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Mismatch Unemployment†

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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 US unemployment by exploiting two sources of cross-sectional data on vacancies, JOLTS and HWOL. Our calculations indicate that mismatch, across industries and three-digit occupations, explains at most one-third of the total observed increase in the unemployment rate. Occupational mismatch has become especially more severe for college graduates, and in the West of the United States. Geographical mismatch unemployment plays no apparent role. (*JEL* E24, J22, J24, J41, J63)

The US unemployment rate rose from an average value of 4.6 percent in 2006 to its peak of 10 percent in October 2009, as the economy experienced the deepest downturn in the postwar period. Three years after its peak, the unemployment rate still hovered above 8 percent. 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 reveals that, while the inflow rate quickly returned to its pre-recession level, the job-finding rate is still substantially below what it was in 2006. Any credible explanation 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, or locations different from those where the available jobs are. Such misalignment between the distribution of vacancies and unemployment would lower the aggregate job-finding rate.

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The mismatch hypothesis is qualitatively consistent with three features of the Great Recession. First, the empirical relationship between aggregate unemployment and aggregate vacancies—the Beveridge Curve—displayed a marked outward movement for the period 2009–2012 in the United States, indicating that for a given level of vacancies, the current level of unemployment is higher than that implied by the last decade of 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 largely weathered the storm such as 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). A homeowner who expects the local housing market to recover may choose to forego job opportunities in other locations to avoid large capital losses from selling her house. Under this "house-lock" conjecture, mismatch between job opportunities and job seekers would arise predominantly across locations.

In this paper, we develop a theoretical framework to conceptualize the notion of mismatch unemployment, and apply this to measure how much of the recent rise in the US unemployment rate is attributable to mismatch across sectors. We envision the economy as comprising a large number of distinct labor markets or sectors, that is, it is segmented by industry, occupation, geography, or a combination of these attributes. Each labor market is frictional, meaning its hiring process is governed by a matching function. To assess the existence of mismatch in the data, we ask whether unemployed workers search in the wrong sectors. Given the observed distribution of productive efficiency, matching efficiency, and vacancies across labor markets, are unemployed workers misallocated? 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 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 equating efficiency-weighted vacancy-unemployment ratios 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 job seeker misallocation. 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] As we explain in detail in this paper, choosing as benchmark the allocation of

[1] See, among others, Elsby, Hobijn, and Şahin (2010); Hall (2010); and Daly et al. (2012). According to these studies, at the 2011 level of vacancies, the pre-recession US unemployment-vacancies relationship predicts an unemployment rate between 1 and 2 percentage points lower than its 2011 value.

[2] According to Barlevy (2011) and Veracierto (2011), the size of this drop from its pre-recession level is between 15 percent and 30 percent, 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 jointly accounted for 54 percent of this decline.

[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 suboptimal joint distribution of worker skills and firm's capital. See, for example, Eeckhout and Kircher (2011).

a planner who can shuffle labor across sectors at no cost has the implication that our estimates of sectoral mismatch are an upper bound.

Our measurement exercise requires disaggregated data on unemployment and vacancies. The standard microdata sources for unemployment and vacancies are the Current Population Survey (CPS) and the Job Openings and Labor Turnover Survey (JOLTS), respectively. Unfortunately, JOLTS only allows for disaggregation of vacancies into four census regions and 17 industries that roughly coincide with two-digit NAICS classification.[5] In this paper, we introduce the use of the Conference Board's Help Wanted OnLine (HWOL) database. The database is designed to collect the universe of unique online job advertisements in the US economy. Through this novel dataset, we can perform our empirical analysis at the two- and three-digit occupational level, at the more detailed geographical level of states and counties, and even by defining labor markets as a combination of occupation and location.[6]

Our empirical analysis yields no significant role for geographical mismatch between unemployed workers and job vacancies across US states or counties. Mismatch at the industry and two- and three-digit occupation level increased markedly during the recession, but declined steadily throughout 2010. This indicates a countercyclical mismatch pattern. A similar but milder hump shape in mismatch is observed around the 2001 recession. In line with this result, Barnichon and Figura (2013) document that aggregate matching efficiency has been strongly procyclical for the period 1976–2012.

We calculate that an additional 4 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 industry-level mismatch unemployment can account for 0.75 percentage points of the 5.4 percentage point total increase in the US unemployment rate from 2006 to October 2009. At the three-digit occupation level, the contribution of mismatch unemployment rises to 1.6 percentage points. When we compute two-digit occupational mismatch separately for different education groups and census regions, we find its contribution to the observed increase in the unemployment rate is the largest among college graduates and for the West; it is the smallest among high school dropouts and in the Northeast.

The Great Recession coincided with an increase in the number of workers who stopped actively searching for jobs because of a discouragement effect. We verify that our conclusions are largely unaffected when we add these discouraged workers—who can be thought of as job seekers with low search intensity—to the unemployed job seeker counts by occupation.

In an extension of the baseline analysis, we allow the misallocation of unemployed workers across sectors to also affect a firm's vacancy creation decisions. Since the presence of job seekers in declining sectors makes it easier to fill jobs in those sectors, it distorts firms' incentives in the direction of inefficiently creating vacancies in the wrong markets. This channel depresses aggregate vacancy creation relative to the planner's solution, giving a further boost to mismatch unemployment.

