$ and vacancies $\{v_t\}$ directly from the data when constructing the counterfactual sequence of $\{u_t^*\}$ from (13), an approach consistent with the theoretical model where vacancy creation and separations are exogenous to the planner.[17]

[17] We avoid the term "constrained efficient" unemployment, because in the extended models of Section 2.2

The gap between actual unemployment u_t and counterfactual unemployment u_t^* is mismatch unemployment. This calculation addresses the key question of interest: what is the contribution of mismatch unemployment to the recent rise in the aggregate U.S. unemployment rate? In the rest of the paper we address this question directly.[18]

4 Data and sectoral matching functions

We begin this section by describing the data sources. Next, we analyze the issue of specification and estimation of the matching function.

We focus on four major definitions of labor markets: the first is a broad industry classification; the second is an occupation classification, based on both the 2-digit and 3-digit standard occupational classification (SOC) system; the third is a geographic classification, based on U.S. counties and metropolitan areas (MSA's); finally, we also study occupational mismatch within four skill categories, based on educational attainment.[19] As discussed in Section 3, our analysis requires information about vacancies, hires, unemployment, productivity, matching efficiency, and job destruction rates across different labor markets.

4.1 Data description

At the industry level, we use vacancy data from the Job Openings and Labor Turnover Survey (JOLTS), which provides survey-based measures of job openings and hires at a monthly frequency, starting from December 2000, for seventeen industry classifications.[20] At the occupation, education and county level, we use vacancy data from the Help Wanted OnLine

the planner also controls labor force participation decisions. Therefore, we prefer to interpret u_t^* as the counterfactual unemployment rate under the planner's allocation rule of unemployed workers across sectors, abstracting from possible discrepancies between the planner's labor force participation choice and the corresponding equilibrium outcome observed in the data.

[18]In a previous version of this paper, we also reported results for an alternative mismatch index equal to the sum across sectors of the absolute deviations between unemployment and vacancy shares. However, this index is much less useful because it only quantifies the number of job-seekers searching in the wrong sectors, but not how such misallocation lowers the job-finding rate. For this reason, this alternative index cannot be used to construct a proper measure of mismatch unemployment. Dickens (2011) studies mismatch in the U.S. labor market with JOLTS data using this index in its simple form, i.e., without allowing for heterogeneity in productive and matching efficiency across sectors.

[19]See Tables B1-B3 in Appendix B for a list of industry and occupation classifications used in the empirical analysis.

[20]Since the JOLTS is a well known and widely used survey, we do not provide further details. For more information, see http://www.bls.gov/jlt/. See also Faberman (2009).

(HWOL) dataset provided by The Conference Board (TCB).[21] This is a novel data series that covers the universe of online advertised vacancies posted on internet job boards or in newspaper online editions.[22] The HWOL database started in May 2005 as a replacement for the Help-Wanted Advertising Index of print advertising maintained by TCB. It covers roughly 1,200 online job boards and provides detailed information about the characteristics of advertised vacancies for between three and four million active ads each month.

Each observation in the HWOL database refers to a unique ad and contains information about the listed occupation at the 6-digit level, the geographic location of the advertised vacancy down to the county level, whether the position is for full-time, part-time, or contract work (essentially self-employed contractors or consultants: e.g., computer specialists, accountants, auditors), the education level required for the position, and the hourly and annual mean wage.[23] For a subset of ads we also observe the industry NAICS classification, the sales volume and number of employees of the company, and the actual advertised salary range. The vast majority of online advertised vacancies are posted on a small number of job boards: about 70% of all ads appear on nine job boards, and about 60% are posted on only five job boards.[24]

It is worth mentioning some measurement issues in the HWOL data: first, the same ad can appear on multiple job boards. To avoid double-counting, a sophisticated unduplication algorithm is used by TCB that identifies unique advertised vacancies on the basis of the combination of company name, job title/description, city or state. Second, the growing use of online job boards over time may induce a spurious upward trend. When we compare JOLTS data to HWOL data below, we do not find large discrepancies between the two time series, suggesting that this problem is not serious, perhaps because the bulk of the shift from newspaper to online ads took place before 2005. Third, the dataset records one vacancy per ad. There is a small number of cases in which multiple positions are listed, but the convention

[21] Note that our analysis is based on data for the December 2000-June 2011 period for the JOLTS and May 2005-June 2011 for the HWOL.

[22] The data are collected for The Conference Board by Wanted Technologies.

[23] The education and wage information is imputed by TCB. Education is imputed from BLS data on the education content of detailed 6-digit level occupations. Wages are imputed using BLS data from the Occupational Employment Statistics (OES), based on the occupation classification.

[24] The nine largest job boards are: Absolutely Health Care, Craigslist, JOBcentral, CareerBuilder, Monster, Yahoo!HotJobs, Recruiter Networks, Dice, and DataFrenzy.

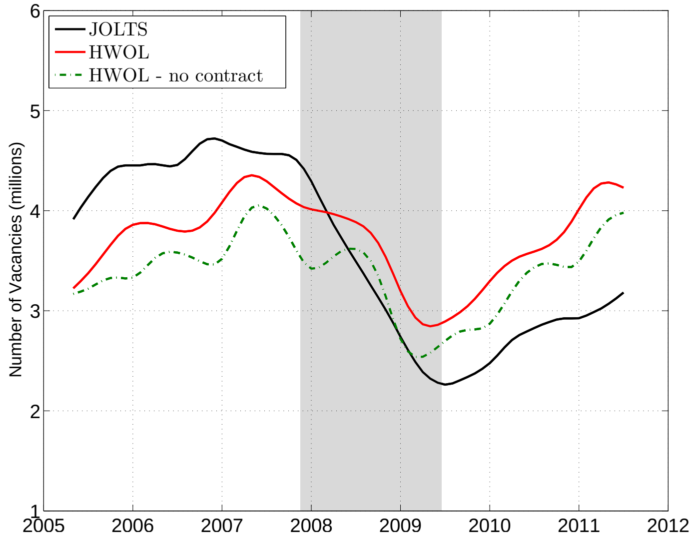

Figure 1: Comparison Between JOLTS and HWOL.

of one vacancy per ad is used for simplicity. Finally, there are some cases in which multiple locations (counties within a state) are listed in a given ad for a given position. Here, we follow the convention that if the counties are in the same MSA the position is taken to represent a single vacancy, but if they appear in different MSA's they reflect distinct vacancies.

A comparison across our two data sources for vacancies shows that the aggregate trends from the HWOL database are roughly consistent with those from the JOLTS data: in Figure 1, we plot JOLTS vacancies and HWOL ads at the national level. The total count of active vacancies in HWOL is below that in JOLTS until the beginning of 2008, and is above from 2008 onwards. As we show in Figure B1 in the Appendix, this difference is most pronounced in the South, and may reflect the growing penetration of online job listings over time. The average difference between the two aggregate series is about 16% of the JOLTS total. The correlation between the two aggregate series is very high, 0.89, indicating that the patterns over time are very similar. We report additional comparisons between the JOLTS and HWOL vacancy series in Appendix B.1.[25]

We calculate unemployment counts from the Current Population Survey (CPS) for the

[25]In the figures we also plot vacancy counts from HWOL excluding contract work, to make the series more comparable to the JOLTS measure of vacancies. JOLTS only reports vacancies posted by establishments for their own direct employees and excludes self-employed outside contractors and consultants which are instead covered by HWOL (see the Appendix for further detail). In all our analyses with HWOL data we consider all vacancies, including contract work.

same industry, occupation, and education classifications that we use for vacancies.[26] For geography, we use the Local Area Unemployment Statistics (LAUS) which provides monthly estimates of total unemployment at the county and MSA level.[27] The CPS reports the industry and occupation of unemployed workers' previous jobs. In keeping with the upper bound nature of our calculation, we begin by assuming that all unemployed workers search only in the sector that they had last worked in. We later relax this assumption. The small sample size of the CPS limits the level of disaggregation of our analysis, and prevents us from using HWOL ads data to their full effect.[28]

We use various proxies for productivity, depending on data availability. At the industry level, we compute labor productivity by dividing gross GDP per year for each industry from the Bureau of Economic Analysis (annual data) by average employment in that industry from the Establishment Survey.[29] At the occupation level, for lack of a better proxy, we use annual data on average hourly wages from the Occupational Employment Statistics (OES).[30] Similarly, at the county level, we use median weekly wage earnings from the Quarterly Census of Employment and Wages (QCEW).[31] We recognize that wage levels might be affected by factors other than productivity like unionization rates, compensating differentials, monopoly rents, etc. To partially address this issue, we normalize the average wage for each occupation to unity at the beginning of our sample and focus on relative wage movements over time. We also apply the same normalization to industry-level productivity measures for consistency.

We calculate job destruction rates at the industry level from the Business Employment Dynamics (BED) as the ratio of gross job losses to employment.[32] Since the BED is quarterly, we assume that the destruction rate is the same for the three months corresponding to a specific quarter and impute the corresponding monthly destruction rates. Since job destruction rates by occupation are not available, we compute the employment to unemployment

[26]Industry affiliations are not available for all unemployed workers in the CPS. From 2000-2010, on average about 13.3% of unemployed do not have industry information. Only about 1.5% of unemployed are missing occupation information. Some of these workers have never worked before and some are self-employed.

[27]See http://www.bls.gov/lau/ for more information on LAUS.

[28]The average number of unemployed in the CPS for the May 2005 to June 2011 period is 4,557 with a range of 2,808 to 12,436.

[29]http://www.bea.gov/industry/

[30]See http://www.bls.gov/oes/

[31]See http://www.bls.gov/cew/

[32]http://www.bls.gov/bdm/

transition rates by occupation in the last job from the CPS semi-panel. Figures B3 and B4 in the appendix show the evolution of productivity and job destruction rates for selected industries and occupations.

The calculation of market-specific matching efficiency parameters, ϕ_i, and vacancy share α is more involved. We describe its details below.

4.2 Matching function estimation

In order to compute market-specific matching efficiency parameters, ϕ_i, and vacancy share α, we estimate aggregate and sector-specific matching functions using various specifications and data sources. The estimation of matching functions is subject to an endogeneity issue, as shocks to unobserved matching efficiency may affect the number of vacancies posted by firms—much like TFP shocks affect firm's choice of labor input. In a recent paper, Borowczyk-Martins, Jolivet and Postel-Vinay (2012) show that the most important movements in matching efficiency inducing a bias in the simple OLS estimator are low-frequency ones and, as a result, modeling the dynamics of matching efficiency through time-varying polynomials and structural breaks goes a long way towards solving the problem. This is the approach we take here. At the aggregate level, we estimate:

$$\log\left(\frac{h_t}{u_t}\right) = const + \gamma' QTT_t + \alpha \log\left(\frac{v_t}{u_t}\right) + \epsilon_t, \tag{14}$$

where QTT_t is a vector of four elements for the quartic time trend which is meant to capture shifts in aggregate matching efficiency.

At the sectoral level, we are interested in the sector-specific component of matching efficiency orthogonal to common aggregate movements in aggregate matching efficiency. Therefore, at the industry and 2-digit occupation level, we perform the following panel regression:

$$\log\left(\frac{h_{it}}{u_{it}}\right) = \gamma' QTT_t + \chi_{\{t\leq 07\}} \log\left(\phi_i^{pre}\right) + \chi_{\{t>07\}} \log\left(\phi_i^{post}\right) + \alpha \log\left(\frac{v_{it}}{u_{it}}\right) + \epsilon_{it}, \tag{15}$$

where $\chi_{\{t>07\}}$ is an indicator for months after December 2007, the official start of the recession, to absorb sector-specific shifts in matching efficiency.

At the industry level, we use vacancies and hires from JOLTS, and unemployment counts from the CPS. At the occupation level, we use vacancies from HWOL but do not have a direct measure of hires as in JOLTS. Therefore, we construct hires from the CPS using flows from unemployment into a given occupation i for people who are surveyed in adjacent months. Because these monthly flows are quite noisy, we use a 3-month moving average of the data, and aggregate occupations into five broad occupation groups. For comparison purposes, we replicate the analysis at the industry level using the constructed "CPS hires" as well.[33] At the aggregate level, we perform the estimation using both JOLTS and HWOL vacancies, and both JOLTS and CPS hires.

We report our estimates for the vacancy share α, using our various specifications, in Table 1. In the aggregate regressions, the estimated vacancy share varies between 0.32 and 0.65; in the panel regressions, the estimates are a bit lower varying between 0.24 and 0.53. To construct our mismatch indices, and in our calculation of mismatch unemployment, we pick a value of $\alpha = 0.5$, for various reasons. First, it is the midpoint of our estimates with aggregate data. Second, our mismatch indices are typically highest for $\alpha = 0.5$; therefore, in the spirit of reporting an upper bound for mismatch unemployment, we use this value.[34] Finally, 0.5 is roughly in the middle of the range of estimates used in other recent papers in the matching literature.[35]

The estimated quartic time trend drops during the recession in all our specifications, consistent with a deterioration of aggregate matching efficiency. With regard to sectoral matching efficiency, in what follows we use the estimates obtained with JOLTS hires for the industry level mismatch analysis, and those with CPS hires for the occupation level analysis. In all cases, we use the *pre-recession* matching efficiency parameter estimates, and verify the robustness of our findings to this choice.[36]

These estimation results assume a Cobb-Douglas specification for the matching function,

[33]See Tables B6 and B7 in Appendix B for the details of these groupings.

[34]In Appendix B, we report a sensitivity analysis using values of α ranging from 0.3 to 0.7.

[35]A few examples are $\alpha = 0.5$ in Davis, Faberman, and Haltiwanger (2010), $\alpha = 0.28$ in Shimer (2005), $\alpha = 0.54$ in Mortensen and Nagypal (2007), α between 0.66 and 0.72 in Barnichon and Figura (2011).

[36]The estimated matching efficiency parameters ϕ_i pre- and post-recession are reported in Appendix B, Tables B5-B7. Beyond movements in the common component Φ_t, changes over time in sector-specific matching efficiencies are small. In Appendix B.3, we document that the mismatch unemployment calculations using both pre- and post-recession ϕ_i's are virtually identical to the baseline.

	Aggregate regressions		Panel regressions	
	JOLTS	HWOL	Industry (JOLTS)	Occupation (HWOL)
JOLTS Hires	0.654		0.532	
	(0.010)	-	(0.013)	-
Sample Size	126		2142	
CPS Hires	0.318	0.332	0.241	0.279
	(0.017)	(0.038)	(0.014)	(0.016)
Sample Size	126	72	404	370

Table 1: Estimates of the vacancy share α using the JOLTS and HWOL datasets. S.E. in parenthesis.

in accordance to our theoretical model. For robustness, we have also estimated a more flexible CES function. We find that, depending on the specification, the elasticity parameter is either not significantly different than unity, or very close to unity (the Cobb-Douglas case). The estimated vacancy share and matching efficiency parameters are also very similar to the Cobb-Douglas case. The details are reported in Table B4 in Appendix B.

5 Results

5.1 Industry-level mismatch

From our definition of mismatch, it is clear that there is a close association between mismatch indexes and the correlation between unemployment and vacancy shares across sectors. The planner's allocation rule implies a perfect correlation between unemployment shares and (appropriately weighted) vacancy shares. A correlation coefficient below one is a signal of mismatch, and a declining correlation is a signal of worsening mismatch.

Figure 2 plots the time series of this correlation coefficient across industries over the sample period. In particular, we report two different correlation coefficients motivated by the definitions of the mismatch indexes we derived in Section 3: 1. ρ: between (u_{it}/u_t) and (v_{it}/v_t) and 2. ρ_x: between (u_{it}/u_t) and $(x_i/\bar{x}_t)^{\frac{1}{\alpha}}(v_{it}/v_t)$. Both series behave very similarly. The basic correlation coefficient (ρ) drops from 0.75 in early 2006 to 0.45 in mid 2009 and recovers thereafter, indicating a rise in mismatch during the recession.[37]

[37]It is also useful to examine the evolution of vacancy and unemployment shares of different industries. In Figure B5, we plot the vacancy and unemployment shares for a selected set of industries using the JOLTS

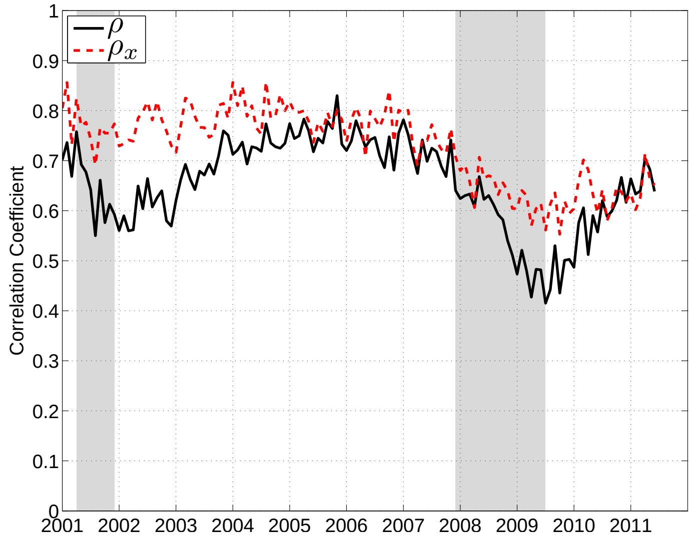

Figure 2: Correlation coefficient between u and v shares across industries.

The left panel of Figure 3 plots the unadjusted index, $\mathcal{M}_t$ and the one adjusted for heterogeneity, $\mathcal{M}_{xt}$.[38] This 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 two to three percent per month, depending on the index used. At the end of the recession, in mid 2009, it had increased to roughly 7-8 percent per month, and it has since dropped again to almost its pre-recession level. To sum up, both indexes indicate a sharp rise in mismatch between unemployed workers and vacant jobs across industries during the recession, and a subsequent fairly rapid decline.

How much of the observed rise in the unemployment rate can be explained by mismatch? The right panel of Figure 3 shows mismatch unemployment (i.e., the difference between the actual and the counterfactual unemployment rates) at the industry level for the 2001-2011

definition in the Appendix. The shares have been relatively flat in the 2004-2007 period. However, starting in 2007, vacancy shares started to change noticeably. Construction and durable goods manufacturing were among the sectors which experienced a decline in their vacancy shares while the health sector saw its vacancy share increase. Concurrently, unemployment shares of construction and durable goods manufacturing went up while the unemployment share of the health sector decreased. Interestingly starting from 2010, unemployment and vacancy shares of sectors began to normalize and almost went back to their pre-recession levels, with the exception of the construction sector. The vacancy share of the construction sector remains well below its pre-recession level.

[38]Note that all mismatch indexes throughout the paper are HP filtered to eliminate high frequency movements and better visualize the variation in the indexes. To facilitate the comparison across different definitions of labor markets, we plot all the mismatch indexes and mismatch unemployment rates using the same vertical distance on the y axis, 0.15 and 2.5 percentage points, respectively.

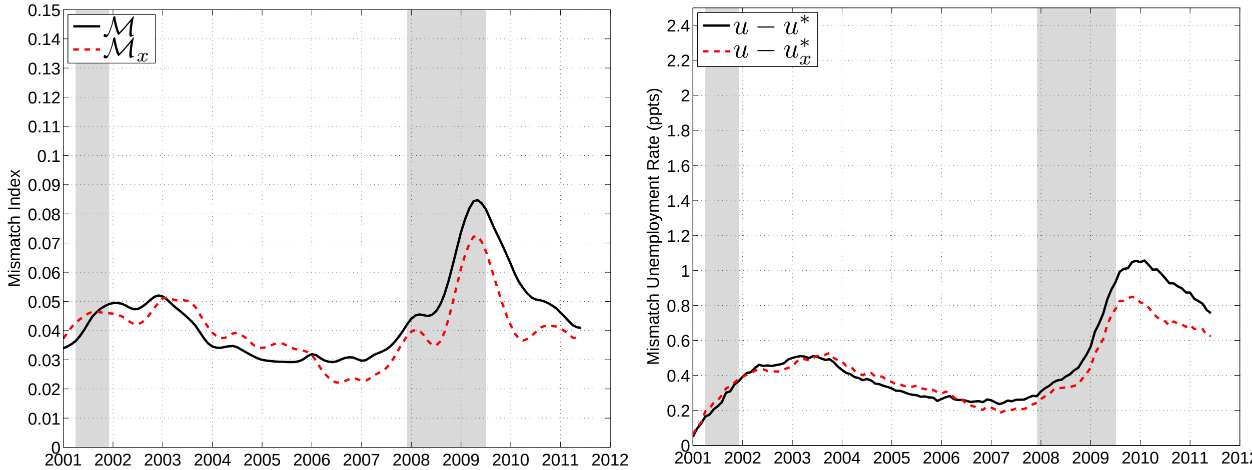

Figure 3: Mismatch index $\mathcal{M}_t$ and $\mathcal{M}_{xt}$ by industry (left panel) and the corresponding mismatch unemployment rates (right panel).

period, as implied by the homogeneous and heterogenous indexes. Table 2 shows the change in mismatch unemployment between October 2009 and the average of 2006.[39] The main finding is that worsening mismatch across these seventeen industries explains between 0.59 and 0.75 percentage points of the rise in U.S. unemployment from 2006 to its peak, i.e., at most 14 percent of the increase.[40] Mismatch unemployment has declined since early 2010, but remains above its pre-recession levels.

In Section 2.2.2, we have shown how the planner's allocation rule changes under the Abraham-Katz interpretation of sectoral employment movements driven by aggregate shocks with different sectors having different sensitivities to the aggregate cycle. Here we recalculate the mismatch index $\mathcal{M}_{xt}$ using the derivation in Section 2.2.2. We call this index $\mathcal{M}_{xt}^{AK}$ since it relates to Abraham and Katz's critique of Lilien's sectoral shift hypothesis. Figure 4 shows the mismatch index and the corresponding mismatch unemployment computed using the benchmark specification and this alternative interpretation. As the figure shows, the two indexes are very similar.

[39] Note that the average unemployment rate was 4.6% in 2006 and 10.0% at its peak in October 2009, indicating a 5.4 percentage point increase. Throughout the paper we compare the average of 2006 with the unemployment peak (October 2009) when we discuss the role of mismatch in the increase in the unemployment rate.

[40] To examine the robustness of our findings, we present various additional results in Appendix B.3 and find that the contribution of mismatch to the rise in the unemployment rate varies between 0.52 and 0.88 percentage points.

	Index	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$
Industry	$\mathcal{M}$	0.26	1.01	0.75	13.9%
	$\mathcal{M}_x$	0.25	0.84	0.59	10.9%
	$\mathcal{M}_x^{AK}$	0.28	0.89	0.61	11.2%
	$\mathcal{M}_{adj}$	0.25	0.89	0.65	11.9%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	0.70	1.91	1.21	22.3%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.36	1.25	0.89	16.5%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.27	0.95	0.68	12.7%
2-digit Occupation	$\mathcal{M}$	0.85	2.00	1.14	21.3%
	$\mathcal{M}_x$	0.42	1.02	0.60	11.1%
	$\mathcal{M}_{adj}$	0.84	2.00	1.16	21.4%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	1.08	2.60	1.52	28.1%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.74	1.81	1.07	19.7%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.58	1.41	0.83	15.3%
3-digit Occupation	$\mathcal{M}$	1.33	2.91	1.58	29.3%
	$\mathcal{M}_x$	0.79	1.73	0.94	17.4%
Routine/Cognitive	$\mathcal{M}_{RC}$	0.41	1.07	0.67	12.3%
County	$\mathcal{M}$	0.32	0.46	0.14	2.6%
	$\mathcal{M}_z$	0.32	0.45	0.13	2.5%

Table 2: Changes in mismatch unemployment at the industry, occupation, and county levels. All the differences are calculated as the difference between October 2009 and the average of 2006. Note that $\Delta u = 5.4$ percentage points.

5.2 Occupation-level mismatch

We now present our results on mismatch between vacancies and unemployment across 2- and 3-digit occupations. Recall that the HWOL ads data used for these calculations begin in May 2005 and the latest observation is June 2011.

Figure 5 plots the correlation between vacancy and unemployment shares across 2-digit SOC's. As for the industry-level analysis, we document a significant decline for both measures during the recession and a subsequent pick-up starting in mid-2009.[41]

Figure 6 plots the $\mathcal{M}_t$ and $\mathcal{M}_{xt}$ indexes (left panels) and the resulting mismatch unem-

[41]Figure B10 in the Appendix shows the unemployment and vacancy shares of selected 2-digit SOC's. As the figure indicates, the shares have changed noticeably during the most recent downturn. Business and financial operations, production and construction/extraction were among the occupations that experienced a decline in their vacancy shares and an increase in their unemployment shares. Concurrently, vacancy shares of health-care practitioner and sales and related occupations went up and the corresponding unemployment shares declined. Starting from 2010, similar to the JOLTS data, unemployment and vacancy shares began to normalize.

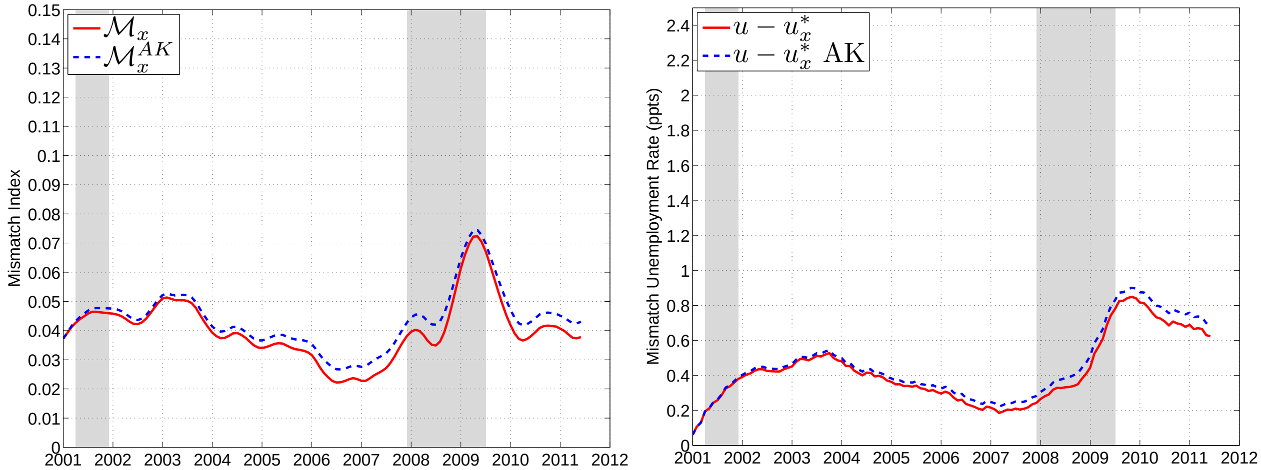

Figure 4: Mismatch indexes $\mathcal{M}_{xt}$ by industry (left panel) and corresponding mismatch unemployment rates (right panel) for the baseline specification and with the specification with heterogenous sensitivities to aggregate shocks.

ployment (right panels) for 2 and 3-digit SOC's.[42] The homogeneous $\mathcal{M}_t$ index rises by almost 0.04 over the same period for 2-digit occupations. Similar to the pattern observed for industries, the rise in mismatch leads the recession by over a year. As seen in the figure and in Table 2, based on the $\mathcal{M}_t$ index, around 1.1 percentage points (or around 21%) of the recent surge in U.S. unemployment can be attributed to occupational mismatch measured at the 2-digit occupation level. At the 3-digit level, the portion of the increase in unemployment attributable to mismatch is around 1.6 percentage points (or roughly 29% of the rise in the unemployment rate).

The efficiency-weighted $\mathcal{M}_{xt}$ index is lower than the unadjusted index and features a smaller rise, implying around 2% of additional hires lost because of mismatch. This index suggests that between 0.6 and 0.9 percentage points of the rise in the unemployment rate (or between 11% and 17% of the increase) was due to mismatch at the 2-digit and 3-digit SOC levels, respectively. Therefore, similar to what we found for industries, the index weighted by matching and productive efficiency implies a smaller role for mismatch unemployment.[43]

[42] There are 22 2-digit SOC's and 93 3-digit SOC's. We use all the 2-digit categories with the exception of Farming, Fishing, and Forestry. We exclude 3-digit SOC's that exhibit fewer than 10 observations in the CPS unemployment counts at least once in the sample period. These small cells account for 60% of the 3-digit SOC's, but represent only 15.6% of unemployed workers in the CPS.

[43] Table B9 and Figures B11-B12 in Appendix B.3 summarizes various additional results for robustness purposes and shows that our findings on occupation level mismatch are quite robust.

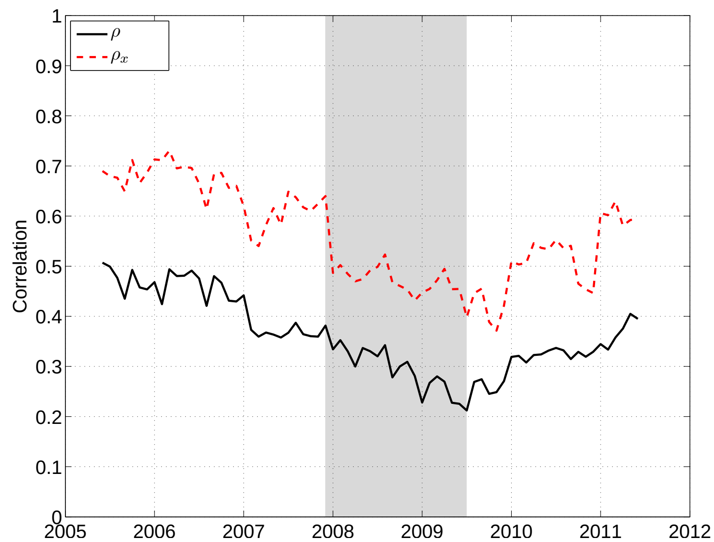

Figure 5: Correlation coefficient between u and v shares for 2-digit occupations.

We also consider a different occupation classification to relate our analysis to the literature on job polarization. Job polarization refers to the increasing concentration of employment in the highest- and lowest-wage occupations, as job opportunities in middle-skill occupations disappear, as documented by Autor et al. (2003) and Acemoglu and Autor (2011). To capture the effect of job polarization on mismatch, we classify 2-digit occupations into four categories: routine cognitive, routine manual, non-routine cognitive and non-routine manual. We call this classification "Routine/Cognitive" and denote the index with $\mathcal{M}_{RC}$.[44] Figure 7 shows the mismatch index across these four occupation groups as well as the homogeneous index calculated at the 2-digit level and the corresponding mismatch unemployment rates. The level of the index is lower across these four occupational categories which suggests additional mismatch within these four categories. Despite the gap in the level of the two indices, the behavior of the $\mathcal{M}_{RC}$ index is very similar to the occupational mismatch index $\mathcal{M}$ computed using 2-digit occupations. In essence, the vacancy (unemployment) share dropped (rose) faster for routine-non cognitive occupations relative to the other groups, accounting for at least half of the increase in mismatch unemployment across 2-digit occupations.

Jaimovich and Siu (2012) link the job polarization hypothesis to jobless recoveries by

[44]We classify occupations at the 2-digit level instead of directly using Acemoglu and Autor's classification. While their way of classifying occupations is more detailed, our classification broadly captures this distinction and is more comparable with the rest of our analysis. See Table B2 in the Appendix for our classification of occupations into these four groups.

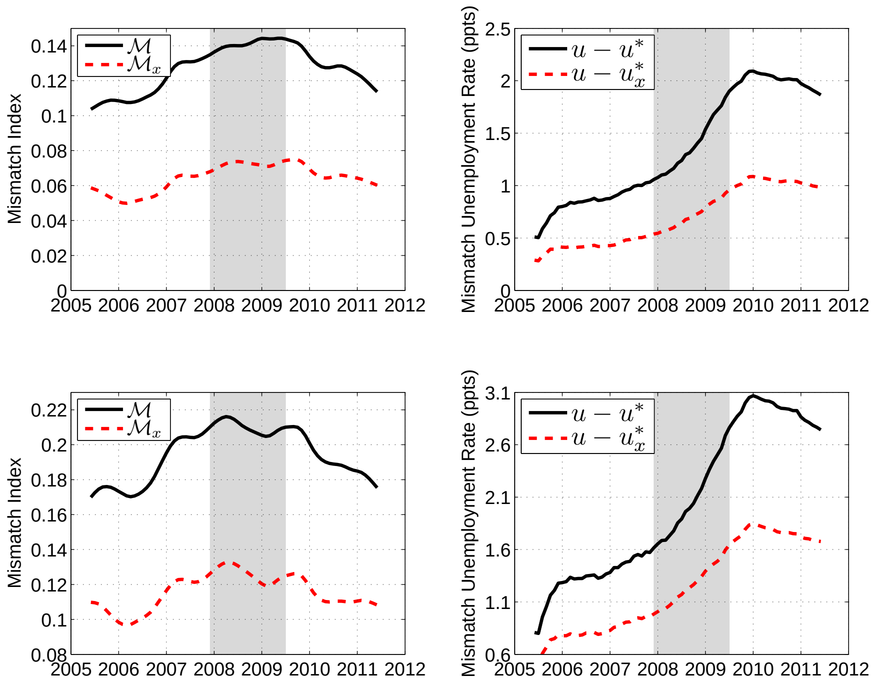

Figure 6: Mismatch indexes $\mathcal{M}_t$ and $\mathcal{M}_{xt}$ by 2-digit occupation (upper left panel) and 3-digit occupation (lower left panel). Corresponding mismatch unemployment rates for 2-digit occupation (upper right panel) and 3-digit occupations (lower right panel).

analyzing employment changes during recessions and recoveries for different occupation classifications. They show that employment declined more in routine occupations during the most current downturn.[45] This relatively large decline is in line with the increase in mismatch during the recession. They also show that employment remained stagnant in all occupational categories during the recovery period, which is consistent with the decline in mismatch after the recession.

5.3 Geographical mismatch

We perform our geographical analysis for U.S. counties using the HWOL data on online job ads coupled with LAUS data on the unemployed. We focus on counties whose population is at least 50,000 and group together counties in the same metropolitan area to capture the notion of local labor markets. The procedure gives a total of 280 local labor markets.[46]

[45] See the bottom panel of Figure 6 in Jaimovich and Siu (2012), p. 12.

[46] We also compute geographic mismatch for the 50 U.S. states using the HWOL data on online job ads coupled with CPS data on the unemployed. The JOLTS provides limited geographic information, enabling us to study mismatch only across the four broad Census regions. Our conclusions from these state- and region-

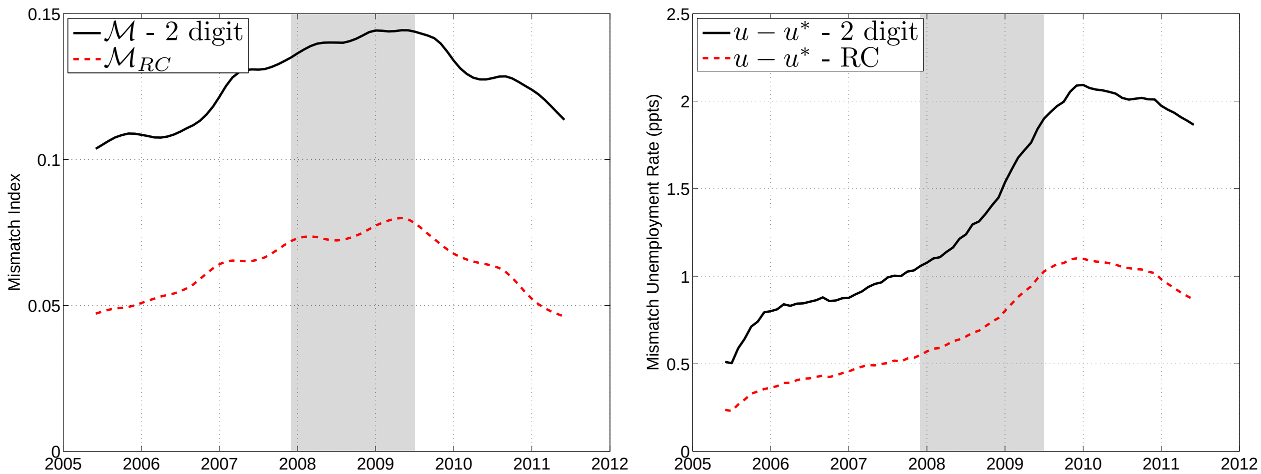

Figure 7: Mismatch indexes $\mathcal{M}$ across four occupations groups and 2-digit occupations (left panel) and corresponding mismatch unemployment rates (right panel).

Figure 8 shows the mismatch indexes $\mathcal{M}_t$ and $\mathcal{M}_{zt}$ and the corresponding mismatch unemployment rates. We find that geographic mismatch is very low (about one fifth of the size of the index for 3-digit occupations, even though the number of active sectors is much higher) and is essentially flat over the sample period under consideration. Unsurprisingly, the rise in mismatch unemployment according to this index is around one tenth of a percentage point, implying that geographical mismatch—across U.S. counties and MSAs—played a negligible role in the recent dynamics of U.S. unemployment. This finding is consistent with other recent work that investigated the role of housing market related problems on the labor market using different methods.[47]

In Appendix B.3 we also examine mismatch defining labor markets as a combination of occupation and location. Since the small sample size of the CPS does not allow us to disaggregate the unemployment data by county and occupation, we define labor markets as the interaction of 2-digit occupations and the nine Census divisions.[48] The resulting mismatch

based analyses are fully aligned with the county-based study.

[47]See, for example, Farber (2012), Karahan and Rhee (2012), Molloy, Smith, and Wozniak (2010), Nenov (2012), and Schulhofer-Wohl (2010). A related concern regarding geographic mobility is the apparent observation that the rate of interstate migration in the U.S. reached a postwar low. However, Kaplan and Schulhofer-Wohl (2010) show that this is largely a statistical artifact arising from a change in survey procedures for missing values. After removing this spurious effect, they find that the annual interstate migration rate follows a smooth downward trend from 1996 to 2010.

[48]Due to the small sample, we compute this index with quarterly data. To facilitate the comparison, we also compute $\mathcal{M}_t$ for 2-digit occupations at the quarterly frequency and report it in Table B9.

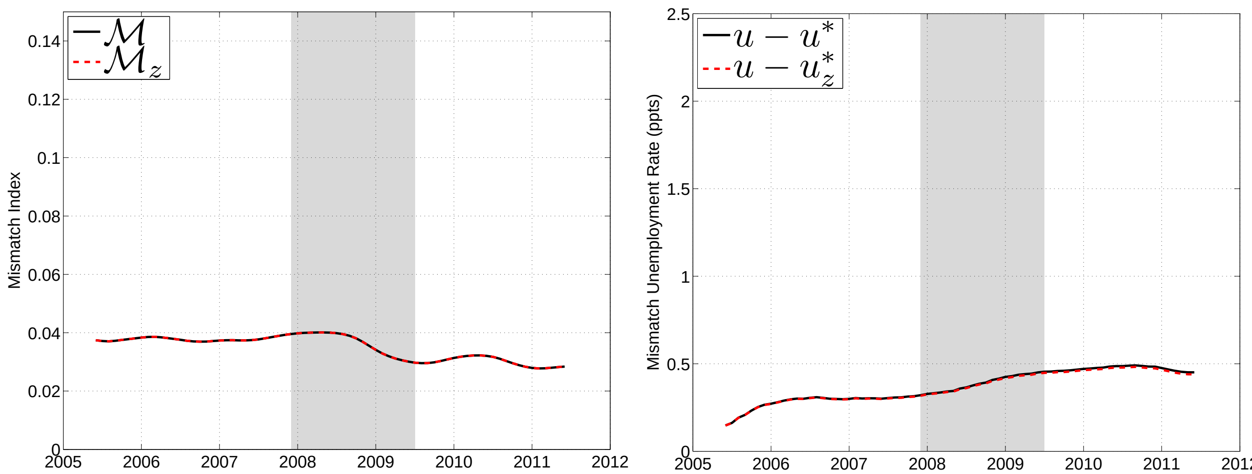

Figure 8: Mismatch indexes $\mathcal{M}_t$ and $\mathcal{M}_{zt}$ by county (left panel) and corresponding mismatch unemployment rates (right panel).

indexes and mismatch unemployment are presented in Figure B13 and Table B9. The evolution of both the index and the level of mismatch unemployment is very similar to those computed at the 2-digit occupation level.

5.4 Mismatch within education groups

Is occupational mismatch a more relevant source of unemployment dynamics for less skilled or for more skilled workers? To answer this question, we define four education categories (less than high school diploma, high school diploma or equivalent, some college or Associate's degree, Bachelor's degree or higher) and analyze mismatch by 2-digit occupation *within* each of these four education groups.