[5] See Table C1 in the online Appendix for a complete list of industries in the JOLTS.

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

This amplification can be very strong if the vacancy creation cost is close to linear, but for specifications of this cost function that are closer to quadratic, in line with the existing literature, the amplification is moderate. 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 half of a percentage point.

With all the necessary caveats discussed throughout the paper, our study indicates that, at the analyzed level of disaggregation, sectoral mismatch can explain at most one-third of the rise in the US unemployment rate since early 2006 to the end of 2009, the period when the average job finding rate dropped sharply.

The model underlying our measurement exercise is a multi-sector version of the standard aggregate search/matching model (Pissarides 2000). Within this class, the closest paper to ours is Jackman and Roper (1987). In a static matching model with many sectors, they show that aggregate hires are maximized by distributing unemployment across sectors so that sectoral labor-market tightnesses are equalized. They propose the use of mismatch indexes to summarize deviations from this allocation.[7] At the time that paper was published, economists were struggling to understand why high unemployment was so persistent in many European countries.[8] Padoa-Schioppa (1991) contains a number of empirical studies for various countries and concludes that mismatch was not an important explanation of European unemployment dynamics in the 1980s. 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 develop a framework 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 microdata. Through the use of this novel data source, we document new facts concerning changes in the correlation of vacancy and unemployment shares across economic sectors. We show that these facts are informative about the extent of sectoral mismatch, in this class of search/matching models.

Shimer (2007) proposes an alternative environment to measure mismatch between firms and workers across labor markets. The crucial difference between these two models is the notion of a vacancy or, equivalently, at which point of the meeting process vacancies are measured. The definition of vacancy we adopt is common to the entire search/matching approach to unemployment. Here, firms desiring to expand post vacancies: a vacancy is a manifestation of a firm's *effort to hire*. In Shimer's

[7] This idea goes back at least as far as Mincer (1966, p. 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."

[8] The conjecture was that the oil shocks of the 1970s and the concurrent shift from manufacturing to services 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 evidence of shifts in the Beveridge curve for some countries.

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 microdata 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. According to Davis, Faberman, and Haltiwanger (2013), job openings in JOLTS have a duration between two and four weeks. This short span seems somewhat more consistent with the hiring effort view, but better data is needed to shed light on this critical point.

The remainder of the paper is organized as follows. Section I presents the theoretical framework. Section II derives the mismatch indexes and explains how we compute our unemployment rate counterfactuals. Here, we also discuss in some depth the interpretation of our measure of mismatch. Section III describes the data. Section IV performs the empirical analysis. Section V analyzes the case in which mismatch also affects vacancy creation. In Section VI we verify the robustness of our results to measurement error in unemployment and vacancy counts, and to specification error in the matching function. Section VII concludes. Online Appendix A contains the proofs of our theoretical results, online Appendix B contains more detail about the data and our measurement exercise, and online Appendix C contains additional figures and tables.

I. Environment and Planner Problem

We begin by describing our benchmark economic environment where sectors differ by their matching efficiency and their stock of vacancies. Next, we generalize the environment by introducing heterogeneity in productivity and job destruction rates across labor markets. For each of these environments, we derive the planner's optimal allocation rule of unemployed workers across sectors—the crucial building block of our theoretical analysis. Note that, in the planner's problem for the generalized environment, maximizing aggregate output is no longer equivalent to maximizing aggregate employment. This observation has implications for our interpretation of the mismatch unemployment index that we discuss in Section IIC. Finally, throughout these derivations, we maintain the assumption that the evolution over time of the vacancy distribution is exogenous. We relax this assumption in Section V.

A. *Benchmark Environment*

Time is discrete and indexed by t. 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_{it}), arise exogenously across sectors.[9] The economy is populated by a measure one of risk-neutral individuals who can be either employed in sector i (e_{it}) or unemployed and searching in sector i (u_{it}). Therefore, $\sum_{i=1}^{I}(e_{it}+u_{it})=1$. On-the-job search is ruled out and an unemployed worker, in

[9] We explain in Section V 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.

any given period, can search for vacancies in one sector only. For the time being, we also rule out nonparticipation, but in the next section we relax this restriction.