As noted before, each job listing recorded in HWOL constitutes an individual observation with a 6-digit occupation classification. The BLS provides information on the distribution of workers employed in each 6-digit occupation broken down by their educational attainment.[49] We allocate the total count of vacancies from HWOL in a given month for a given 6-digit occupation to each of the four education groups we consider, proportionally to the educational attainment distributions from the BLS.[50] Finally, we aggregate up to the 2-digit

[49]This information comes from the American Community Survey microdata from 2006-08. See the BLS website at http://www.bls.gov/emp/ep_table_111.htm; see also http://www.bls.gov/emp/ep_education_tech.htm for additional details.

[50]For robustness, we have also experimented with other allocation rules, for instance not imputing vacancies

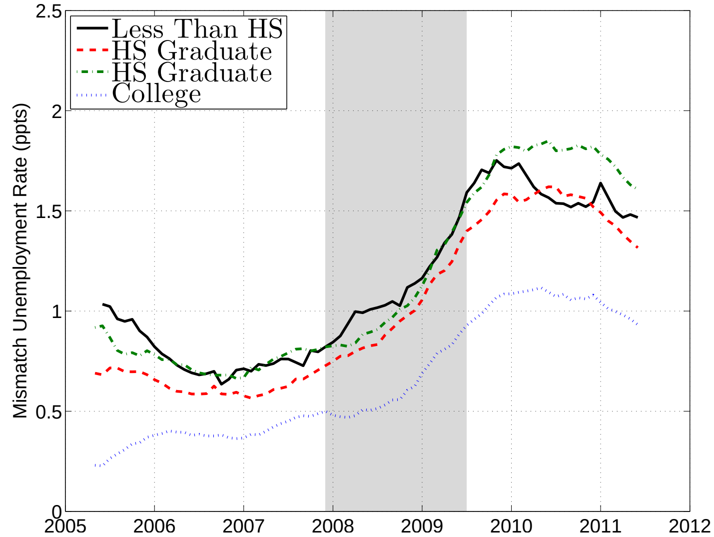

Figure 9: Mismatch unemployment rates measured at the 2-digit occupation level for different education groups.

occupation level to obtain vacancy counts for each occupation by education cell. The CPS provides information on the education level of the unemployed.

Figure 9 shows mismatch unemployment measured at the 2-digit occupation level for different education groups.[51] Note that unemployment dynamics differ greatly by education: for workers with less than a high school degree, the unemployment rate rose from about 7% in 2006 to about 15.3% in 2010, an increase of about 8.5 points. The increase in the unemployment rate over the same time period for high school graduates and those with some college was, respectively, 6.9 and 5.3 percentage points. For college graduates, the unemployment rate went from 2% to 4.7%, an increase of only 2.7 percentage points over the same period.

The counterfactual exercises summarized in Table 3 reveal a very clear pattern: the contribution of occupational mismatch to the rise in unemployment between 2006 and 2010 grows as we move from the lowest to the highest education category. In particular, for the less than high school group, mismatch explains a little less than one percentage point

of a given 6-digit SOC to an education level that accounts for less than 15% of the workers in that occupation. The results are very similar.

[51] Figures B14 in the Appendix illustrate our findings on occupational mismatch within each broad education category. The occupational mismatch index rose within all four education groups, but more so in the "some college" and "college" categories.

	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	Δu	$\Delta(u - u^*)/\Delta u$
Less than High School	0.71	1.69	0.98	8.5 ppts	11.5%
High School Degree	0.60	1.50	0.89	6.9 ppts	12.9%
Some College	0.71	1.68	0.97	5.3 ppts	18.2%
College Degree	0.38	1.03	0.65	2.7 ppts	23.9%

Table 3: Changes in mismatch unemployment for different education groups. All the changes are calculated as the difference between October 2009 and the average of 2006. Note that $\Delta u = u_{10.09} - u_{06}$ and that Δu varies by education.

(12%) of the 8.5 percentage point increase in unemployment for that group. For high school graduates, mismatch explains 0.89 (13%) out of the 6.9 percentage point increase in unemployment. For those with some college, mismatch explains about 1.0 (18%) out of a 5.3 percentage point rise in unemployment, and for college graduates 0.65 (24%) out of the 2.7 percentage point observed increase. Thus, the fraction of the rise in unemployment that can be attributed to the rise in occupational mismatch increases monotonically with education from about one eighth to roughly one quarter of the increase for each group.

6 Robustness on job-seeker and vacancy measures

In our empirical implementation, we have so far assumed that the number of job seekers in sector i is given by the number of unemployed workers whose last job was in sector i. There are two potential sources of bias that might affect our mismatch measures. The first is the assumption that each unemployed worker is searching in the same industry or occupation as the one where she was last employed. Second, our unemployment counts do not include discouraged workers. Since some workers get discouraged from job search and drop out of the labor force temporarily during periods of high unemployment, we might underestimate the true number of potential job seekers in some sectors.

Finally, it is possible that vacancies are measured with error since not all hires occur through formal advertisement (see, e.g., Galenianos, 2012, for an analysis of hiring through referrals). In this section, we verify the robustness of our findings to these measurement issues.

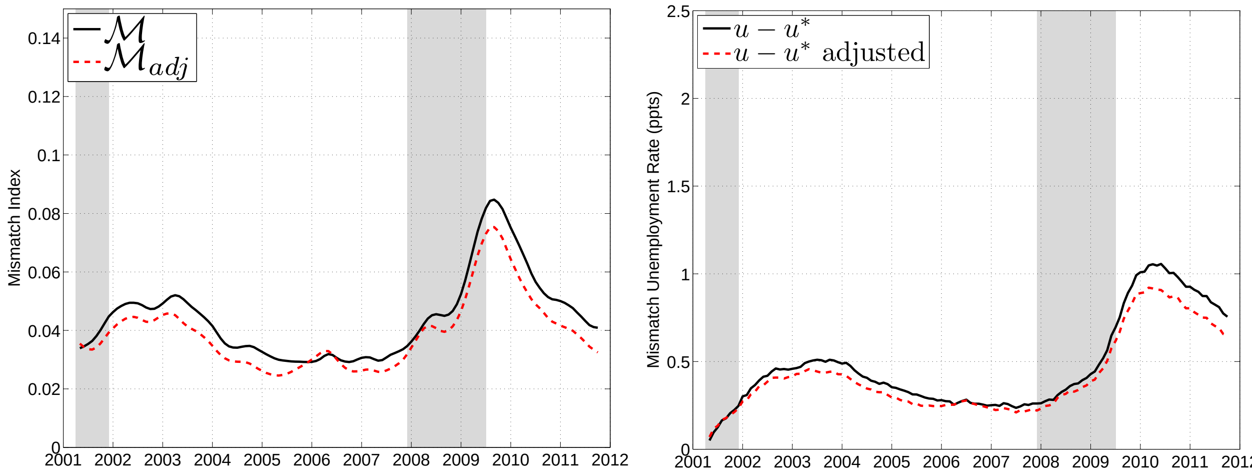

Figure 10: Mismatch index using unadjusted ($\mathcal{M}$) and adjusted $\mathcal{M}_{adj}$ unemployment counts by industry (left panel) and the corresponding mismatch unemployment rates (right panel).

6.1 Adjustment for direction of search

The number of unemployed workers *searching* for jobs in a particular sector does not necessarily coincide with the number of workers whose last employment was in that sector. Here, we propose an alternative calculation of the number of job-seekers in each industry or occupation by exploiting the semi-panel dimension of the CPS. Since respondents in the CPS are interviewed for several consecutive months, we can track unemployed workers who find new employment from one month to the next and record: 1. industry (and occupation) of the job prior to the workers unemployment spell; 2. industry (and occupation) of the new job. We then create annual transition matrices (from sector i to sector j) by aggregating monthly flows.[52] We then infer the number of job seekers in each sector using a simple statistical algorithm, whose key assumption is that every unemployed searching for a job in sector j has the same probability of being hired, independently of the sector of origin, except when coming from sector j itself in which case she is allowed to have a higher job-finding rate. The method is outlined in detail in Appendix B.4.

We first report our results by industry. The left panel of Figure 10 shows the mismatch index calculated using the adjusted unemployment counts, which we call $\mathcal{M}_{adj}$, as well the unadjusted $\mathcal{M}$ index. The adjustment causes the level of the index to decrease somewhat dur-

[52]In implementing this procedure, we closely follow Hobijn (2012).

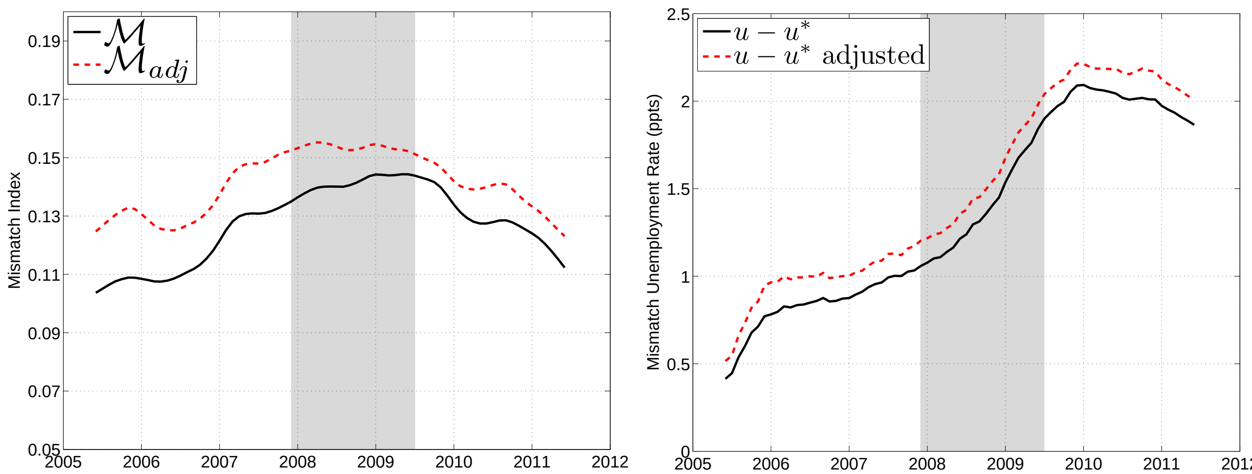

Figure 11: Mismatch index $\mathcal{M}_t$ using adjusted and unadjusted unemployment counts by occupation (left panel) and corresponding mismatch unemployment rates (right panel).

ing the sample period. Similarly, as shown in the right panel of Figure 10, the counterfactual unemployment rate implied by the adjusted counts is slightly lower than our baseline case. However in terms of accounting for the increase in the unemployment rate both indexes have similar quantitative implications. When using the adjusted counts, 0.65 percentage points of the roughly 5.4 percentage point rise in the U.S. unemployment rate is due to industry-level mismatch (compared to 0.75 percentage points without the adjustment).

Figure 11 reports our analysis by occupation. Again, the behavior of the adjusted $\mathcal{M}_{adj}$ index and of the resulting mismatch unemployment is very similar to the case without adjustment. In contrast to the industry-level analysis, the adjusted index for occupations is slightly higher than in the baseline case. Quantitatively, the contribution of mismatch to the rise in the U.S. unemployment rate is virtually the same when using adjusted unemployment counts by occupation (see Table 2).

6.2 Adjustment for discouraged workers

According to the CPS, an individual is unemployed if he or she does not have a job, has actively looked for employment in the past four weeks and is currently available to work. However, it is possible that some workers get discouraged from unsuccessful job search and drop out of the labor force temporarily during periods of high unemployment.[53] If workers from certain occupations or industries are more likely than others to get discouraged, our mismatch measures may be biased. For example, if a high fraction of the unemployed whose prior occupation was construction-related drop out of the labor force and stay on the sidelines (to re-enter the labor force at a later stage), the number of unemployed construction workers is an under-estimate of the true number of potential job seekers in the construction sector. In this example, actual mismatch would be larger.

To examine the size of this bias, we calculate the unemployment to non-participation (UN) and unemployment to discouraged (UD) flow rates conditional on workers' previous occupations and industries. Tables B10 and B11 in the Appendix show that the rates at which unemployed workers flow into the discouraged worker state are very similar across industries and occupations. As a consequence, adjusting the unemployment counts by including discouraged workers affects the unemployment shares of different industries and occupations only marginally. As a robustness check, we recomputed the basic mismatch index $\mathcal{M}_t$ using an extended definition of unemployment where we include workers who flow from unemployment to discouragement. The difference between the modified mismatch index and the original index is quantitatively insignificant (a difference of 0.0002 on average).

6.3 Measurement error in vacancies

Suppose that true vacancies (V_{it}) in market i are proportional to the observed vacancies (v_{it}) by a factor $\upsilon_i^{\frac{1}{\alpha}}$ which captures the importance of informal hiring channels in that sector. Therefore, $V_{it} = \upsilon_i^{\frac{1}{\alpha}} \cdot v_{it}$. In Appendix B.5, we show that the fixed matching-efficiency effect ϕ_i absorbs this factor as well. For example, markets where vacancies are severely underreported (i.e., $\upsilon_i >> 1$) look like markets with higher matching efficiency.

For the purpose of calculating the planner's allocation rule needed for the mismatch indexes, it makes no difference whether ϕ_i is high in a sector because pure matching efficiency is high or because actual vacancies are larger than the observed ones: in both cases, the plan-

[53] The Current Population Survey classifies as discouraged workers those individuals "not in the labor force who want and are available for a job and who have looked for work sometime in the past 12 months (or since the end of their last job if they held one within the past 12 months), but who are not currently looking because they believe there are no jobs available or there are none for which they would qualify."

ner would like to allocate many job-seekers in that sector. Therefore, our analysis remains unchanged as long as we appropriately correct mismatch indexes with the estimated fixed effects of the sectoral matching functions, as in (8).

7 Endogenous vacancy distribution

In this section, we relax the assumption of exogeneity of the distribution of vacancies maintained so far. Why would endogenizing vacancies affect our calculations? If, in equilibrium, too many job-seekers search in the sectors with low matching and productive efficiency, private firms' job creation decisions are distorted: an excessive number of vacancies will be posted in those sectors (because of the higher probability of recruitment) compared to the choice of a planner who allocates vacancies and job seekers purely based on relative efficiency across sectors. The result is a lower number of aggregate vacancies and a lower aggregate job-finding rate in equilibrium—another "feedback" effect of mismatch stemming, this time, from the vacancy side.

We begin by stating some additional assumptions on the equilibrium data generating process needed to measure the cost of vacancy creation. We then proceed to explain formally this additional feedback effect of mismatch. Finally, we present our findings. Appendix A.6 contains more details on all the derivations.

7.1 Measurement of the vacancy creation cost

Let the cost, in terms of final good, of creating v_i vacancies in sector i be

$$K_i\left(v_i\right) = \kappa_i^{\varepsilon} \cdot \frac{v_i^{1+\varepsilon}}{1+\varepsilon}, \tag{16}$$

with $\varepsilon \in (0, \infty)$ to guarantee convexity of the K_i function.[54] With this isoelastic specification, ε measures the elasticity of vacancy creation, i.e., how the (log of the) the marginal cost increases with the (log of the) number of vacancies. The variable κ_i shifts the cost of vacancy creation across sectors and over time. We let κ_i be i.i.d. across sectors and independent of

[54]Because of constant returns in the sector-specific matching function, it is the convexity of the cost function that prevents concentrating all vacancies and unemployed workers in the sector with the highest efficiency. We follow the convention, common in this literature, that this cost has to be paid every period the vacancy is maintained open.

the other idiosyncratic shocks, and denote its conditional distribution as $\Gamma_{\kappa}(\kappa', \kappa)$.[55] The choice of how many vacancies to post takes place before the allocation of unemployment across sectors, but after observing sectoral and aggregate states.

The first challenge we face is how to estimate the marginal cost elasticity ε and the time-varying sector-specific vector $\{\kappa_i\}$. For the cost elasticity, we resort to existing estimates suggesting that ε is between one and two (Yashiv, 2007; Merz and Yashiv, 2007; Coşar, Guner, and Tybout, 2010). Up to this point, we could abstain from modeling behavior and choices of firms and workers in equilibrium. However, measurement of $\{\kappa_i\}$ requires imposing a minimal amount of structure on the equilibrium data generating process. Three assumptions suffice: 1) free entry of vacancies in each sector; 2) no within-market congestion externality, in the spirit of Hosios (1990); and 3) a bargaining protocol between firms and workers such that the firm obtains a share λ, and the worker a share $(1-\lambda)$, of the expected discounted output flow—in particular, outside options do not matter for the bargaining outcome (as in Shaked and Sutton, 1984; Acemoglu, 1996).[56]

This choice of bargaining protocol is convenient because, in the absence of within-sector congestions, it enables us to remain agnostic about the determination of the equilibrium value of unemployment for a worker—therefore reducing to a bare minimum the structure needed on the equilibrium model—and because it isolates mismatch unemployment as the unique source of discrepancy between the efficient and equilibrium distributions of vacancies.[57]

To clearly see this last point, we must compare the equilibrium condition for vacancy creation in sector i to that of the planner. We begin from the equilibrium condition in the economy of Section 2.2.1 with heterogeneity in $\{\phi_i, z_i, \delta_i, \kappa_i\}$:

$$\kappa_i^{\varepsilon}(v_i)^{\varepsilon} = \Phi\phi_i\left(\frac{v_i}{u_i}\right)^{\alpha-1}\lambda\frac{Zz_i}{1-\beta(1-\Delta)(1-\delta_i)} \tag{17}$$

stating that the marginal cost of a vacancy in sector i (the left hand side), also heterogeneous

[55] We could also introduce an aggregate cost-shifter, common across all sectors. Since the results in this section would be unaffected, we omit it to simplify the notation.

[56] The extensive form game corresponding to this bargaining outcome is spelled out in Acemoglu (1996, Appendix 1). The key assumption is that if, once the pair is formed, a party wants to quit the bargaining, it can rematch within the period within the same sector (i.e., with an identical partner) by paying a small fixed cost.

[57] With the more common Nash bargaining protocol, another discrepancy would arise between the equilibrium value of unemployment and the net shadow value of an additional unemployed worker for the planner $\mu-\xi$, see equation $(A14)$.

across sectors, is equated to its expected marginal gain for the firm (the right hand side). Note that the individual firm takes the sectoral meeting probability as given. Note that, as $\varepsilon \to \infty$, $v_i = \kappa_i$, i.e., vacancies are entirely cost-determined. This special case corresponds to the economy of Section 2.

All variables in condition (17) are observable, except for κ_i and ε. For a given value of the elasticity ε, we derive the sequence for κ_i that makes that condition hold exactly at every date in each sector. This strategy amounts to attributing, residually, fluctuations in vacancies to variation in the cost of job creation, once exogenous variation in productivity and separation rates have been accounted for.[58]

7.2 Comparison between equilibrium and planner FOCs

In Appendix A.6, we show that the planner problem of Section 2.2.1, augmented with a vacancy creation decision where the planner faces the cost function (16), yields the first-order condition

$$\kappa_i^{\varepsilon} \left(v_i^*\right)^{\varepsilon} = \Phi\phi_i \left(\frac{v_i^*}{u_i^*}\right)^{\alpha-1} \alpha \frac{Zz_i}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)} \tag{18}$$

equating the marginal cost of a vacancy to its marginal gain, in turn equal to the expected discounted value of output conditional on matching times the marginal decline in the probability of meeting an unemployed worker allocated to sector i.

A comparison of equations (17) and (18) is instructive. With $\lambda = \alpha$ within-market congestion externalities are ruled out and the only reason why equilibrium vacancies in sector i differ from their efficient counterpart is that the number of unemployed workers is the "wrong" one, i.e., the only reason is mismatch unemployment. If in equilibrium an excessive number of unemployed workers search for jobs in declining sectors, firms would create more vacancies than the planner in those sectors, amplifying the initial source of misallocation.

[58] It is well known that productivity shocks alone are unable to explain fluctuations in vacancies in a matching model with standard parameterization (Shimer, 2005). Investigating the fundamental sources of vacancy fluctuations is beyond the scope of this paper. We limit ourselves to point out that recent papers (e.g., Petrosky-Nadeau, 2009) have emphasized the role of credit shocks and asymmetric information in lending for the observed collapse of job creation during the last recession. In these models, this mechanism works through the free entry condition, precisely as a source of fluctuations in κ_i. A planner subject to the same asymmetric information would face the same fluctuations in κ_i.

Combining equations (17) and (18), and maintaining the assumption $\lambda = \alpha$, we arrive at

$$\frac{v_i}{v_i^*} = \left(\frac{u_i}{u_i^*}\right)^{\frac{1-\alpha}{1-\alpha+\varepsilon}}$$

which demonstrates that the extent to which mismatch unemployment, i.e. deviations of u_i from u_i^*, translate into misallocation of vacancies in equilibrium (i.e., deviation of v_i from v_i^*) depends on the value of the elasticity ε. If the marginal cost function is steep (ε high), large differences in the ratio (u_i/u_i^*) and, therefore, in meeting probabilities and expected output gains, translate into small differences in the ratio (v_i/v_i^*). In this case, planner's vacancies are close to equilibrium vacancies, as assumed in our benchmark analysis. We will provide results for a very broad range of values for ε, and in keeping with the upper bound nature of our exercise, we set $\varepsilon = 1$ in our baseline.

In Appendix A.6, we lay out a simple algorithm to compute the planner's optimal allocation of vacancies across sectors $\{v_{it}^*\}$, and we explain how to modify the calculation of counterfactual unemployment to take into account this additional margin of choice for the planner. It is instructive to examine the relationship between the planner and the equilibrium aggregate job-finding rate in this economy:

$$f_t^* = f_t \cdot \underbrace{\frac{1}{(1-\mathcal{M}_t^x)}}_{\text{Direct Effect}} \cdot \underbrace{\left(\frac{u_t}{u_t^*}\right)^{\alpha}}_{\text{Feedback through } u} \cdot \underbrace{\left[\left(\frac{\bar{\phi}_{xt}^*}{\bar{\phi}_{xt}}\right) \cdot \left(\frac{v_t^*}{v_t}\right)^{\alpha}\right]}_{\text{Feedback through } v}, \tag{19}$$

where $\bar{\phi}_{xt}$ is given by equation (11) and $\bar{\phi}_{xt}^*$ is the same aggregator, but with the planner's vacancy shares v_{it}^*/v_t^* instead of the observed shares. Compared to (12), the equation above features an additional feedback effect of mismatch that operates through vacancies and has two components. Mismatch reduces the aggregate job-finding rate by (i) distorting the distribution of vacancy shares across sectors, and (ii) lowering total vacancies.

7.3 Results

We first estimate the vacancy cost creation parameters κ_i by sector. Next, we compute the distribution of planner's vacancies and the implied planner's aggregate job-finding rate with endogenous vacancies (19), which we then feed into the law of motion for the unemployment rate to perform our counterfactual exercise. Our estimates of the vacancy cost parameter κ

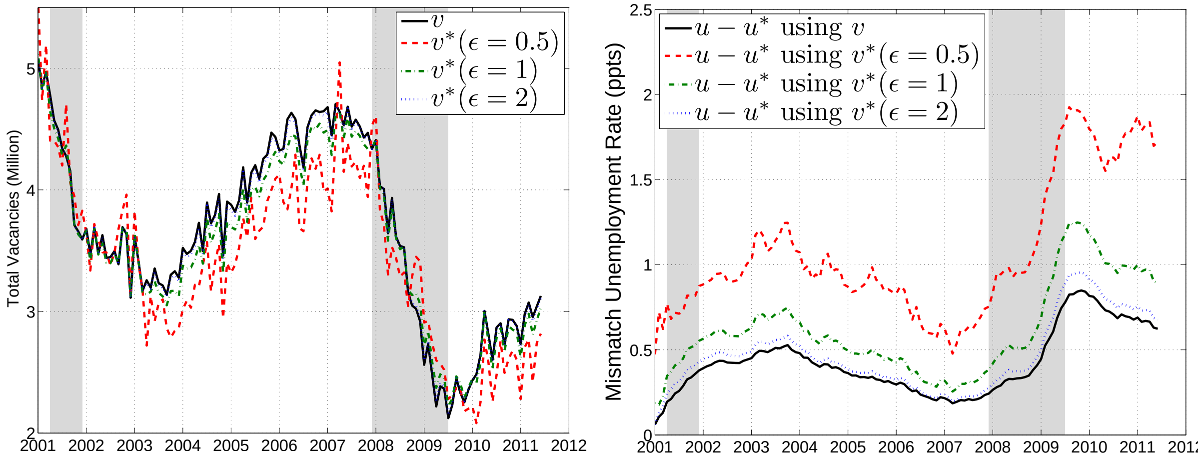

Figure 12: Aggregate vacancies and (left panel) and corresponding mismatch unemployment rates (right panel) at the industry level using endogenous vacancies specification with JOLTS.

increase for almost all industries and occupations during the recession, therefore contributing to the observed drop in vacancies. Figure B17 in Appendix B.3 plots the estimated sequences of κ_i in some selected industries for the case $\varepsilon = 1$.

Table 2 summarizes the results.[59] We first present our analysis by industry. Figure 12 (left panel) plots aggregate vacancies v_t^* in the planner's economy for different values of ε. The main result is that quantitatively significant deviations between v_t^* and v_t (the data) occur only for low values of the cost elasticity ε. For $\varepsilon \geq 1$, planner and equilibrium vacancies line up closely. This finding is reflected into the calculation of mismatch unemployment (right panel). For $\varepsilon = 1$, with endogenous vacancy creation, mismatch unemployment rises by 0.89 percentage points between 2006 and October 2009, i.e., an additional 0.3 percentage points relative to the exogenous vacancy calculation.[60] For $\varepsilon = 0.5$, mismatch unemployment is generally higher, but its increase between 2006 and October 2009 is still about 1.2 percentage points—not far from the case of unit elasticity.

Turning to occupations, for $\varepsilon = 1$, planner and equilibrium vacancies line up fairly closely and, as Figure 13 indicates, the contribution of mismatch unemployment to the rise in the U.S. unemployment rate between 2006 and October 2009 is 1.1 percentage points.[61]

[59] The indexes computed with endogenous vacancies have superscript v^*.

[60] Figure B18 in the Appendix also reports our analysis with endogenous vacancies done with the $\mathcal{M}_t$ index. Here, mismatch unemployment rises by about 1.1 percentage points between 2006 and October 2009.

[61] In the case of no heterogeneity in matching and productive efficiency across markets, that contribution rises to 1.8 percentage points, or roughly one third of the total rise in unemployment as shown in Figure B19.

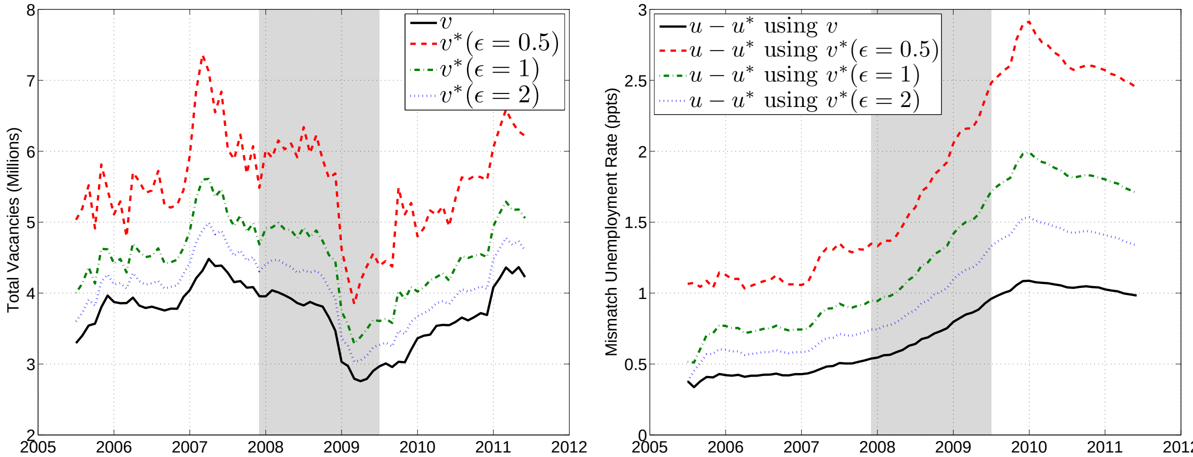

Figure 13: Aggregate vacancies and (left panel) and corresponding mismatch unemployment rates (right panel) at the occupation level using endogenous vacancies specification with HWOL.

For $\varepsilon = 0.5$, it increases up to 1.5%, or 28% of the total rise in unemployment.

To summarize, as expected, the contribution of mismatch unemployment is larger when the distribution of vacancies is endogenized. Nevertheless, our results of Section 5 derived under exogenous vacancies (or infinite marginal cost elasticity) are close to those obtained from the model with endogenous vacancy creation and unitary marginal cost elasticity, a value supported by existing estimates. Our calculations also show that mismatch could have played a major role in the recent rise of unemployment, by dampening aggregate vacancy creation, only if one is willing to maintain that, the cost elasticity is very low (below 1/2).

8 Conclusion

How much did mismatch contribute to the dynamics of U.S. unemployment around the Great Recession? To address this question, we developed a framework to coherently define and measure mismatch unemployment. Plausible parameterizations of the model imply that mismatch can explain at most 1/3 of the recent rise in the U.S. unemployment rate. Our formalization of mismatch, and several choices made in our measurement exercise, mean that this estimate should be considered as an upper bound.

While, admittedly, our approach does not put us in the best position to separately identify the many potential causes of mismatch, we argued that analyzing different layers of disaggregation (e.g., occupation, industry, education, geography), as we do, is informative nevertheless. The absence of an increase in geographical mismatch casts doubts on the “house lock” hypothesis, a conclusion in line with existing research. The non-negligible role played by occupational mismatch, especially for high-skilled workers, leaves room for explanations based on labor demand shifts combined with human capital specialization or with relative wage rigidity. Alvarez and Shimer (2010), Birchenall (2010), Carrillo-Tudela and Visscher (2010), and Herz and van Rens (2011) among others, have proposed models where unemployed workers, in equilibrium, make explicit mobility decisions across distinct labor markets. While less amenable to disaggregated measurement than our framework, these models are, potentially, well suited to study the structural causes of mismatch. Of special interest is the finding of Herz and van Rens (2011) who argue that what hampered the mobility of job-seekers towards the sectors with vacant jobs in the last recession was not moving or retraining costs, but slow wage adjustment.

If mismatch only accounts for a portion of the persistently high unemployment rate, what are the other economic forces at work? As we explained, both the aggregate vacancy rate and aggregate matching efficiency are still well below their pre-recession level of 2006. Weak aggregate demand combined with wage rigidity (Shimer, 2012), uncertainty about future productivity (Schaal, 2012) and future economic policy (Baker, Bloom, and Davis, 2011), or selective restructuring by firms during recessions (Berger, 2012) do, qualitatively, imply a slow recovery in job creation. The disincentive effects on job search effort from prolonged extension of unemployment benefits (Farber and Valletta, 2011), and the diminished recruitment intensity on firm’s side (Davis, Faberman, and Haltiwanger, 2012) are consistent with the fall in aggregate matching efficiency. Going forward, disentangling these channels will be paramount in achieving a comprehensive picture of the Great Recession.

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A Theoretical Appendix

This Appendix formally derives all the theoretical results of Sections 2 and 7.

A.1 Heterogeneous matching efficiencies

We solve the planner's problem of Section 2.1. The efficient allocation at any given date is the solution of the following planner's problem that we write in recursive form:

$$
\begin{aligned}
V\left(\mathbf{e};\mathbf{v},\phi,Z,\Delta,\Phi\right) &= \max_{\{u_i\geq 0\}} \sum_{i=1}^{I} Z\left(e_i+h_i\right)+\beta\mathbb{E}\left[V\left(\mathbf{e}';\mathbf{v}',\phi',Z',\Delta',\Phi'\right)\right] \\
s.t. &: \\
\sum_{i=1}^{I}\left(e_i+u_i\right) &= 1 \qquad \text{(A1)}\\
h_i &= \Phi\phi_i m\left(u_i,v_i\right) \qquad \text{(A2)}\\
e_i' &= \left(1-\Delta\right)\left(e_i+h_i\right) \qquad \text{(A3)}\\
&\Gamma_{Z,\Delta,\Phi}\left(Z',\Delta',\Phi';Z,\Delta,\Phi\right),\ \Gamma_{\mathbf{v}}\left(\mathbf{v}';\mathbf{v},Z',\Delta',\Phi'\right),\Gamma_{\phi}\left(\phi';\phi\right) \qquad \text{(A4)}
\end{aligned}
$$

The per period output for the planner is equal to $Z\left(e_i+h_i\right)$ in each market i. The first constraint $(A1)$ states that the planner has $1-\sum_{i=1}^{I} e_i$ unemployed workers available to allocate across sectors. Equation $(A2)$ states that, once the allocation $\{u_i\}$ is chosen, the frictional matching process in each market yields $\Phi\phi_i m\left(u_i,v_i\right)$ new hires which add to the existing e_i active matches. Equation $(A3)$ describes separations and the determination of next period's distribution of active matches $\{e_i'\}$ in all sectors. Line $(A4)$ in the problem collects all the exogenous stochastic processes the planner takes as given.

It is easy to see that this is a concave problem where first-order conditions are sufficient for optimality. At an interior solution ($u_i>0$ for all i), the choice of how many unemployed workers u_i to allocate in market i yields the first-order condition

$$
Z\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right)+\beta\mathbb{E}\left[V_{e_i}\left(\mathbf{e}';\mathbf{v}',\phi',Z',\Delta',\Phi'\right)\right]\left(1-\Delta\right)\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right)=\mu, \qquad \text{(A5)}
$$

where μ is the multiplier on constraint $(A1)$. The right-hand side (RHS) of this condition is the shadow value of an additional worker in the unemployment pool available to search.

The left-hand side (LHS) is the expected marginal value of an additional unemployed worker allocated to sector i. The derivative of the sector-specific matching function m is written as a function of local market tightness only (with a slight abuse of notation) because of its CRS specification.

The Envelope condition with respect to the state e_i yields:

$$V_{e_i}\left(\mathbf{e};\mathbf{v},\phi,Z,\Delta,\Phi\right)=Z-\mu+\beta(1-\Delta)\mathbb{E}\left[V_{e_i}\left(\mathbf{e}';\mathbf{v}',\phi',Z',\Delta',\Phi'\right)\right], \tag{A6}$$

from which it is immediate to see, by iterating forward, that $\mathbb{E}\left[V_{e_i}\left(\mathbf{e}';\mathbf{v}',\phi',Z',\Delta',\Phi'\right)\right]$ is independent of i, since productivity and the job destruction rate are common across all sectors.[62] Using this result into $(A5)$, the optimal rule for the allocation of unemployed workers across sectors can be written as equation (1) in the main text.

A.2 Heterogenous productivities and destruction rates

We extend the baseline model of Section 2.1 as follows. Individuals (still in measure one) can be either employed in sector i (e_i), or unemployed and searching in sector i (u_i), or out of the labor force. The aggregate labor force is $\ell=\sum_{i=1}^{I}\left(e_i+u_i\right)\leq 1$. We normalize to zero utility from non participation, and let $\xi>0$ denote the disutility of search for the unemployed. Labor productivity in sector i is given by $Z\cdot z_i$, where each idiosyncratic component z_i is strictly positive, i.i.d. across sectors and independent of Z. Let the conditional distribution of the vector $\mathbf{z}=\{z_i\}$ be $\Gamma_z\left(\mathbf{z}',\mathbf{z}\right)$. The idiosyncratic component of the exogenous destruction rate in sector i is δ_i, i.i.d. across sectors and independent of Δ, Z and z_i. Let the conditional distribution of the vector $\delta=\{\delta_i\}$ be $\Gamma_\delta\left(\delta',\delta\right)$. The survival probability of a match is then $\left(1-\Delta\right)\left(1-\delta_i\right)$. The vector $\{Z,\Delta,\Phi,\mathbf{z},\mathbf{v},\phi,\delta\}$ takes strictly positive values.

It is convenient to impose additional structure on some conditional distributions: as specified in the text, we assume that $(Z,1-\Delta,z_i,1-\delta_i)$ all follow independent unit root processes. The timing of events is exactly as before, with the decision on the size of the labor force for next period taken at the end of the current period. The recursive formulation of the planner's problem has three additional states compared to the problem of Section 2.1: the

[62] We are also using the transversality condition $\lim_{t\to\infty}\beta^t(1-\Delta)^t\mathbb{E}\left[V_{e_{it}}\right]=0$.

current number of unemployed workers u, the vector of productive efficiencies $\mathbf{z}$, and the vector of destruction rates δ. The planner solves the problem:

$$
\begin{aligned}
V(u,\mathbf{e};\mathbf{z},\mathbf{v},\phi,\delta,Z,\Delta,\Phi) &= \max_{\{u_i,\ell'\}} \sum_{i=1}^{I} Zz_i(e_i+h_i) - \xi u + \beta\mathbb{E}\left[V(u',\mathbf{e}';\mathbf{z}',\mathbf{v}',\phi',\delta',Z',\Delta',\Phi')\right] \\
s.t. &: \\
\sum_{i=1}^{I} u_i &\leq u && \text{(A7)} \\
h_i &= \Phi\phi_i m(u_i,v_i) && \text{(A8)} \\
e_i' &= (1-\Delta)(1-\delta_i)(e_i+h_i) && \text{(A9)} \\
u' &= \ell' - \sum_{i=1}^{I} e_i' && \text{(A10)} \\
u_i &\in [0,u], \ell' \in [0,1], && \text{(A11)}
\end{aligned}
$$

$$\Gamma_{Z,\Delta,\Phi}(Z',\Delta',\Phi';Z,\Delta,\Phi),\ \Gamma_{\mathbf{v}}(\mathbf{v}';\mathbf{v},Z',\Delta',\Phi',\mathbf{z}'),\Gamma_{\phi}(\phi';\phi),\Gamma_{\mathbf{z}}(\mathbf{z}';\mathbf{z}),\Gamma_{\delta}(\delta',\delta) \quad \text{(A12)}$$

where the conditional distributions in the last line are restricted as described above. The choice of how many unemployed workers u_i to allocate in the i market yields the first-order condition

$$Zz_i\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) + \beta\mathbb{E}\left[-V_u'(\cdot)+V_{e_i}'(\cdot)\right](1-\Delta)(1-\delta_i)\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) = \mu, \quad \text{(A13)}$$

where μ is the multiplier on constraint $(A7)$. The Envelope conditions with respect to the states u and e_i yield:

$$
\begin{aligned}
V_u(u,\mathbf{e};\mathbf{z},\mathbf{v},\phi,\delta,Z,\Delta,\Phi) &= \mu - \xi && \text{(A14)} \\
V_{e_i}(u,\mathbf{e};\mathbf{z},\mathbf{v},\phi,\delta,Z,\Delta,\Phi) &= Zz_i + \beta(1-\Delta)(1-\delta_i)\mathbb{E}\left[V_{e_i}' - V_u'\right]. && \text{(A15)}
\end{aligned}
$$

According to the first Envelope condition, the marginal value of an unemployed to the planner equals the shadow value of being available to search (μ) net of the disutility of search ξ. The second condition states that the marginal value of an employed worker is its flow output this period plus its discounted continuation value net of the value of search, conditional on the match not being destroyed.

The optimal decision on the labor force size next period ℓ' requires

$$\mathbb{E}\left[V_u(u',\mathbf{e}';\mathbf{z}',\mathbf{v}',\phi',\delta',Z',\Delta',\Phi')\right] = 0, \quad \text{(A16)}$$

i.e., the expected marginal value of moving a nonparticipant into job search should be equal to its value as nonparticipant, normalized to zero. By combining $(A16)$ with $(A14)$, we note that the planner will choose the size of the labor force so that the expected shadow value of an unemployed worker $\mathbb{E}\left[\mu'\right]$ equals search disutility ξ.[63]

Using $(A16)$ into the Envelope condition $(A15)$ under the additional assumption that all the elements of the vector $x = (Z, 1-\Delta, z_i, 1-\delta_i)$ are independent unit root processes, and iterating forward, we arrive at:

$$\mathbb{E}\left[V'_{e_i}\right] = \frac{Zz_i}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)} \tag{A17}$$

which, substituted into equation $(A13)$ yields

$$Zz_i\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) + \frac{\beta\left(1-\Delta\right)\left(1-\delta_i\right)}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)}Zz_i\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) = \mu. \tag{A18}$$

Rearranging, we conclude that the planner allocates idle labor to equalize

$$\frac{z_i}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)}\phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right)$$

across sectors, which is expression (2) in Section $(2.2.1)$ in the main text.