Labor markets are frictional: new matches, or hires, (h_{it}) between unemployed workers (u_{it}) and vacancies (v_{it}) in market i are determined by the matching function $\Phi_t \phi_{it} m(u_{it}, v_{it})$, with m strictly increasing and strictly concave in both arguments and homogeneous of degree one in (u_{it}, v_{it}). The term $\Phi_t \phi_{it}$ measures matching efficiency (i.e., the level of fundamental frictions) in sector i, with Φ_t denoting the aggregate component and ϕ_{it} 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_t units of output in every sector. Matches are destroyed exogenously at rate Δ_t, also common across sectors. Aggregate shocks Z_t, Δ_t, and Φ_t, and the vector of vacancies $\mathbf{v}_t = \{v_{it}\}$ are drawn from the conditional distribution functions $\Gamma_{Z,\Delta,\Phi}(Z_{t+1}, \Delta_{t+1}, \Phi_{t+1}; Z_t, \Delta_t, \Phi_t)$ and $\Gamma_{\mathbf{v}}(\mathbf{v}_{t+1}; \mathbf{v}_t, Z_t, \Delta_t, \Phi_t)$. The notation shows that we allow for autocorrelation in $\{Z_t, \Delta_t, \Phi_t, \mathbf{v}_t\}$, and for correlation between vacancies and all the aggregate shocks. The sector-specific matching efficiencies ϕ_{it} are independent across sectors and are drawn from $\Gamma_{\phi}(\phi_{t+1}; \phi_t)$, where $\phi_t = \{\phi_{it}\}$. The vector $\{Z_t, \Delta_t, \Phi_t, \mathbf{v}_t, \phi_t\}$ takes strictly positive values.

Within each period, events unfold as follows. At the beginning, the aggregate shocks (Z_t, Δ_t, Φ_t), vacancies $\mathbf{v}_t$, and matching efficiencies ϕ_t are observed. At this stage, the distribution of active matches $\mathbf{e}_t = \{e_{1t}, \ldots, e_{It}\}$ across markets (and hence the total number of unemployed workers u_t) is also given. Next, unemployed workers are allocated to market i without any impediment to labor mobility. Once the unemployed workers are allocated, the matching process takes place and $h_{it} = \Phi_t \phi_{it} m(u_{it}, v_{it})$ new hires are generated in each market. Production occurs in the e_{it} (preexisting) plus h_{it} (new) matches. Finally, a fraction Δ_t of matches are destroyed exogenously in each market i, determining the next period's employment distribution $\{e_{i,t+1}\}$ and stock of unemployed workers u_{t+1}.

Planner's Solution.—In online Appendix A.A1 we prove that the planner's optimal rule for the allocation of unemployed workers across sectors can be written as

$$\phi_{1t} m_{u_1}\left(\frac{v_{1t}}{u_{1t}^*}\right) = \ldots = \phi_{it} m_{u_i}\left(\frac{v_{it}}{u_{it}^*}\right) = \ldots = \phi_I m_{u_I}\left(\frac{v_{It}}{u_{It}^*}\right), \tag{1}$$

where m_{u_i} is the derivative of the m function with respect to u_i, and where we have used the "$*$" to denote the planner's allocation. This condition states that the planner allocates more job seekers to those labor markets with more vacancies and higher matching efficiency until their marginal contribution to the hiring process is equalized across markets.[10]

[10] In equation (1), the derivative of the sector-specific matching function m is written as a function of sectoral market tightness only (with a slight abuse of notation) because of its CRS specification.

B. *Heterogeneous Productivities and Job Destructions*

We now allow for sector-specific shocks to productivity and destruction rates that are uncorrelated across sectors and independent of the aggregate shocks Z_t and Δ_t. In the derivations below, we first keep worker separations exogenous. Next, we allow the planner to choose whether to endogenously dissolve some existing matches and show that, under some conditions, she never chooses to do so. Throughout this extension, we also allow the planner to choose the size of the labor force.

Let labor productivity in sector i at date t be given by $Z_t z_{it}$, where each component z_{it} is strictly positive, i.i.d. across sectors and independent of Z_t. Similarly, denote the idiosyncratic component of the exogenous destruction rate in sector i as δ_{it}. Then, the survival probability of a match is $(1-\Delta_t)(1-\delta_{it})$. It is convenient to proceed under the assumption that $\{Z_t, 1-\Delta_t, z_{it}, 1-\delta_{it}\}$ are all positive martingales, which amounts to simple restrictions on the conditional distributions $\Gamma_{Z,\Delta,\Phi}$, Γ_z, and Γ_δ.[11] All the nonemployed individuals produce output ζZ_t (which can be interpreted as home production or the value of leisure). In addition, the unemployed incur a disutility cost of search.

Online Appendix A.A2 proves that the planner's optimal allocation rule of unemployed workers equates

$$\frac{z_{it}-\zeta}{1-\beta(1-\Delta_t)(1-\delta_{it})}\phi_{it} m_{u_i}\left(\frac{v_{it}}{u^*_{it}}\right) \tag{2}$$

across markets. This rule establishes that the higher the 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 searching in sector i (net of the opportunity cost of employment ζ) is discounted differently by the planner in different sectors because of the heterogeneity in the expected duration of matches.

We now allow the planner to move workers employed in sector i into unemployment or out of the labor force, before choosing the size of the labor force for the next period.

In online Appendix A.A3 we demonstrate that, if the planner always has enough individuals to pull into (out of) unemployment from (into) out of the labor force, she 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.

C. *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

[11] As we explain in online Appendix A.A2, the martingale assumption is convenient to solve forward, in closed form, the expected marginal value of an employed worker in sector i. A closed form solution can also be obtained if the components of the vector $\{Z_t, 1-\Delta_t, z_{it}, 1-\delta_{it}\}$ follow an AR(1) process. However, the derivations are more convoluted, and we do not make use of this more general assumption in the empirical analysis because our variables are well represented, statistically, by martingales.

appear to be driven by aggregate shocks with different sectors having different sensitivities to the aggregate cycle. Here we derive the planner allocation rule (2) under this alternative interpretation of the source of sectoral labor demand shifts.

Let productivity in sector i be $z_{it} = Z_t^{\eta_i}$ where η_i is a parameter measuring the elasticity of sectoral productivity to the aggregate shock Z with mean normalized to one. Let $\log Z_t$ follow a unit root process with innovation ϵ_t distributed as a $N(-\sigma_\epsilon/2, \sigma_\epsilon)$. In online Appendix A.A4, we show that the planner will allocate unemployed workers to equalize

$$(3) \quad \left[\frac{Z_t^{\eta_i - 1}}{1 - \beta(1-\Delta_t)(1-\delta_{it})\Omega_i} - \frac{\zeta}{1 - \beta(1-\Delta_t)(1-\delta_{it})}\right] \phi_{it} m_{u_i}\left(\frac{v_{it}}{u_{it}^*}\right)$$

across sectors, where $\Omega_i \equiv \exp\left(\eta_i(\eta_i - 1)\frac{\sigma_\epsilon}{2}\right)$. The new term Ω_i 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 future output in that sector. As for z_{it} in equation (2), the elasticity terms Ω_i can also be estimated from productivity data.

Understanding the nature of sectoral fluctuations exceeds the scope of this paper. A comparison of equations (2) and (3) reveals that 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. In our empirical analysis, we explore both specifications.

II. Mismatch Index and Mismatch 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. This mismatch index quantifies the fraction of hires lost because of misallocation, i.e., $(1 - h_t/h_t^*)$, where h_t denotes the observed aggregate hires and h_t^* the planner's hires. Next, we describe how to use this index to construct counterfactuals to measure the mismatch component of equilibrium unemployment.

From this point onward we must state an additional assumption, which is well supported by the data, as we show below. The sectoral matching function $m(u_{it}, v_{it})$ is Cobb-Douglas:

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

where h_{it} are hires in sector i at date t, and $\alpha \in (0, 1)$ is the vacancy share common across all sectors (in Section VIF, we allow α to vary across sectors).

A. *Mismatch Index*

From (4), summing across markets, the aggregate number of new hires can be expressed as

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

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

$$h_t^* = \Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^{I} \phi_{it} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}^*}{u_t} \right)^{1-\alpha} \right]. \tag{6}$$

Consider first the benchmark environment of Section IA. The optimality condition (1) dictating how to allocate unemployed workers between market i and market j implies

$$\frac{v_{it}}{u_{it}^*} = \left(\frac{\phi_{jt}}{\phi_{it}} \right)^{\frac{1}{\alpha}} \frac{v_{jt}}{u_{jt}^*}. \tag{7}$$

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

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

$\mathcal{M}_{\phi t}$ 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 the optimal allocation rule, how many additional jobs would she 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 (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 (the "feedback" effect of mismatch). $\mathcal{M}_{\phi t}$ measures only the direct effect of mismatch on hires, but the counterfactual of Section IIB fully incorporates the feedback effect as well.[12]

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

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

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 relatively few vacancies). The term $\overline{\phi}_t$ can also contribute to a reduction in aggregate matching efficiency when the vacancy shares of the sectors with high ϕ fall.

[12] Dickens (2010) and Lazear and Spletzer (2012) use an alternative index proposed by Mincer (1966). In a previous version of this paper, we also reported results based on this index and argued that it is much less useful than the one we propose here because it only quantifies the number of job seekers searching in the wrong sectors, but not how such misallocation lowers the job-finding rate and raises unemployment. In addition, the analysis in these papers does not allow for heterogeneity in productive and matching efficiency, a key determinant of the optimal allocation of job seekers across labor markets.

In online Appendix A.A5, 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 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 described earlier, where labor markets also differ in their level of productive efficiency. It is useful to define overall market efficiency as $x_{it} \equiv \phi_{it}(z_{it} - \zeta)/[1 - \beta(1 - \Delta_t)(1 - \delta_{it})]$. Following the same steps, we arrive at the index

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

where

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

$\overline{\phi}_{xt}$ is an aggregator of the market-level overall efficiencies weighted by their vacancy share. When this index is calculated following the Abraham-Katz view of sectoral fluctuations, it will be denoted by $\mathcal{M}_{xt}^{AK}$. The only difference with $\mathcal{M}_{xt}$ is the exact definition of overall market efficiency x_{it}, as discussed in Sections IB and IC.

Finally, 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 $\mathcal{M}_{zt}$ and $\mathcal{M}_{\delta t}$ to denote mismatch indexes for an economy where the only source of heterogeneity is productivity and the rate of job destruction, respectively.

B. *Mismatch Unemployment*

The mismatch index allows us to construct the counterfactual unemployment rate, u_t^*, in the absence of mismatch. Using (10), the actual aggregate job-finding rate in the economy at date t can be written as

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

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 $\overline{\phi}_{xt}\Phi_t v_t^{\alpha}(u_t^*)^{1-\alpha}$. Therefore, the optimal job-finding rate (in absence of mismatch) is

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

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 can cause mismatch unemployment to remain above average for some time even if $\mathcal{M}_{xt}$ quickly reverts to its average after an increase, because it takes time for the additional unemployed to be reabsorbed. This is a pattern we observe 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. The gap between actual unemployment u_t and counterfactual unemployment u_t^* is mismatch unemployment.