A.3 Heterogeneous sensitivities to aggregate shock

Let productivity in sector i be $z_i = \exp\left(\zeta_i\right)Z^{\eta_i}$ and let $\log Z$ follow a unit root process with innovation ϵ independent of Δ and distributed as $N\left(-\sigma_\epsilon/2, \sigma_\epsilon\right)$. Note that $\mathbb{E}\left[(Z')^{\eta_i}\right] = Z^{\eta_i}\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)$. We maintain that $(1-\Delta, 1-\delta_i)$ also follow unit root processes. The envelope condition $(A15)$ becomes

$$V_{e_i} = \exp\left(\zeta_i\right)Z^{\eta_i} + \beta(1-\Delta)(1-\delta_i)\mathbb{E}\left[V'_{e_i}\right].$$

which, solving forward and using the unit root assumption, yields

$$\mathbb{E}\left[V'_{e_i}\right] = \frac{\exp\left(\zeta_i\right)Z^{\eta_i}\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}.$$

Substituting the above expression for $\mathbb{E}\left[V'_{e_i}\right]$ into (the appropriately modified) equation $(A13)$, yields

$$\exp\left(\zeta_i\right)Z^{\eta_i}\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) + \beta\left(1-\delta\right)\frac{\exp\left(\zeta_i\right)Z^{\eta_i}\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}\Phi\phi_i m_{u_i}\left(\frac{v_i}{u_i}\right) = \mu.$$

[63] It is clear that our result is robust to allowing ξ to be stochastic and correlated with (Z, Δ, Φ).

Rearranging, we conclude that the planner allocates unemployed workers so to equalize

$$\frac{\exp\left(\zeta_i\right) Z^{\eta_i}}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right)}\phi_i m_{u_i}\left(\frac{v_i}{u_i^*}\right),$$

across sectors, which is expression (3) in Section $(2.2.2)$ in the main text. A necessary technical condition we must impose is $\beta\left(1-\Delta\right)\left(1-\delta_i\right)\exp\left(\eta_i\left(\eta_i-1\right)\frac{\sigma_\epsilon}{2}\right) < 1$ for all i.

A.4 Endogenous separations

Consider the environment of Section $2.2.1$ and allow the planner to move workers employed in sector i into unemployment (or out of the labor force) at the end of the period, before choosing the size of the labor force for next period. There are two changes to the planner's problem. First, the law of motion for employment becomes

$$e_i' = \left(1-\Delta\right)\left(1-\delta_i\right)\left(e_i+h_i\right)-\sigma_i. \tag{A19}$$

Second, the planner has another vector of choice variables $\{\sigma_i\}$, with $\sigma_i \in \left[0,\left(1-\Delta\right)\left(1-\delta_i\right)\left(e_i+h_i\right)\right]$.

The decision of how many workers to separate from sector i employment into unemployment is:

$$\mathbb{E}\left[V_u'\left(\cdot\right)-V_{e_i}'\left(\cdot\right)\right]\begin{cases} <0 & \rightarrow \sigma_i = 0 \\ =0 & \rightarrow \sigma_i \in \left(0,\left(1-\Delta\right)\left(1-\delta_i\right)\left(e_i+h_i\right)\right) \\ >0 & \rightarrow \sigma_i = \left(1-\Delta\right)\left(1-\delta_i\right)\left(e_i+h_i\right)\end{cases} \tag{A20}$$

depending on whether at the optimum a corner or interior solution arises. If the first-order conditions $(A16)$ hold with equality, then the optimality condition $(A20)$ holds with the "$<$" inequality and $\sigma_i = 0$. As a result, the planner's allocation rule (2) remains unchanged.

A.5 Properties of the mismatch index

First, we prove that $0 \leq \mathcal{M}_{\phi t} \leq 1$. Since all the components of the sum in (8) are positive, $\mathcal{M}_{\phi t} \leq 1$. Under maximal mismatch (no markets where unemployment and vacancies coexist), the index is exactly equal to one. To show that $\mathcal{M}_{\phi t} \geq 0$, note that

$$\begin{aligned} 1 - \mathcal{M}_{\phi t} &= \frac{1}{v_t^{\alpha} u_t^{1-\alpha}} \frac{1}{\left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t} \right) \right]^{\alpha}} \sum_{i=1}^{I} \left(\phi_{it}^{\frac{1}{\alpha}} v_{it} \right)^{\alpha} (u_{it})^{1-\alpha} \\ &\leq \frac{1}{v_t^{\alpha} u_t^{1-\alpha}} \frac{1}{\left[\sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t} \right) \right]^{\alpha}} \left[\sum_{i=1}^{I} \left(\phi_{it}^{\frac{1}{\alpha}} v_{it} \right) \right]^{\alpha} \left(\sum_{i=1}^{I} u_{it} \right)^{1-\alpha} \\ &= 1 \end{aligned}$$

where the $\leq$ sign follows from Hölder's inequality. It is easy to show that the index becomes exactly zero in absence of mismatch by substituting the allocation rule (6) into the index.

By inspecting (8) , it is also easy to see that the $\mathcal{M}_{\phi t}$ index is invariant to "pure" aggregate shocks that shift the total number of vacancies and unemployed up or down, but leave the vacancy and unemployment shares across markets unchanged.

To show that the mismatch index is increasing in the level of disaggregation, consider an economy where the aggregate labor market is described by two dimensions indexed by (i, j), e.g., I regions $\times$ J occupations. Let $\mathcal{M}_{\phi It}$ be the mismatch index over the I sectors and $\mathcal{M}_{\phi IJt}$ be the one over the $I \times J$ sectors. From the disaggregated matching function, we have $h_{ijt} = \Phi \phi_{ijt} v_{ijt}^{\alpha} u_{ijt}^{1-\alpha}$. Summing this expression over j yields

$$h_{it} = \sum_{j=1}^{J} \Phi \phi_{ijt} v_{ijt}^{\alpha} u_{ijt}^{1-\alpha} = \Phi \left[\sum_{j=1}^{J} \phi_{ijt} \left(\frac{v_{ijt}}{v_{it}} \right)^{\alpha} \left(\frac{u_{ijt}}{u_{it}} \right)^{1-\alpha} \right] v_{it}^{\alpha} u_{it}^{1-\alpha}. \qquad \text{(A21)}$$

At the aggregated level, we have $h_{it} = \Phi \phi_{it} v_{it}^{\alpha} u_{it}^{1-\alpha}$ and so (A21) implies that

$$\phi_{it} = \sum_{j=1}^{J} \phi_{ijt} \left(\frac{v_{ijt}}{v_{it}} \right)^{\alpha} \left(\frac{u_{ijt}}{u_{it}} \right)^{1-\alpha}. \qquad \text{(A22)}$$

Now consider the disaggregated matching index. We have

$$1 - \mathcal{M}_{\phi IJt} = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{\phi_{ijt}}{\bar{\phi}_{IJt}} \left(\frac{v_{ijt}}{v_t} \right)^{\alpha} \left(\frac{u_{ijt}}{u_t} \right)^{1-\alpha} \qquad \text{(A23)}$$

for

$$\bar{\phi}_{IJt} = \left[\sum_{i=1}^{I} \sum_{j=1}^{J} \phi_{ijt}^{\frac{1}{\alpha}} \left(\frac{v_{ijt}}{v_t} \right) \right]^{\alpha}. \qquad \text{(A24)}$$

Manipulating the above expression yields

$$
\begin{aligned}
1-\mathcal{M}_{\phi IJt} &= \frac{1}{\bar{\phi}_{IJt} v_t^{\alpha} u_t^{1-\alpha}} \sum_{i=1}^{I} \sum_{j=1}^{J} \phi_{ijt} v_{ijt}^{\alpha} u_{ijt}^{1-\alpha} \\
&= \frac{1}{\bar{\phi}_{IJt} v_t^{\alpha} u_t^{1-\alpha}} \sum_{i=1}^{I} v_{it}^{\alpha} u_{it}^{1-\alpha} \sum_{j=1}^{J} \phi_{ijt} \left(\frac{v_{ijt}}{v_{it}}\right)^{\alpha} \left(\frac{u_{ijt}}{u_{it}}\right)^{1-\alpha} \\
&= \frac{1}{\bar{\phi}_{IJt}} \sum_{i=1}^{I} \phi_{it} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}
\end{aligned}
$$

where the third step above follows from (A22). Next, manipulating (A24) delivers

$$
\begin{aligned}
\bar{\phi}_{IJt} &= \left\{ \frac{1}{v_t} \sum_{i=1}^{I} v_{it} \left(\left[\sum_{j=1}^{J} \phi_{ijt}^{\frac{1}{\alpha}} \left(\frac{v_{ijt}}{v_{it}}\right) \right]^{\alpha} \right)^{\frac{1}{\alpha}} \right\}^{\alpha} \\
&= \left\{ \frac{1}{v_t} \sum_{i=1}^{I} v_{it} \left(\left[\sum_{j=1}^{J} \phi_{ijt}^{\frac{1}{\alpha}} \left(\frac{v_{ijt}}{v_{it}}\right) \right]^{\alpha} \cdot \left[\sum_{j=1}^{J} \frac{u_{ijt}}{u_{it}} \right]^{1-\alpha} \right)^{\frac{1}{\alpha}} \right\}^{\alpha}
\end{aligned}
$$

where the second step above follows from the identity $\sum_{j=1}^{J} u_{ijt} = u_{it}$. Applying Holder's inequality now yields

$$
\begin{aligned}
\bar{\phi}_{IJt} &\geq \left\{ \frac{1}{v_t} \sum_{i=1}^{I} v_{it} \left(\sum_{j=1}^{J} \phi_{ijt} \left(\frac{v_{ijt}}{v_{it}}\right)^{\alpha} \left(\frac{u_{ijt}}{u_{it}}\right)^{1-\alpha} \right)^{\frac{1}{\alpha}} \right\}^{\alpha} \\
&= \left\{ \sum_{i=1}^{I} \phi_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right) \right\}^{\alpha} = \bar{\phi}_{It}
\end{aligned}
$$

where $\bar{\phi}_{It}$ is the equivalent expression to $\bar{\phi}_{IJt}$ in (A23) for the aggregated case. Combining results, we have shown that

$$
1-\mathcal{M}_{\phi IJt} \leq \sum_{i=1}^{I} \frac{\phi_{it}}{\bar{\phi}_{It}} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha} = 1-\mathcal{M}_{\phi It}
$$

and so we must have $\mathcal{M}_{\phi IJt} \geq \mathcal{M}_{\phi It}$.

A.6 Planner's problem with endogenous vacancies

Optimal vacancy creation Consider the planner's problem of Section 2.2.1 solved in Appendix A.2, the most general of our environments, and let the creation of vacancies $\{v_i\}$

be under the control of the planner.

$$V\left(u,\mathbf{e};\mathbf{z},\phi,\delta,\kappa,Z,\Delta,\Phi\right) = \max_{\{u_i,v_i,\ell'\}} \sum_{i=1}^{I} Zz_i\left(e_i+h_i\right)-K_i\left(v_i\right)-\xi u+\beta\mathbb{E}\left[V\left(u',\mathbf{e}';\mathbf{z}',\phi',\delta',\kappa',Z',\Delta',\Phi'\right)\right]$$

$$s.t. :$$

$$\sum_{i=1}^{I} u_i \leq u \tag{A25}$$

$$h_i = \Phi\phi_i m\left(u_i,v_i\right) \tag{A26}$$

$$e_i' = \left(1-\Delta\right)\left(1-\delta_i\right)\left(e_i+h_i\right) \tag{A27}$$

$$u' = \ell' - \sum_{i=1}^{I} e_i' \tag{A28}$$

$$u_i \in \left[0,u\right], \ell' \in \left[0,1\right], v_i \geq 0 \tag{A29}$$

$$\Gamma_{Z,\Delta,\Phi}\left(Z',\Delta',\Phi';Z,\Delta,\Phi\right),\ \Gamma_{\phi}\left(\phi';\phi\right),\Gamma_{\mathbf{z}}\left(\mathbf{z}';\mathbf{z}\right),\Gamma_{\delta}\left(\delta',\delta\right),\Gamma_{\kappa}\left(\kappa',\kappa\right) \tag{A30}$$

The optimality condition for vacancy creation is

$$K_{v_i}\left(v_i\right) = \Phi\phi_i m_{v_i}\left(\frac{v_i}{u_i}\right)\left\{Zz_i+\beta\left(1-\Delta\right)\left(1-\delta_i\right)\mathbb{E}\left[V_{e_i}'\left(\cdot\right)\right]\right\}.$$

Using the expression for $\mathbb{E}\left[V_{e_i}'\left(\cdot\right)\right]$ obtained in $(A17)$ and the functional forms for K_i and m specified in the main text, we obtain expression (18).

Calculation of planner's vacancies We now lay out an algorithm to compute the planner's optimal allocation of vacancies across sectors. Rearranging condition $(A18)$ dictating the optimal allocation of unemployed workers across sectors, given the distribution of vacancies $\{v_i^*\}$, yields

$$\frac{v_i^*}{u_i^*} = \left[\frac{\mu}{1-\alpha}\cdot\frac{1}{\frac{Zz_i\Phi\phi_i}{1-\beta(1-\Delta)(1-\delta_i)}}\right]^{\frac{1}{\alpha}} \tag{A31}$$

where μ is the multiplier on the resource constraint $\sum_{i=1}^{I} u_i \leq u$. Substituting $(A31)$ into (18) yields an equation for the optimal number of vacancies in sector i which reads

$$v_i^* = \frac{1}{\kappa_i}\left(\frac{\alpha}{1-\alpha}\right)^{1/\varepsilon}\cdot\left(\frac{1}{\mu}\right)^{\frac{(1-\alpha)/\varepsilon}{\alpha}}\cdot\left[\left(1-\alpha\right)\cdot\frac{Zz_i\Phi\phi_i}{1-\beta\left(1-\Delta\right)\left(1-\delta_i\right)}\right]^{\frac{1/\varepsilon}{\alpha}}. \tag{A32}$$

Summing over all $i's$, we arrive at the optimal share of vacancies in sector i

$$\frac{v_i^*}{v_t^*} = \frac{\frac{1}{\kappa_i}\left[\frac{z_i\phi_i}{1-\beta(1-\Delta)(1-\delta_i)}\right]^{\frac{1/\varepsilon}{\alpha}}}{\sum_{i=1}^{I}\frac{1}{\kappa_i}\left[\frac{z_i\phi_i}{1-\beta(1-\Delta)(1-\delta_i)}\right]^{\frac{1/\varepsilon}{\alpha}}} \tag{A33}$$

only as a function of parameters, which is quite intuitive: the higher is productive, matching and job creation efficiency in sector i, relative to the other sectors, the larger its share of vacancies. However, to solve the model, we need to determine the *level* of v_i^* which requires eliminating μ from $(A32)$. Combining again the two first order conditions, and summing across all sectors, we arrive at

$$u^* = \left(\frac{\alpha}{1-\alpha}\right)^{1/\varepsilon} \cdot [Z\Phi \cdot (1-\alpha)]^{\frac{1+1/\varepsilon}{\alpha}} \cdot \left(\frac{1}{\mu}\right)^{\frac{1+(1-\alpha)/\varepsilon}{\alpha}} \cdot \sum_{i=1}^{I} \frac{1}{\kappa_i} \left[\frac{z_i \phi_i}{1-\beta(1-\Delta)(1-\delta_i)}\right]^{\frac{1+1/\varepsilon}{\alpha}}, \tag{A34}$$

which establishes a unique inverse relationship between μ and u^*: the higher the number of idle workers, the lower the shadow value of the constraint.

Equation $(A34)$ suggests an algorithm to solve for v_i^*. At any date, before choosing how to allocate vacancies and unemployed workers, the total number of idle workers is a state variable for the planner, i.e., u^* is known. One can therefore back out μ from $(A34)$, and then v_i^* from $(A32)$ and u_i^* from $(A31)$.

Counterfactual unemployment To perform the counterfactual on unemployment with endogenous vacancies, we use the same iterative procedure described in Section 3.2, with the caveat that the relationship between the planner's job-finding rate and the empirical job-finding rate at date t is now given by

$$f_t^* = \frac{h_t^*}{u_t^*} = \Phi_t \bar{\phi}_{xt}^* \left(\frac{v_t^*}{u_t^*}\right)^{\alpha} = f_t \cdot \frac{1}{1-\mathcal{M}_{xt}} \cdot \left(\frac{u_t}{u_t^*}\right)^{\alpha} \cdot \left[\left(\frac{\bar{\phi}_{xt}^*}{\bar{\phi}_{xt}}\right) \cdot \left(\frac{v_t^*}{v_t}\right)^{\alpha}\right], \tag{A35}$$

where $\bar{\phi}_{xt}$ is given by equation (11), and $\bar{\phi}_{xt}^*$ is the same aggregator with shares (v_{it}^*/v_t^*) instead of (v_{it}/v_t). When $v_{it}^* = v_{it}$ (i.e., $\varepsilon \to \infty$), equation $(A35)$ collapses to the relationship $f^* = [f/(1-\mathcal{M}_{xt})](u_t/u_t^*)^{\alpha}$ that we have used in our baseline calculations with exogenous vacancies.

B Data Appendix

B.1 Comparison between JOLTS and HWOL vacancies

As noted in Section 4, the vacancy counts in the HWOL database are derived from job listings posted by employers on hundreds of internet job boards and online newspapers. Vacancies recorded in JOLTS are instead derived from a sample of about 16,000 business establishments. In particular, JOLTS vacancies represent "all unfilled, posted positions available at an establishment on the last day of the month. The vacancy must be for a specific position where work can start within thirty days, and an active recruiting process must be underway for the position." (Faberman, 2009, p. 86).

Further, sample establishments in the JOLTS only report their own direct employees and exclude "employees of temporary help agencies, employee leasing companies, outside contractors, and consultants," which are counted by their employer of record, not by the establishment where they are working.[64] Thus, this approach captures temp-help and leasing workers as long as their employers are sampled in the JOLTS, but does not capture the self-employed contract workforce (these workers typically receive a 1099-MISC form instead of a W-2 form to report payments received for services they provide). On the other hand, the HWOL series includes postings for contract work but may miss positions that are not commonly advertised online. As such, neither the JOLTS or the HWOL data are perfect, since each may miss or overstate specific types of vacancies.

We perform several exercises to compare the vacancy counts we get from each data source. First, we compare total vacancies by Census region in Figure B1. For the national totals, the HWOL series tend to be lower than the JOLTS series before 2008 (especially in the South), and higher from 2008 onwards (especially in the Northeast). The two series are closest in the West: here the correlation between the HWOL and JOLTS series is 0.98. In the other three regions the correlation ranges from 0.73 in the Midwest to 0.80 in the South.

For further comparison, we exploit one important feature of the HWOL data: for about 57% of the job listings, we observe the NAICS code of the employer. Therefore, we are able to directly compare vacancy counts by industry from HWOL to those in the JOLTS.

[64]see JOLTS Technical Note, http://www.bls.gov/news.release/jolts.tn.htm.

We report in Figure B2 scatterplots of vacancy shares by industry from JOLTS and from HWOL—for the latter, we report both total vacancies, as well as vacancies without contract work. The top panel of the figure reports average vacancy shares over the sample period under consideration. Most data points are close to the 45-degree line, indicating that the vacancy shares by industry in the two series line up fairly well, especially when we omit contract work from HWOL to make it more comparable to the JOLTS. The only two sectors where JOLTS and HWOL show significant differences in vacancy shares are "Public Administration" and "Accommodation and Food Services." The bottom panel reports the change in average vacancy shares between 2006 and the 12 month period around December 2009 for each series. Again, the JOLTS and HWOL series are quite close to each other, with the exception of "Public Administration."[65]

We also investigated whether the missing industry information in HWOL exhibits any systematic patterns that may have skewed our analysis. For robustness, we re-weighted the industry observations in HWOL as follows: first, we dropped observations from individual Job Boards with the highest rates of missing NAICS codes. Then, we re-weighted the remaining observations to correct for any correlation between NAICS missing values and Job Board, occupation or Census region. In other words, if vacancies for specific (Job Board, SOC, Census region) combinations are more likely to have missing NAICS codes, the vacancies that do have NAICS information in those cells are assigned a larger weight in computing total vacancies by industry.[66] The resulting vacancy shares are almost identical to those based on the raw data.

[65]We have also looked at average vacancy shares over the period pre- and post-recession separately, and the patterns are very similar.

[66]For example, suppose a (Job Board, SOC, Census region) cell has four observations. Observation one is in NAICS code 11, observations two and three are in NAICS code 13, and observation four has a missing NAICS. Thus, the missing NAICS rate is 0.25. Then, a weight of $1/(1-.25) = 1.333$ is applied to each observation with non-missing NAICS. So we find 1.333 job vacancies in NAICS code 11, and 2.667 job vacancies in NAICS code 13.