In the next section we briefly discuss our methodology and the proper interpretation of our measure of mismatch unemployment. In the rest of the paper we apply this methodology to quantify the contribution of mismatch to the recent rise in the aggregate US unemployment rate.

C. *Interpretation of Our Measure of Mismatch*

Our formalizing of mismatch unemployment as "distance from a benchmark allocation" essentially follows the same insights of the vast literature on misallocation and productivity (Lagos 2006; Restuccia and Rogerson 2008; Hsieh and Klenow 2009; Moll 2011; Jones 2013). 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, or price determination). We simply take the empirical joint distribution of unemployment and vacancies across sectors as the equilibrium outcome.[13] Second, we construct the counterfactual distribution (in absence of mismatch) from a simple planner's problem which can be solved analytically. The strength of these two combined features is that finer disaggregation in the available microdata 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.

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

Our methodology yields a measure of *mismatch across sectors*—defined by the jointly observable characteristics of job vacancies and unemployed job seekers—not within sectors. Put differently, concluding that mismatch plays a small role at the level of two-digit occupations does not necessarily rule out its importance at the three or five-digit level.[14] It follows that, when quantifying the contribution of mismatch unemployment through our approach, it is important to clearly specify the level of disaggregation of the analysis. Moreover, our measure of mismatch captures the sectoral misallocation between job vacancies and *unemployed job seekers*. We therefore abstract from another class of job seekers, employed workers who search on the job. We conjecture that, in the generalized planner problem where the planner can let employed workers search for jobs in more productive sectors, optimality would push the planner toward equalizing the efficiency-weighted ratio of vacancies to total job seekers.[15] In Section VID, we verify that mismatch between vacancies and unemployment behaves very similarly to an index that also includes, among the job seekers, employed workers who report to search on the job.

The notion of mismatch in the baseline model without heterogeneity in productivity is very intuitive. In this economy, the planner wants to maximize employment (or minimize unemployment) since workers are equally productive everywhere. Once sectors differ in their productivity and/or in the expected duration of the matches formed, the planner wants to maximize the present discounted value of aggregate output. The planner's allocation of job seekers across sectors does not, therefore, necessarily minimize unemployment. Put differently, the planner's hires could, theoretically, be lower than equilibrium hires in a given period, and in that period the mismatch index M_{xt} could be negative. Reassuringly, in our empirical analysis, the estimated patterns of the M_{xt} index are always similar to those of the other indexes.

The empirical method we have developed allows us to learn about the relative importance of different dimensions of mismatch by partitioning the labor market based on several characteristics (e.g., industry, occupation, education, geography). Studying how mismatch dynamics vary across these dimensions is surely informative about the forces at work in the economy. However, our methodology is not well-suited to separately quantify the deeper sources of misallocation. This task requires specifying and solving a fully structural equilibrium model which, under the level of generality of our analysis, would be computationally unfeasible. Factors explaining the discrepancy between the empirical and planner's distribution of unemployment across sectors—that these structural models should incorporate—include moving costs of retraining or migration, relative wage rigidity, risk-aversion and imperfect insurance, or certain government policies that may hamper the reallocation of idle labor from shrinking to expanding sectors. Since moving costs are

[14] This caveat applies even at a very high level of disaggregation. Observing a high number of vacancies for web developers (a five-digit occupation) in Santa Clara county, and a high number of job seekers in that same labor market would be interpreted as a sign of low mismatch across narrowly defined sectors. However, a situation where those same job seekers do not have the technical knowledge required by the employers to staff their vacancies (e.g., the technology has changed and the skills of the unemployed have become obsolete), is a form of "skill mismatch."

[15] The other forces affecting the planner's solution depend on the details of how on-the-job search is modeled. For example, the degree of substitutability of unemployed and employed job seekers in the matching function determines the congestion effect that the marginal job seeker of one type imposes on the other type. Whether on-the-job search is costless, or has a cost in terms of foregone output or disutility, will determine the fraction of employed workers searching and their target sectors.

a characteristic of the physical environment which would also feature in a planner's problem, whereas our benchmark planner's allocation is derived under costless between-sector mobility, our calculations on the role of mismatch have the nature of an upper bound. Analysis by Herz and van Rens (2011) suggests that, relative wage rigidity (across locations and industries) is more important than moving costs as a source of mismatch. In light of their finding, our planner problem may provide a tight upper bound.

III. Data

We focus on three definitions of labor markets. The first is a broad industry classification. The second is an occupation classification, based on both the two and three-digit Standard Occupational Classification (SOC) system.[16] The third is a geographic classification, based on US counties and metropolitan areas (MSAs).[17]

To be empirically viable, our methodology calls for: (i) sectoral data on vacancies, unemployment, and the vacancy share of the matching function for the $\mathcal{M}_t$ index; (ii) the same data as in (i) plus market-specific matching efficiency parameters for the $\mathcal{M}_{\phi t}$ index; and (iii) the same data as in (ii) plus information on productive efficiency (productivity and separation rates) by sector for the $\mathcal{M}_{xt}$ index and its corresponding counterfactual. Deriving market-specific matching efficiencies, as well as the vacancy share, involves estimating matching functions, so it requires data on hires.