B.2 CES matching function estimation

In order to examine the plausibility of the Cobb-Douglas matching function specification, we generalize (15) and estimate the following CES specification via minimum distance:

$$\ln\left(\frac{h_{it}}{u_{it}}\right) = \gamma' QTT_t + \chi_{\{t\leq 07\}} \ln\left(\phi_i^{pre}\right) + \chi_{\{t>07\}} \ln\left(\phi_i^{post}\right) + \frac{1}{\sigma} \ln\left[\alpha \left(\frac{v_{it}}{u_{it}}\right)^{\sigma} + (1-\alpha)\right] + \epsilon_{it}. \tag{B1}$$

Recall that $\sigma \in (-\infty, 1)$ with $\sigma = 0$ in the Cobb-Douglas case. A simulated annealing algorithm is used to ensure that we obtain a global minimum. 95% confidence intervals are computed via bootstrap methods. The estimation results are reported in Table B4. The point estimates of σ range from -0.11 to 0.18 depending on the specification, implying an elasticity between 0.9 and 1.2. In the specification with HWOL vacancies and CPS hires, we cannot reject the null that $\sigma = 0$ at the 5% significance level. In the other specifications with JOLTS data, $\sigma = 0$ lies outside the 95% confidence interval, but the point estimates are close to zero, implying values close to unity for the elasticity of the matching function (i.e., close to the Cobb-Douglas case).

B.3 Additional results on industrial and occupational mismatch

To examine the robustness of our results, we present various other specifications. In particular, we compute the indexes adjusted for one source of heterogeneity at a time in Figure B6, and present the indexes for different values of α in Figure B7. We also compute the index using ϕ_i estimated from the CPS flows data. This index and the corresponding mismatch unemployment are shown in Figure B8. In addition, we compute the mismatch index using ϕ's separately estimated for the periods before and after the recession. We denote this index as $\mathcal{M}_x^{break}$. Table B8 summarizes these results and shows that our findings on industry level mismatch are remarkably robust. The contribution of mismatch to the increase in the unemployment rate varies between 0.52 and 0.77 percentage points, and accounts for 11-14% of the rise in the unemployment rate. Finally, we repeat our analysis at the 2-digit industry level using the HWOL data. Figure B9 paints a very similar picture to that obtained from JOLTS. Both $\mathcal{M}_t$ and $\mathcal{M}_t^x$ are somewhat higher for HWOL than for JOLTS, but peak and decline in a very similar fashion. The contribution of mismatch to the increase in unemployment rate is slightly larger with HWOL, as reported in Table B8—between 0.79 and 0.88 percentage points.

We also show additional results for occupational-level mismatch. First of all, Figure B11 presents indexes adjusted for one source of heterogeneity at a time for 2-digit occupations. We also compute the indexes for different values of α in B12. Table B9 summarizes these results and shows that our findings on occupation level mismatch are quite robust.

B.4 Adjustment in sectoral unemployment count

Let u_{it} be the number of unemployed workers at date t whose last job is in sector i, and U_{it} be the true number of unemployed actually searching in sector i at date t. Also let u_{it}^j be the number of unemployed whose last job is in sector i and who are searching in sector j. By definition, we have $u_{it} = \sum_{j=1}^{I} u_{it}^j$. The key unknown at each date t is the vector $\{U_{it}\}$.

From the panel dimension of CPS we observe h_{it}^j, the number of unemployed workers hired in sector j in period t whose last job was in sector i. Let the total number of hires in sector j in period t be h_t^j. Assume that the job-finding rate in sector j is the same for all unemployed, independent of the sector of provenance, with the sole exception if their previous job was in that same sector, in which case their job-finding rate is higher by a factor $\gamma_t \geq 1$, or:

$$\frac{h_{jt}^j}{u_{jt}^j} = (1+\gamma_t)\,\frac{h_{it}^j}{u_{it}^j}, \text{ for } i \neq j. \tag{B2}$$

The average hiring rate of sector j is the total number of hires for j divided by the total number of unemployed looking in sector j or:

$$\frac{h_t^j}{U_{jt}} = \sum_{i \neq j} \left(\frac{h_{it}^j}{u_{it}^j}\right)\left(\frac{u_{it}^j}{U_{jt}}\right) + \left(\frac{h_{jt}^j}{u_{jt}^j}\right)\left(\frac{u_{jt}^j}{U_{jt}}\right).$$

Substituting $(B2)$ into the above equation delivers:

$$\frac{h_t^j}{U_{jt}} = \sum_{i \neq j} \left(\frac{h_{it}^j}{u_{it}^j}\right)\left(\frac{u_{it}^j}{U_{jt}}\right) + (1+\gamma_t)\,\frac{h_{it}^j}{u_{it}^j}\left(\frac{u_{jt}^j}{U_{jt}}\right).$$

Because the ratio h_{it}^j/u_{it}^j is the same across all $i \neq j$, we can pull it out of the sum above and obtain, after rearranging:

$$\frac{h_{it}^{j}}{u_{it}^{j}} = \begin{cases} \left(\frac{h_t^j}{U_{jt}}\right)\left[1+\gamma_t\left(\frac{u_{jt}^j}{U_{jt}}\right)\right]^{-1} & \text{if } i \neq j \\ (1+\gamma_t)\left(\frac{h_t^j}{U_{jt}}\right)\left[1+\gamma_t\left(\frac{u_{jt}^j}{U_{jt}}\right)\right]^{-1} & \text{if } i = j \end{cases} \tag{B3}$$

Since we do not observe u_{jt}^{j}/U_{jt}, we want to substitute it out. Note that

$$\frac{u_{jt}^{j}}{U_{jt}} = \frac{\frac{h_{jt}^{j}}{h_t^j}\left(\frac{1}{1+\gamma_t}\right)}{1-\frac{h_{jt}^{j}}{h_t^j}\left(\frac{\gamma_t}{1+\gamma_t}\right)}$$

and using this expression in $(B3)$, we arrive at a relationship between the hiring rate from i to j and the average hiring rate in j:

$$\frac{h_{it}^{j}}{u_{it}^{j}} = \xi_{it}^{j}\cdot\frac{h_t^j}{U_{jt}} \tag{B4}$$

where

$$\xi_{it}^{j} = \begin{cases} 1-\frac{h_{jt}^{j}}{h_t^j}\left(\frac{\gamma_t}{1+\gamma_t}\right) & \text{if } i \neq j \\ (1+\gamma_t)\left[1-\frac{h_{jt}^{j}}{h_t^j}\left(\frac{\gamma_t}{1+\gamma_t}\right)\right] & \text{if } i = j \end{cases}$$

Rearranging equation $(B4)$ and summing across all j yields, at every t, the I equations:

$$u_{it} = \sum_{j=1}^{N}\frac{1}{\xi_{it}^{j}}\left(\frac{h_{it}^{j}}{h_t^j}\right)U_t^j$$

in the $(I+1)$ unknowns $\{U_{jt}\}, \gamma_t$. The last equation needed is the "aggregate consistency" condition

$$\sum_{j=1}^{I} U_{jt} = \sum_{j=1}^{I} u_{jt} \tag{B5}$$

stating that the true distribution of unemployed across sectors must sum to the observed total number of unemployed. We therefore have a system of $(I+1)$ equations in $(I+1)$ unknowns.

In our calculation of unemployment counts, to guarantee a non-negative solution to the linear system, we set to zero all entries in the transition matrices h_{it}^{j} which account for less than 5% of hires h_t^j in any given sector at any date t. We find that the estimated values of φ_t are all close to one. Figures B15 and B16 plot the adjusted and unadjusted unemployment counts for some selected industries and occupations. As expected, for example, this correction reduces the number of unemployed workers searching in construction and increases that of those seeking jobs in healthcare.

B.5 Measurement error in vacancies

Suppose that true vacancies (V_{it}) in market i are proportional to the observed vacancies (υ_{it}) by a factor $\upsilon_i^{\frac{1}{\alpha}}$, i.e., $V_{it} = \upsilon_i^{\frac{1}{\alpha}} \cdot \upsilon_{it}$. For simplicity, consider the economy without heterogeneity in productive or matching efficiency of Section 2.1. The true mismatch index is

$$\begin{aligned} \mathcal{M}_t^{\upsilon} &= 1 - \sum_{i=1}^{I} \left(\frac{V_{it}}{V_t} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} = 1 - \sum_{i=1}^{I} \left(\frac{\upsilon_i^{\frac{1}{\alpha}} \upsilon_{it}}{\sum_{i=1}^{I} \upsilon_i^{\frac{1}{\alpha}} \upsilon_{it}} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \\ &= 1 - \sum_{i=1}^{I} \left(\frac{\upsilon_i}{\bar{\upsilon}_t} \right) \left(\frac{\upsilon_{it}}{\upsilon_t} \right)^{\alpha} \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \qquad \text{(B6)} \end{aligned}$$

for

$$\bar{\upsilon}_t = \left[\sum_{i=1}^{I} \upsilon_i^{\frac{1}{\alpha}} \upsilon_{it} \right]^{\alpha}.$$

Note that the correction term $\upsilon_i / \bar{\upsilon}_t$ due to measurement error is exactly analogous to the correction term $\phi_i / \bar{\phi}_t$ for the index $\mathcal{M}_t^{\phi}$ in (8) . Is it possible to identify measurement error in vacancies υ_i in each sector? With a Cobb-Douglas specification, the true sectoral matching function is $h_{it} = \Phi_t V_{it}^{\alpha} u_{it}^{1-\alpha}$. Substituting observed variables measured with error in place of true ones, we arrive at

$$h_{it} = \Phi_t \cdot \upsilon_i \cdot \upsilon_{it}^{\alpha} u_{it}^{1-\alpha}.$$

Therefore, in a panel regression of log hires on log vacancies and log unemployment augmented with a time polynomial and fixed sector-specific effects, the estimated sector fixed-effect is precisely the measurement error in vacancies υ_i. One can therefore obtain an estimate of υ_i in the same way we propose to estimate ϕ_i. To sum up, sectors where vacancies are especially underreported (i.e., $\upsilon_i >> 1$) will look like sectors with higher matching efficiency.

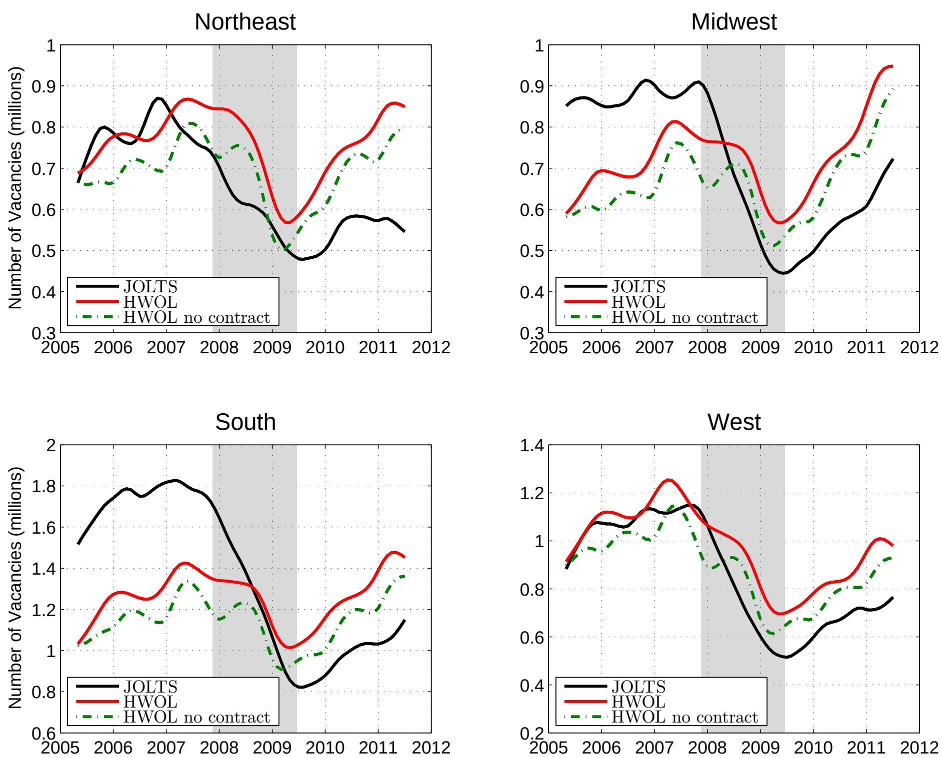
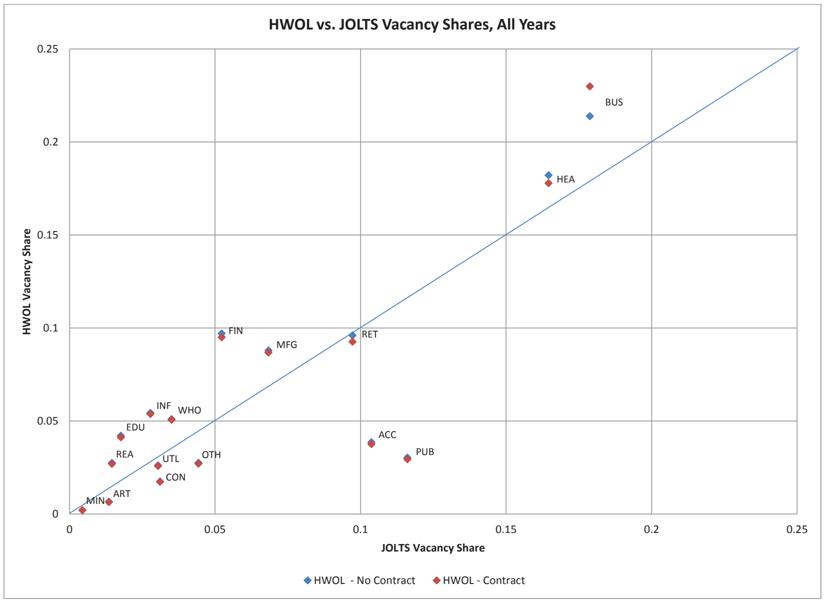


Figure B1: Comparison between JOLTS and HWOL. Top-left panel: Northeast, Top-right panel: Midwest, Bottom-left panel: South, Bottom-right panel: West.



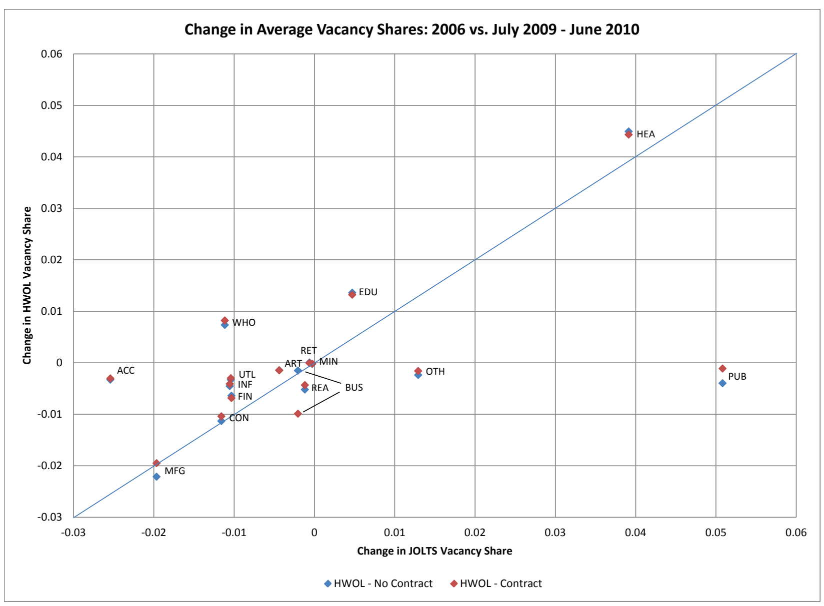


Figure B2: Top panel: comparison between vacancy shares in the JOLTS and HWOL for the May 2005 to June 2011 period. Bottom panel: change in average vacancy shares from 2006 to July 2009-June 2010 in the JOLTS and the HWOL. See Table B1 for an explanation of industry labels.

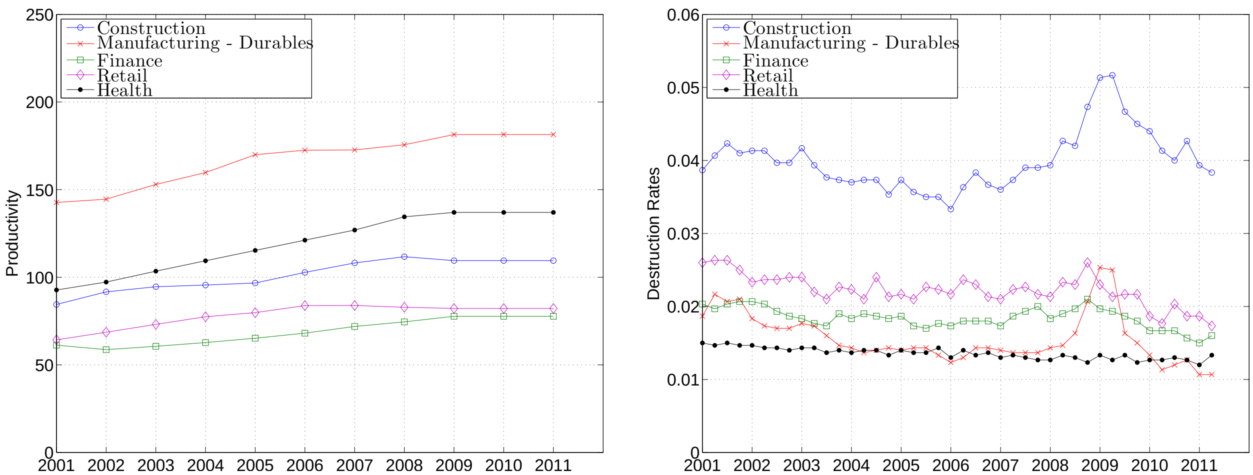


Figure B3: Productivity levels (left panel) and job destruction rates (right panel) for selected industries. Source: BEA and BLS for productivity levels and BED for job destruction rates.

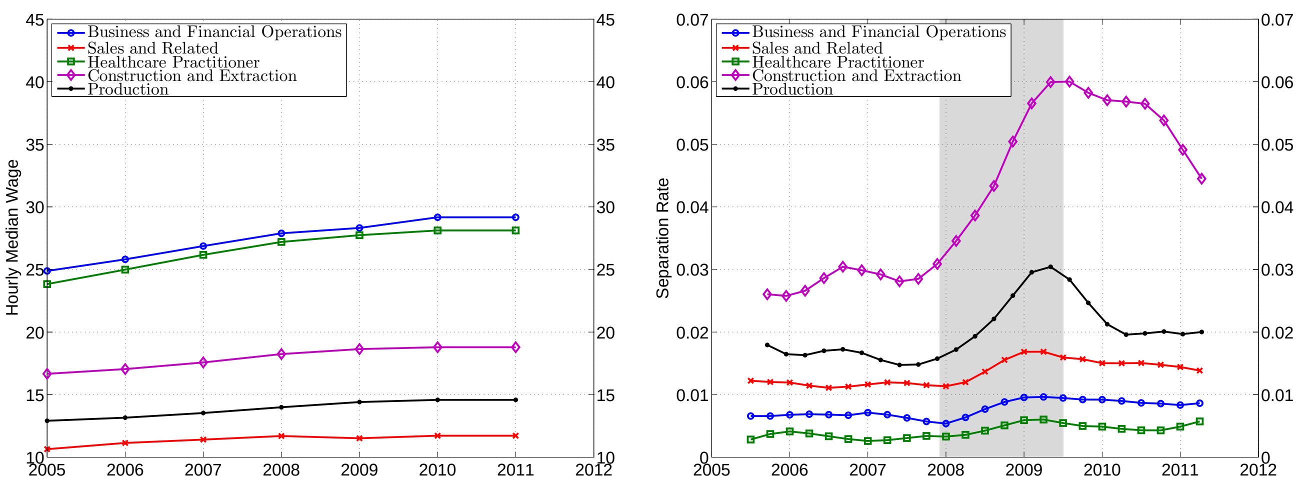


Figure B4: Wages (left panel) and job separation rates (right panel) for selected occupations. Source: OES for wages and CPS for job separation rates.