A. *Vacancies from the JOLTS and the HWOL*

At the industry level, we use vacancy data from the JOLTS, which provides survey-based measures of job openings and hires at a monthly frequency, starting from December 2000, for 17 industries roughly corresponding to the two-digit NAICS classification.[18] At the occupation and county level, we use vacancy data from the HWOL dataset provided by The Conference Board (TCB). This is a novel dataset containing the universe of online advertised vacancies posted on Internet job boards or in newspaper online editions. It covers roughly 16,000 online job boards and provides detailed information about the characteristics of advertised vacancies for three to four million unique active ads each month.[19] The HWOL database started in May 2005 as a replacement for the Help-Wanted Advertising Index of print advertising maintained by TCB.[20]

[16] See Tables C1–C3 in online Appendix C for a list of industries and occupations used in the empirical analysis. In total, there are 22 two-digit SOCs and 93 three-digit SOCs. We use all the two-digit categories with the exception of Farming, Fishing, and Forestry. We exclude three-digit SOCs exhibiting fewer than ten observations in the CPS unemployment counts at least once in the sample period. These small cells account for 60 percent of the three-digit SOCs, but represent only 15.6 percent of unemployed workers in the CPS.

[17] We focus on counties whose population is at least 50,000 and group together counties in the same metropolitan area. This procedure results in a total of 280 local labor markets.

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

[19] The data are collected for The Conference Board by Wanted Technologies. For detailed information on survey coverage, concepts, definitions, and methodology see the Technical Notes at http://www.conference-board.org/data/helpwantedonline.cfm.

[20] Our empirical analysis covers the December 2000–June 2011 period for the JOLTS, and May 2005–June 2011 for the HWOL.

Each observation in the HWOL database refers to a unique ad and contains information about the listed six-digit occupation, 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.[21] For 57 percent of ads we also observe the industry NAICS classification. The majority of online advertised vacancies are posted on a small number of job boards: about 60 percent of all ads appear on five job boards.[22]

It is worth mentioning some measurement conventions in the HWOL data. First, the same ad can appear on multiple job boards. To avoid double-counting, TCB uses a sophisticated unduplication algorithm that identifies unique advertised vacancies on the basis of the combination of company name, job title/description, city, or state. Second, there are some cases in which multiple locations (counties within a state) are listed in a given ad for a given position. TCB follows the rule that if the counties are in the same state or MSA, then the position is taken to represent a single vacancy, but if they appear in different MSAs and in different states, then they reflect distinct vacancies. In addition, the dataset records one vacancy per ad. In a small number of cases multiple positions are listed in one ad, but the convention used is one vacancy per ad.

More importantly, the growing use of online job boards over time may induce a spurious upward trend. Figure 1 plots 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 it from 2008 onwards, a pattern which may reflect the increasing penetration of online job listings over time. Nevertheless, the average difference between the two aggregate series is only about 16 percent of the JOLTS total, and the correlation between the two aggregate series is about 0.65. To the extent that this trend toward online recruitment does not differ too much across sectors, our calculations are not affected. In Section VIE, we propose a reweighing scheme for HWOL that aligns it more closely to JOLTS and show that our findings remain robust. We report additional detailed comparisons between the JOLTS and HWOL vacancy series in online Appendix B.B1.

B. *Unemployment from the CPS*

We calculate unemployment counts from the Current Population Survey (CPS) for the same industry and occupation classification that we use for vacancies.[23] For geography, we use the Local Area Unemployment Statistics (LAUS) which provides

[21] The education and wage information is imputed by TCB. Education is imputed from BLS data on the education content of detailed six-digit level occupations. Wages are imputed using BLS data from the Occupational Employment Statistics (OES), based on the occupation classification. For a subset of the ads we also observe the sales volume and the number of employees of the company, as well as the actual advertised salary range, but in this paper we do not attempt to use this additional information.

[22] The five largest job boards are CareerBuilder, Craigslist, JOBcentral, Monster, and Yahoo!HotJobs.

[23] Industry affiliations are not available for all unemployed workers in the CPS. From 2000–2010, on average about 13 percent of unemployed do not have industry information. But only about 1.5 percent of unemployed are missing occupation information. Some of these workers have never worked before and some are self-employed.

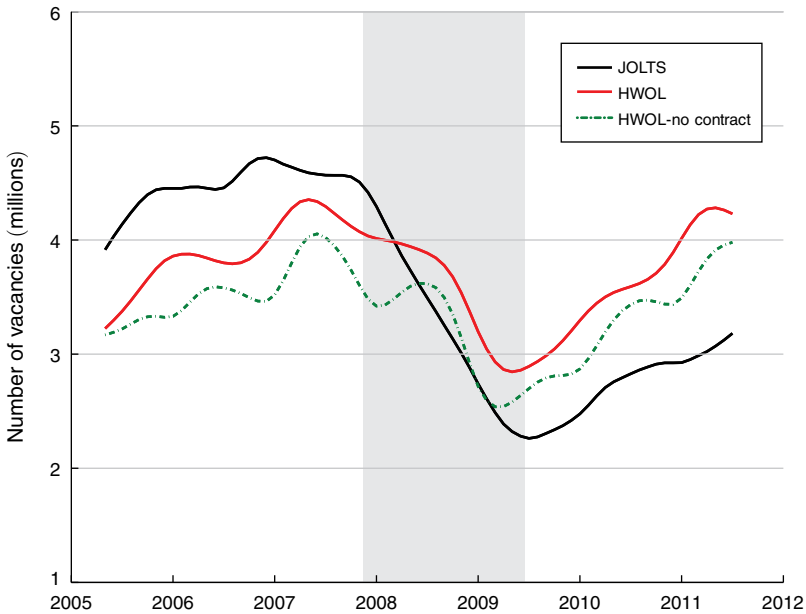

FIGURE 1. COMPARISON BETWEEN THE JOLTS AND THE HWOL AGGREGATE TIME SERIES

monthly estimates of total unemployment at the county and MSA level.[24] The CPS reports the industry and occupation of unemployed workers' previous jobs. We begin by assuming that all unemployed workers search only in the sector where they last worked. We relax this assumption in Section VI. 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.[25]

C. *Matching Functions*

To compute market-specific matching efficiency parameters, ϕ_i, and vacancy share α, we estimate aggregate and sector-specific (constant-returns to scale) matching functions using various specifications, estimation methods, and data sources. In particular, we follow Borowczyk-Martins, Jolivet, and Postel-Vinay (2013) in dealing with the well-known endogeneity issues in matching function estimation. Online Appendix B.B2 contains a detailed description of our methodology and results.

Our findings (see Table C4 in online Appendix C) indicate that a value of the vacancy share $\alpha = 0.5$ is appropriate. This value is roughly in the middle of the range of estimates used in other recent papers in the matching literature.[26] Moreover, our mismatch indices are typically highest for $\alpha = 0.5$; therefore, this value is consistent

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

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

[26] A few examples are $\alpha = 0.28$ in Shimer (2005); $\alpha = 0.5$ in Davis, Faberman, and Haltiwanger (2013); $\alpha = 0.54$ in Mortensen and Nagypál (2007); and α between 0.66 and 0.72 in Barnichon and Figura (2013).

with the spirit of reporting an upper bound for mismatch unemployment. Tables C6–C8 in online Appendix C contain estimates of sector-specific matching efficiencies.

D. *Productive Efficiency*

We use various proxies for productivity, depending on data availability. At the industry level, we compute labor productivity by dividing value added for each industry from the Bureau of Economic Analysis (annual data) by average employment in that industry from the Establishment Survey.[27] For the Abraham-Katz version of the mismatch index (see Section IC), we compute σ_ϵ as the variance of aggregate productivity growth (computed as the log change in GDP divided by aggregate employment), and estimate the industry-specific elasticities η_i from regressions of log sectoral productivity on log aggregate productivity.

At the occupation level, we use annual data on average hourly wages from the Occupational Employment Statistics (OES) for lack of a better proxy.[28] Similarly, at the county level, we use median weekly wage earnings from the Quarterly Census of Employment and Wages (QCEW).[29] We recognize that wage levels might be affected by factors other than productivity such as unionization rates, compensating differentials, and monopoly rents. 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.[30] 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. Because job destruction rates by occupation are not available, we compute the employment to unemployment transition rates by occupation in the last job from the CPS semi-panel. Figures C3 and C4 in online Appendix C show the evolution of productivity and job destruction rates for selected industries and occupations.

Finally, with respect to output from home production for the nonemployed, ζ, our quantitative analysis indicates that the impact of mismatch is the largest when $\zeta = 0$. In keeping with our measurement exercise's upper bound nature, we use this value in baseline calculations, but verify the robustness of our conclusions for a range of values for ζ between 0 and 0.25.

[27] See http://www.bea.gov/industry/.

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

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

[30] See http://www.bls.gov/bdm/. We recognize this is an imperfect proxy for separations, but monthly employment-unemployment transitions computed from CPS semi-panel at the industry level are much noisier, and during 2001–2010, only 16 percent of quits ended in unemployment, as opposed to 91 percent of layoffs (see Elsby, Hobijn, and Şahin 2010).