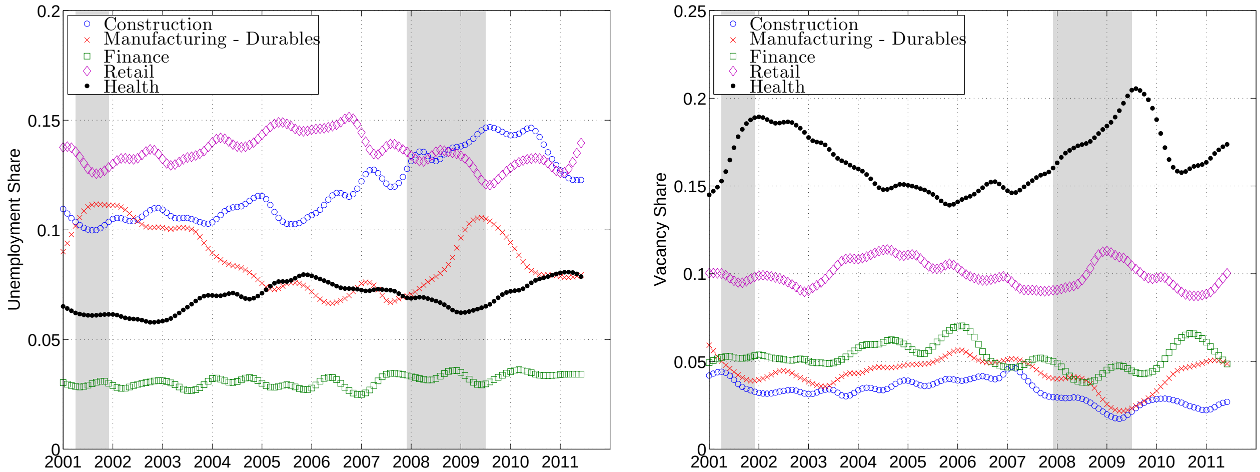


Figure B5: Unemployment and vacancy shares by selected industry.

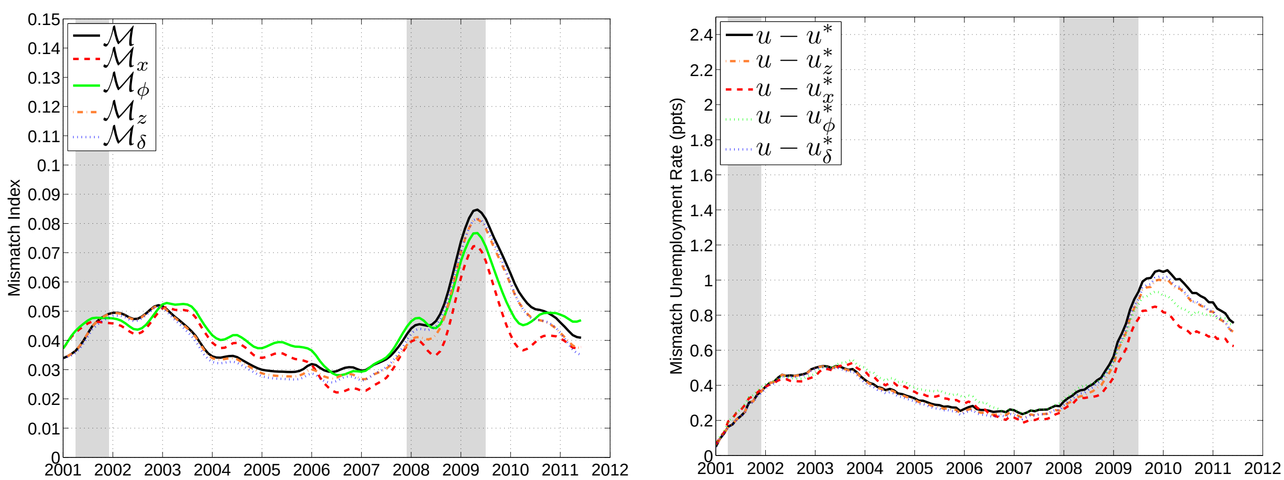


Figure B6: Mismatch indexes $\mathcal{M}_t$, $\mathcal{M}_{xt}$, $\mathcal{M}_{\phi t}$, $\mathcal{M}_{zt}$, and $\mathcal{M}_{\delta t}$ by industry (left panel) and the corresponding mismatch unemployment rates (right panel).

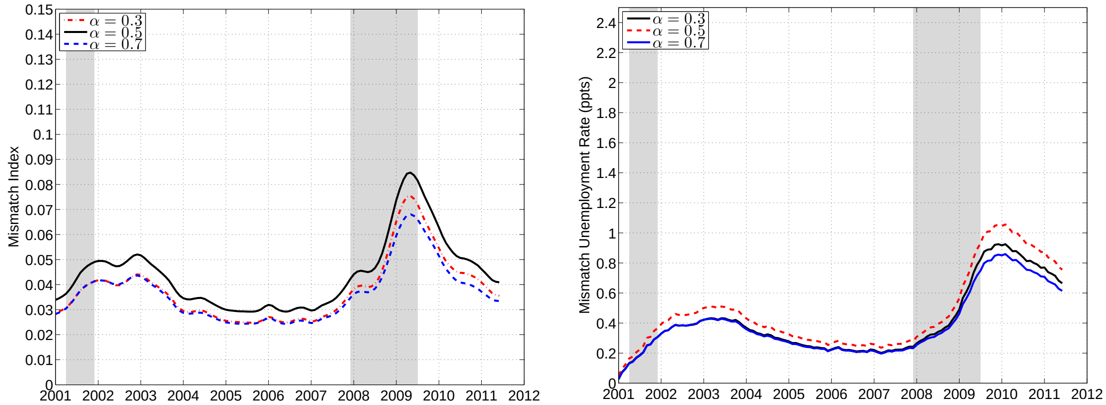


Figure B7: Mismatch index $\mathcal{M}_t$ by industry (left panel) and the corresponding mismatch unemployment rates (right panel) for various values of α.

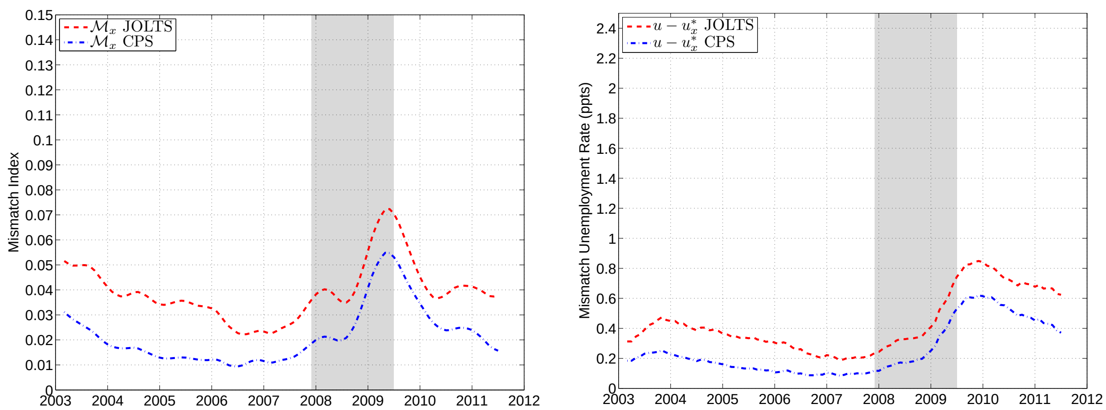


Figure B8: Mismatch index $\mathcal{M}_{xt}$ by industry (left panel) and the corresponding mismatch unemployment rates (right panel) using CPS measure of hires from unemployment.

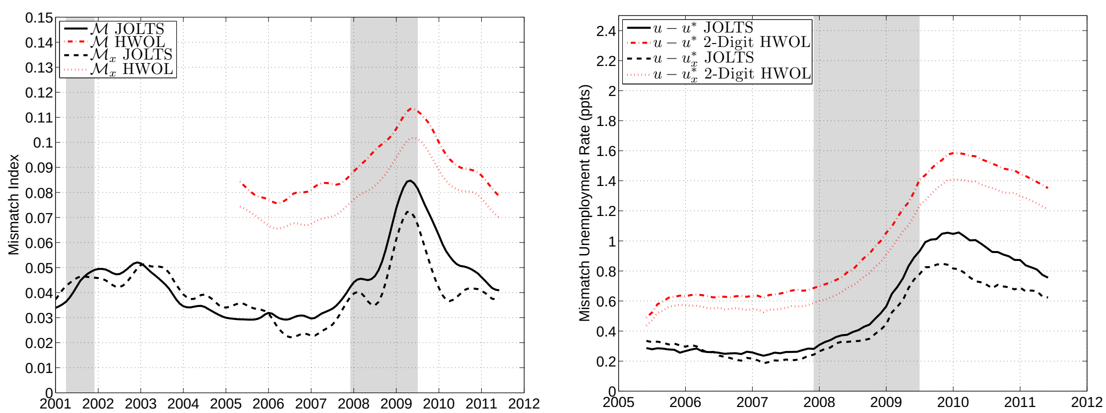


Figure B9: Mismatch indexes $\mathcal{M}_t$ (left panel) and the corresponding mismatch unemployment rates (right panel) using the JOLTS and HWOL datasets.

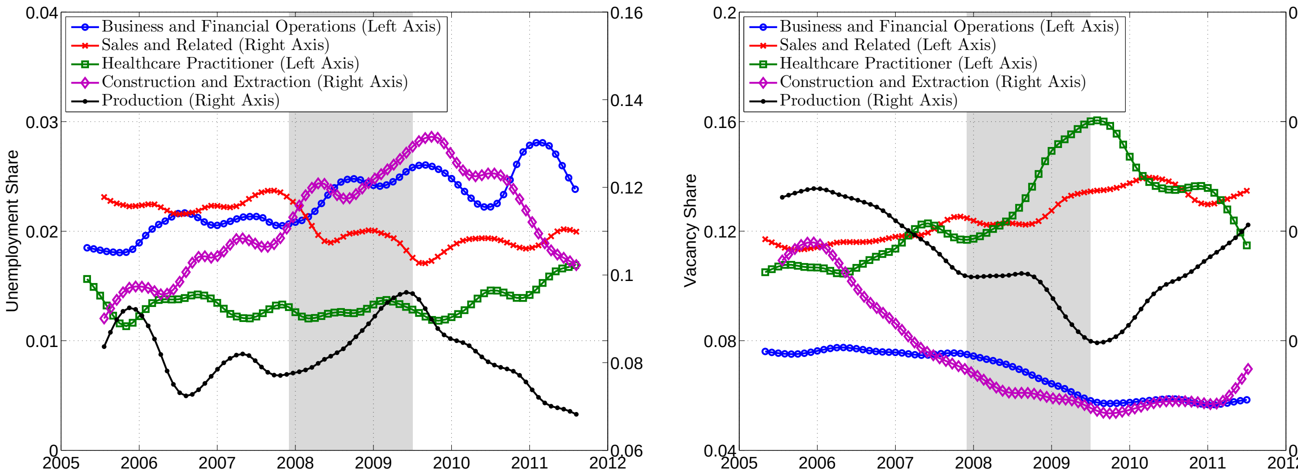


Figure B10: Unemployment and vacancy shares by selected occupation.

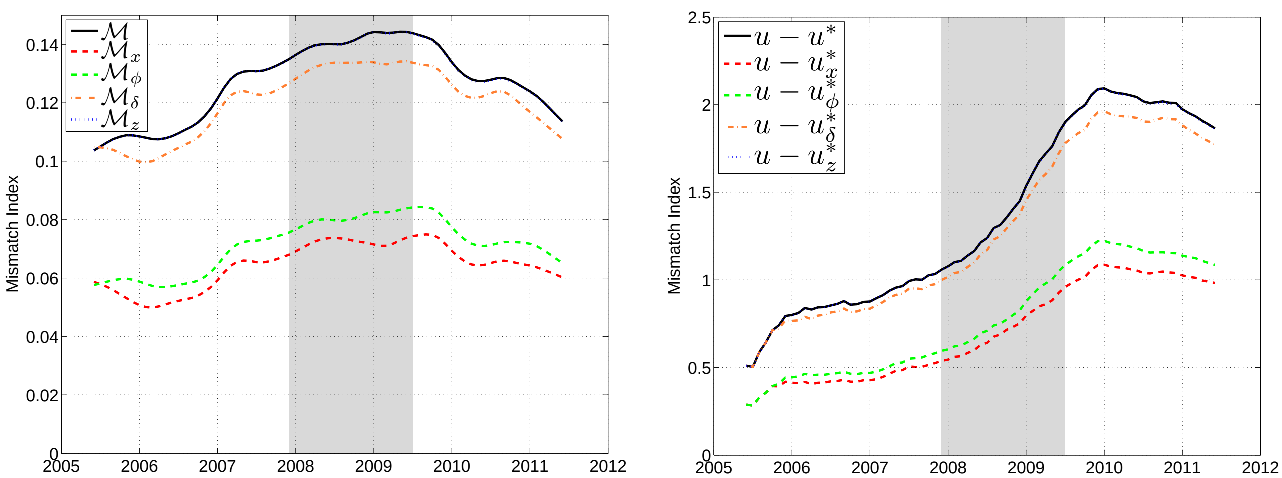


Figure B11: Mismatch indexes $\mathcal{M}_t$, $\mathcal{M}_{xt}$, $\mathcal{M}_{\phi t}$, $\mathcal{M}_{zt}$, and $\mathcal{M}_{\delta t}$ by occupation (left panel) and the corresponding mismatch unemployment rates (right panel).

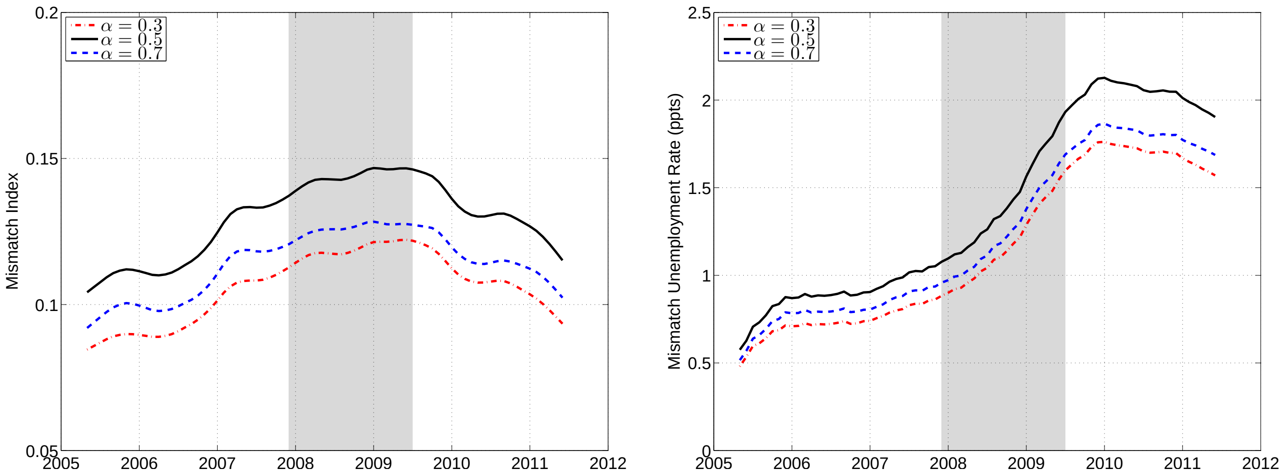


Figure B12: Mismatch index $\mathcal{M}_t$ by occupation (left panel) and the corresponding mismatch unemployment rates (right panel) for various values of α.

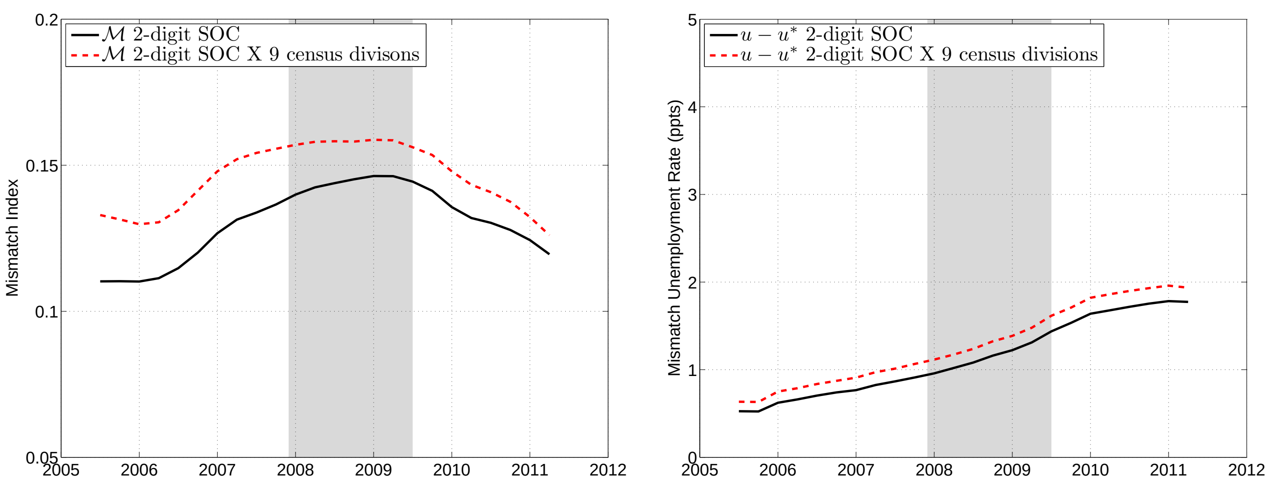


Figure B13: Mismatch index $\mathcal{M}_t$ by occupation and location (left panel) and the corresponding mismatch unemployment rates (right panel).

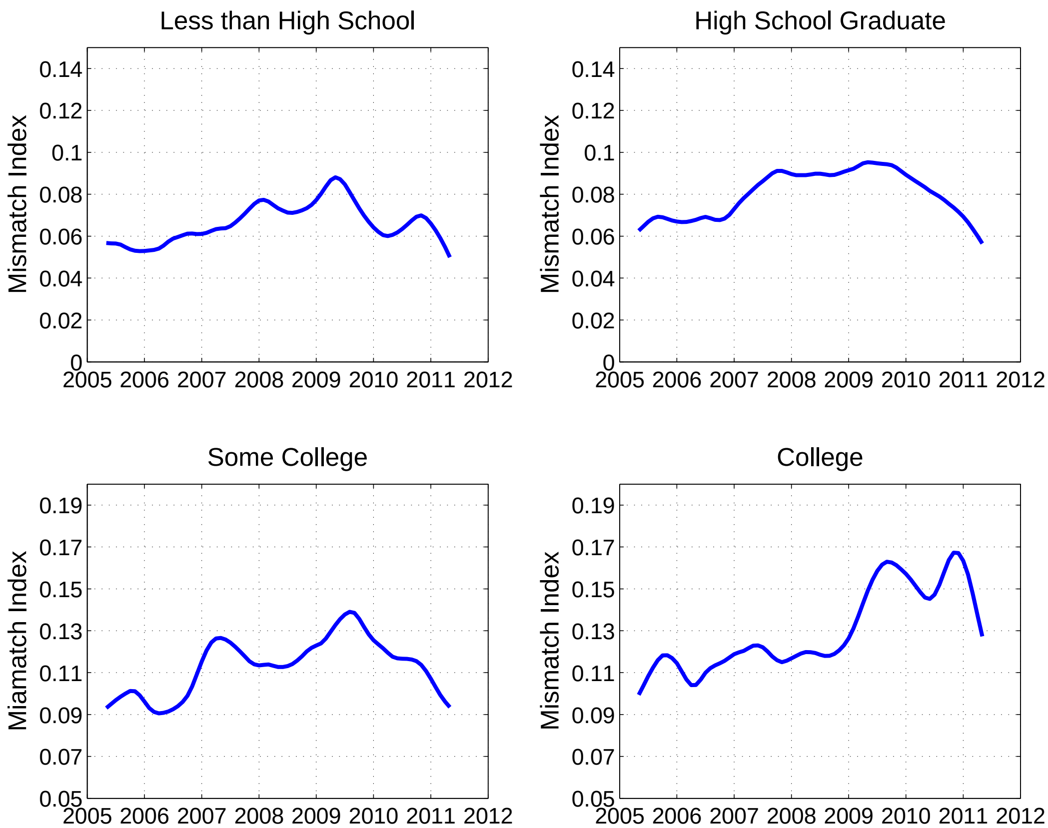


Figure B14: Mismatch indexes ($\mathcal{M}_t$) by occupation for different education groups.

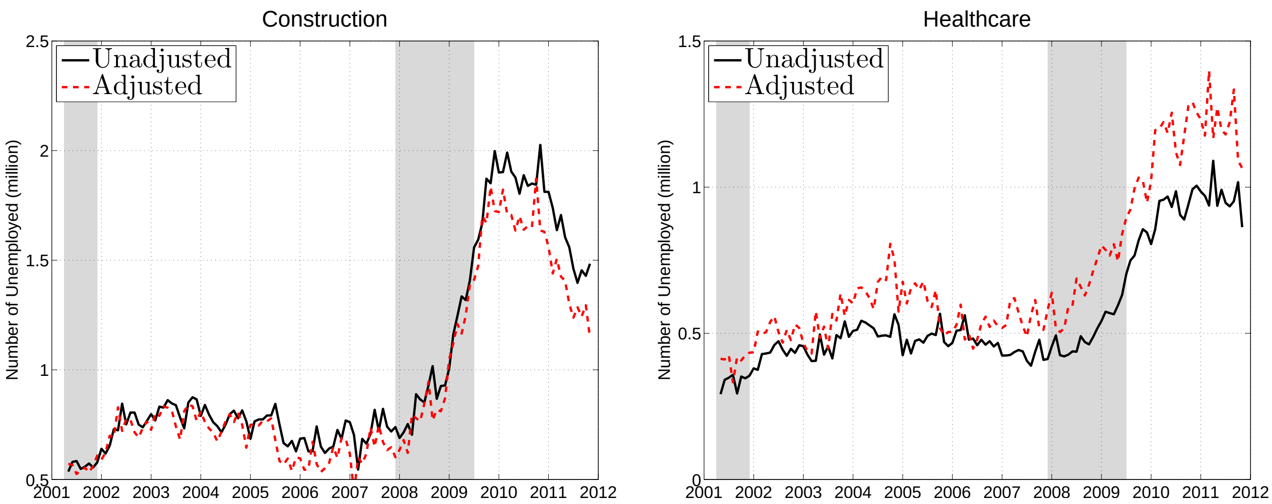


Figure B15: Adjusted unemployment counts for selected industries.

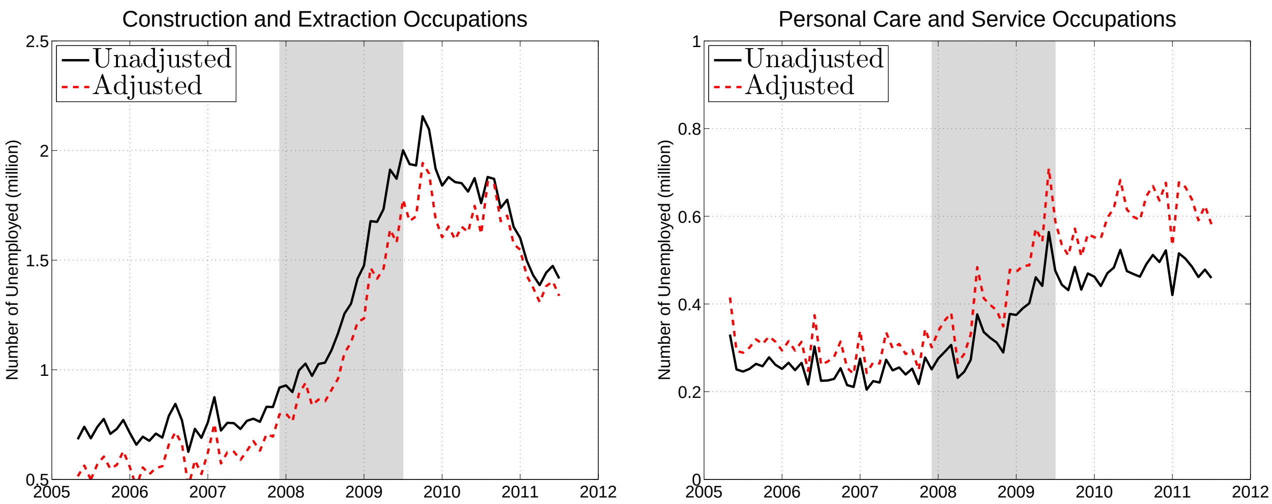


Figure B16: Adjusted unemployment counts for selected occupations.

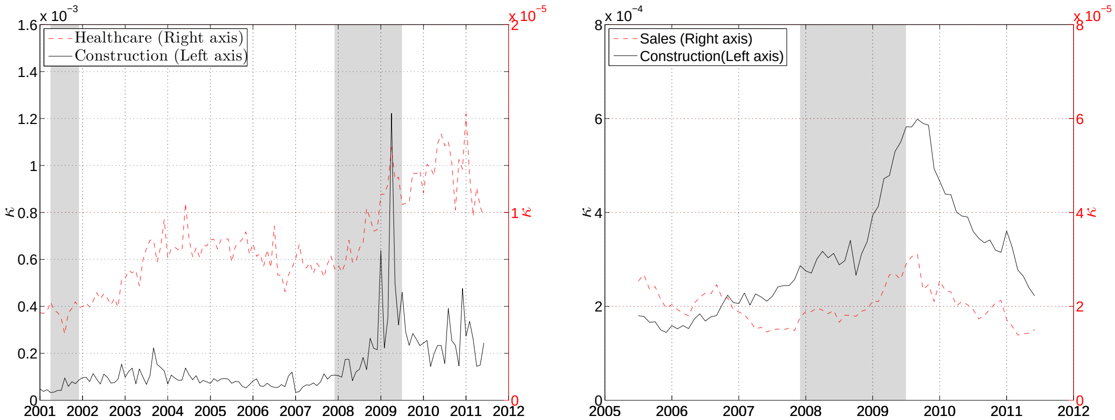


Figure B17: Time series of κ for two selected industries: construction and healthcare (left panel) and two selected occupations: construction and extraction occupations, and sales and related occupations (right panel). The cost is normalized by average annual labor productivity of the industry (annual wage for the occupation).

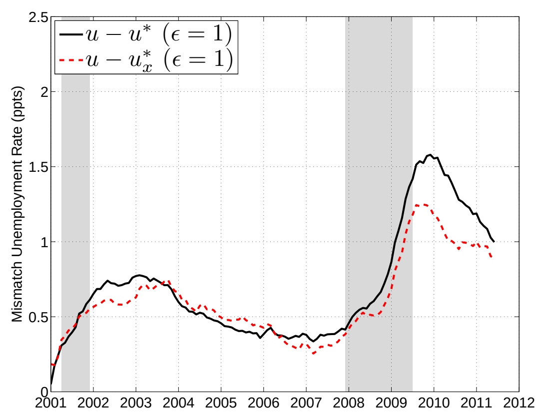


Figure B18: Mismatch unemployment with $\mathcal{M}_t^{v^*}$ at the industry level using endogenous vacancies specification with JOLTS.

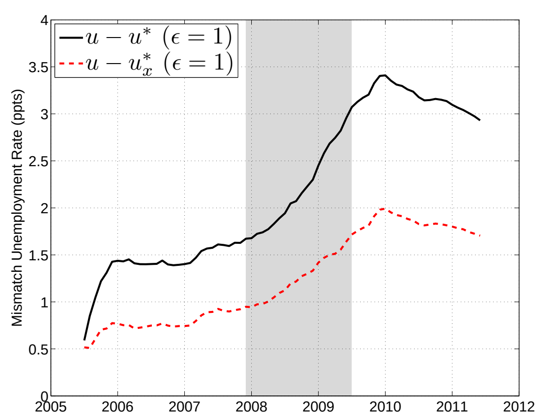


Figure B19: Mismatch unemployment with $\mathcal{M}_t^{v^*}$ at the occupation level using endogenous vacancies specification with HWOL.

Code	Industry
ACC	Accomodation and Food Services
ART	Arts, Entertainment and Recreation
CON	Construction
EDU	Education Services
FIN	Finance and Insurance
PUB	Government
HEA	Health Care and Social Assistance
INF	Information
MFG	Manufacturing-Durable Goods
MFG	Manufacturing-Nondurable Goods
MIN	Mining
OTH	Other Services
BUS	Professional and Business Services
REA	Real Estate and Rental and Leasing
RET	Retail Trade
UTL	Transportation, Warehousing and Utilities
WHO	Wholesale Trade

Table B1: Industry classification in the JOLTS. The codes in the left column are those used in Figure B2.

Code	Occupation	Classification
110000	Management Occupations	Cognitive/Non-routine
130000	Business and Financial Operations Occupations	Cognitive/Non-routine
150000	Computer and Mathematical Occupations	Cognitive/Non-routine
170000	Architecture and Engineering Occupations	Cognitive/Non-routine
190000	Life, Physical, and Social Science Occupations	Cognitive/Non-routine
210000	Community and Social Service Occupations	Cognitive/Non-routine
230000	Legal Occupations	Cognitive/Non-routine
250000	Education, Training, and Library Occupations	Cognitive/Non-routine
270000	Arts, Design, Entertainment, Sports, and Media Occupations	Cognitive/Non-routine
290000	Healthcare Practitioners and Technical Occupations	Cognitive/Non-routine
310000	Healthcare Support Occupations	Manual/Non-routine
330000	Protective Service Occupations	Manual/Non-routine
350000	Food Preparation and Serving Related Occupations	Manual/Non-routine
370000	Building and Grounds Cleaning and Maintenance Occupations	Manual/Non-routine
390000	Personal Care and Service Occupations	Manual/Non-routine
410000	Sales and Related Occupations	Cognitive/Routine
430000	Office and Administrative Support Occupations	Cognitive/Routine
470000	Construction and Extraction Occupations	Manual/Routine
490000	Installation, Maintenance, and Repair Occupations	Manual/Routine
510000	Production Occupations	Manual/Routine
530000	Transportation and Material Moving Occupations	Manual/Routine

Table B2: 2-digit SOC Codes used in our empirical analysis. The classification in the right column is that used in Figure 7.

Code	Occupation
111000	Top Executives
113000	Operations Specialties Managers
119000	Other Management Occupations
131000	Business Operations Specialists
132000	Financial Specialists
151000	Computer Occupations
211000	Counselors, Social Workers, and Other Community and Social Service Specialists
252000	Preschool, Primary, Secondary, and Special Education School Teachers
272000	Entertainers and Performers, Sports and Related Workers
291000	Health Diagnosing and Treating Practitioners
311000	Nursing, Psychiatric, and Home Health Aides
339000	Other Protective Service Workers
352000	Cooks and Food Preparation Workers
353000	Food and Beverage Serving Workers
359000	Other Food Preparation and Serving Related Workers
372000	Building Cleaning and Pest Control Workers
373000	Grounds Maintenance Workers
399000	Other Personal Care and Service Workers
411000	Supervisors of Sales Workers
412000	Retail Sales Workers
413000	Sales Representatives, Services
419000	Other Sales and Related Workers
433000	Financial Clerks
434000	Information and Record Clerks
435000	Material Recording, Scheduling, Dispatching, and Distributing Workers
436000	Secretaries and Administrative Assistants
439000	Other Office and Administrative Support Workers
452000	Agricultural Workers
472000	Construction Trades Workers
493000	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers
499000	Other Installation, Maintenance, and Repair Occupations
512000	Assemblers and Fabricators
514000	Metal Workers and Plastic Workers
519000	Other Production Occupations
533000	Motor Vehicle Operators
537000	Material Moving Workers

Table B3: 3-digit SOC Codes used in our empirical analysis.

	JOLTS		HWOL	
	α	σ	α	σ
JOLTS Hires	0.576 [0.542,0.603]	0.152 [0.051,0.242]	-	-
CPS Hires	0.301 [0.267,0.350]	0.18 [0.08,0.303]	0.239 [0.194,0.291]	-0.108 [-0.226,0.004]

Table B4: Estimates of the vacancy share α and CES substitutability parameter σ, using industry and occupation level data. 95-5 confidence intervals computed via bootstrap. Sample sizes are the same as in Table 1.

Industry	ϕ^{pre}	ϕ^{post}
Mining	1.71	1.36
Arts	1.69	1.87
Construction	1.66	1.73
Accommodations	1.53	1.60
Retail	1.47	1.46
Professional and Business Services	1.43	1.45
Real Estate	1.41	1.22
Wholesale	1.21	1.35
Other	1.14	1.16
Transportation and Utilities	1.14	1.16
Manufacturing - Nondurables	0.96	1.00
Education	0.94	1.02
Health	0.93	1.05
Government	0.87	0.89
Finance	0.85	0.73
Manufacturing - Durables	0.84	0.78
Information	0.76	0.70

Table B5: Estimates of industry-specific match efficiencies using hires from the JOLTS.

Industry Groups	Industry	ϕ^{pre}	ϕ^{post}
Group 1	Construction Mining	0.50	0.55
Group 2	Manufacturing Other Transportation and Utilities	0.42	0.44
Group 3	Accommodations Arts Professional and Business Services Retail Wholesale	0.38	0.39
Group 4	Education Finance Government Health Information Real Estate	0.33	0.33

Table B6: Estimates of industry-specific match efficiencies using hires from the CPS.

Occupation Groups	Occupation	ϕ^{pre}	ϕ^{post}
Service	Protective Service Occupations Food Preparation and Serving Related Occupations Building and Grounds Cleaning and Maintenance Occupations Personal Care and Service Occupations	0.58	0.63
Natural Resources, Construction and Maintenance	Construction and Extraction Occupations Installation, Maintenance, and Repair Occupations	0.56	0.63
Production, Transportation and Material Moving	Production Occupations Transportation and Material Moving Occupations	0.48	0.52
Sales and Office	Sales and Related Occupations Office and Administrative Support Occupations	0.37	0.35
Management, Professional and Related	Management Occupations Business and Financial Operations Occupations Computer and Mathematical Occupations Architecture and Engineering Occupations Life, Physical, and Social Science Occupations Community and Social Service Occupations Legal Occupations Education, Training, and Library Occupations Arts, Design, Entertainment, Sports, and Media Occupations Healthcare Practitioners and Technical Occupations Healthcare Support Occupations	0.32	0.33

Table B7: Estimates of occupation-specific match efficiencies using hires from the CPS.

	Index	α	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$
JOLTS Hires	$\mathcal{M}$	0.5	0.26	1.01	0.75	13.9%
	$\mathcal{M}_x$	0.5	0.25	0.84	0.59	10.9%
	$\mathcal{M}_\phi$	0.5	0.29	0.92	0.63	11.7%
	$\mathcal{M}_z$	0.5	0.25	0.96	0.72	13.3%
	$\mathcal{M}_\delta$	0.5	0.23	0.98	0.74	13.7%
	$\mathcal{M}$	0.3	0.22	0.89	0.67	12.4%
	$\mathcal{M}$	0.5	0.26	1.01	0.75	13.9%
	$\mathcal{M}$	0.7	0.22	0.82	0.60	11.1%
	$\mathcal{M}_x^{AK}$	0.5	0.28	0.89	0.61	11.2%
	$\mathcal{M}_x^{break}$	0.5	0.25	0.92	0.67	12.4%
	$\mathcal{M}_{adj}$	0.5	0.25	0.89	0.65	11.9%
	$\mathcal{M}^{v^*}(\varepsilon = 1.0)$	0.5	0.38	1.52	1.14	21.1%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	0.5	0.70	1.91	1.21	22.3%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.5	0.36	1.25	0.89	16.5%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.5	0.27	0.95	0.68	12.7%
CPS Hires	$\mathcal{M}$	0.5	0.27	1.03	0.77	12.4%
	$\mathcal{M}_x$	0.5	0.10	0.62	0.52	9.6%
HWOL	$\mathcal{M}$	0.5	0.63	1.51	0.88	16.3%
	$\mathcal{M}_x$	0.5	0.56	1.35	0.79	14.7%

Table B8: Changes in mismatch unemployment at the industry level. All the changes are calculated as the difference between October 2009 and the average of 2006. Note that $\Delta u = 5.4$ percentage points.

	Index	α	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$
2-digit	$\mathcal{M}$	0.5	0.85	2.00	1.14	21.3%
	$\mathcal{M}_x$	0.5	0.42	1.02	0.60	11.1%
	$\mathcal{M}_\phi$	0.5	0.46	1.15	0.69	12.8%
	$\mathcal{M}_z$	0.5	0.85	2.00	1.15	21.2%
	$\mathcal{M}_\delta$	0.5	0.80	1.86	1.05	19.5%
	$\mathcal{M}$	0.3	0.72	1.68	0.96	17.8%
	$\mathcal{M}$	0.5	0.85	2.00	1.14	21.3%
	$\mathcal{M}$	0.7	0.79	1.77	0.98	18.1%
	$\mathcal{M}_x^{break}$	0.5	0.42	0.98	0.56	10.4%
	$\mathcal{M}_{adj}$	0.5	0.84	2.00	1.16	21.4%
	$\mathcal{M}^{v^*}(\varepsilon = 1.0)$	0.5	1.41	3.20	1.79	33.1%
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	0.5	1.08	2.60	1.52	28.1%
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.5	0.74	1.81	1.07	19.7%
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.5	0.58	1.41	0.83	15.3%
3-digit	$\mathcal{M}$	0.5	1.33	2.91	1.58	29.3%
	$\mathcal{M}_x$	0.5	0.79	1.73	0.94	17.4%
	$\mathcal{M}_\phi$	0.5	0.83	1.85	1.02	18.8%
	$\mathcal{M}_z$	0.5	1.33	2.91	1.58	22.2%
	$\mathcal{M}_\delta$	0.5	1.29	2.80	1.50	27.8%
Routine/Cognitive	$\mathcal{M}_{RC}$	0.5	0.41	1.07	0.67	12.3%
2-digit $\times$ region (quarterly)	$\mathcal{M}$	0.5	0.81	1.71	0.90	16.9%
2-digit (quarterly)	$\mathcal{M}$	0.5	0.68	1.53	0.85	16.0%

Table B9: Changes in mismatch unemployment at the occupation level. All the changes are calculated as the difference between October 2009 and the average of 2006. Note that $\Delta u = 5.4$ percentage points.

	July 2005-June 2007		July 2007-June 2009		July 2009-June 2011	
INDUSTRY	UN	UD	UN	UD	UN	UD
Agriculture and Mining	0.17	0.08	0.17	0.07	0.15	0.06
Construction	0.16	0.08	0.15	0.08	0.13	0.07
Manufacturing	0.21	0.10	0.18	0.08	0.16	0.08
Trade	0.24	0.10	0.23	0.10	0.21	0.10
Transportation and Utilities	0.23	0.10	0.19	0.09	0.17	0.08
Information	0.21	0.10	0.18	0.08	0.17	0.09
Financial	0.21	0.09	0.19	0.09	0.17	0.09
Professional Business Services	0.23	0.10	0.20	0.09	0.18	0.08
Education and Health	0.25	0.11	0.24	0.10	0.21	0.10
Leisure	0.29	0.11	0.25	0.10	0.24	0.10
Other	0.28	0.11	0.25	0.11	0.20	0.10
Public Administration	0.25	0.11	0.25	0.09	0.20	0.10
All	0.23	0.10	0.20	0.09	0.18	0.08

Table B10: UN and UD flow rates by industry.

	July 2005-June 2007		July 2007-June 2009		July 2009-June 2011	
OCCUPATION	UN	UD	UN	UD	UN	UD
Management	0.15	0.07	0.16	0.07	0.14	0.07
Business and Financial Operations	0.19	0.11	0.17	0.08	0.14	0.06
Computer and Mathematical	0.19	0.11	0.17	0.08	0.14	0.08
Architecture and Engineering	0.20	0.10	0.17	0.09	0.13	0.06
Life, Physical and Social Science	0.20	0.12	0.17	0.10	0.17	0.07
Community and Social Service	0.29	0.13	0.19	0.08	0.18	0.10
Legal	0.20	0.06	0.18	0.07	0.18	0.08
Education, Training, and Library	0.25	0.10	0.21	0.09	0.20	0.09
Arts, Design, Entertainment, Sports, and Media	0.20	0.08	0.19	0.08	0.18	0.08
Healthcare Practitioners and Technical	0.21	0.09	0.23	0.10	0.18	0.08
Healthcare Support	0.29	0.12	0.27	0.12	0.22	0.09
Protective Service	0.25	0.11	0.23	0.07	0.21	0.09
Food Preparation and Serving Related	0.29	0.11	0.25	0.10	0.24	0.09
Building and Grounds Cleaning and Maintenance	0.28	0.11	0.25	0.10	0.23	0.10
Personal Care and Service	0.30	0.13	0.26	0.11	0.26	0.10
Sales and Related	0.26	0.10	0.25	0.10	0.22	0.09
Office and Administrative Support	0.24	0.10	0.22	0.09	0.20	0.08
Construction and Extraction	0.17	0.08	0.16	0.08	0.13	0.07
Installation, Maintenance, and Repair	0.21	0.10	0.16	0.08	0.14	0.07
Production	0.22	0.10	0.18	0.08	0.16	0.08
Transportation and Material Moving	0.23	0.10	0.19	0.09	0.19	0.09
All	0.23	0.10	0.21	0.09	0.18	0.08

Table B11: UN and UD flow rates by occupation.