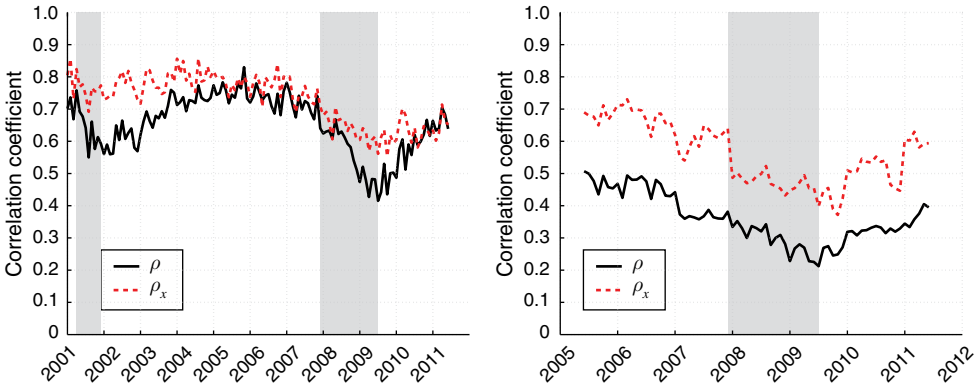

FIGURE 2. CORRELATION COEFFICIENT BETWEEN u AND v SHARES ACROSS INDUSTRIES (*Left panel*) AND TWO-DIGIT OCCUPATIONS (*Right panel*)

IV. Results

We begin by documenting the dynamics of the cross-sectoral correlation between vacancy and unemployment shares, which anticipates some of our findings on the mismatch indexes. Next, we study industry-level, occupational-level, and geographical mismatch unemployment, in that order.

A. *Correlation between Vacancy and Unemployment Shares*

From our definition of mismatch, it is clear that mismatch indexes are closely associated with 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 (left panel) and occupation (right panel) over the sample period. For each case, we report two different correlation coefficients motivated by the definitions of the mismatch indexes we derived in Section II. These are ρ: between (u_{it}/u_t) and (v_{it}/v_t), and ρ_x: between (u_{it}/u_t) and $(x_i/\overline{x}_t)^{\frac{1}{\alpha}}(v_{it}/v_t)$. The two series behave similarly. They drop sharply from early 2006 to mid-2009 and recover thereafter, indicating a relatively short-lived rise in mismatch during the recession.

B. *Industry-Level Mismatch*

The left panel of Figure 3 plots $\mathcal{M}_t$ and $\mathcal{M}_{xt}$ across two-digit industries.[31] 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

[31] 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.

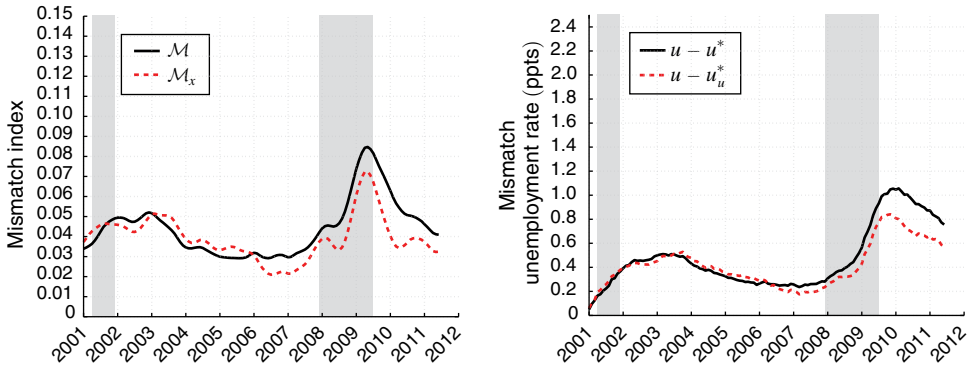

FIGURE 3. MISMATCH INDEX $\mathcal{M}_t$ AND $\mathcal{M}_{xt}$ BY INDUSTRY (*Left panel*) AND THE CORRESPONDING MISMATCH UNEMPLOYMENT RATES (*Right panel*)

2 to 3 percent per month, depending on the index used. In mid-2009, at the end of the recession, it had increased to roughly 7 to 8 percent per month, and it has since dropped again almost to its pre-recession level. To summarize, 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.[32]

How much of the observed rise in the unemployment rate can be explained by mismatch? Table 1 shows the change in mismatch unemployment between the average of 2006 and October 2009.[33] The main finding is that worsening mismatch across these 17 industries explains (depending on the index used) between 0.59 and 0.75 percentage points of the rise in US unemployment from 2006 to its 2009 peak, i.e., at most 14 percent of the increase. The right panel of Figure 3 shows mismatch unemployment—the difference between the actual and the counterfactual unemployment rates—at the industry level for the 2001–2011 period, computed as described in Section IIB. Mismatch unemployment has declined since early 2010, but it remains above its pre-recession levels. Figure C6 in online Appendix C shows mismatch indexes with one source of heterogeneity at a time, $\mathcal{M}_{\phi t}$, $\mathcal{M}_{zt}$, $\mathcal{M}_{\delta t}$, and the corresponding mismatch unemployment rates. The results are very similar.

In Section IC, we have shown how the planner's allocation rule changes under the alternative Abraham-Katz interpretation of sectoral employment movements. As

[32] To shed more light on the dynamics of the mismatch index, it is useful to examine the evolution of vacancy and unemployment shares of different industries, such as the individual components of the index. In Figure C5, we plot the vacancy and unemployment shares for a set of industries using the JOLTS definition in online Appendix C. The shares have been relatively flat in the 2004–2007 period. However, starting in 2007, vacancy shares started to change noticeably. Vacancy shares declined in construction and durable goods manufacturing while the health sector saw its vacancy shares increase. Concurrently, unemployment shares of construction and durable goods manufacturing went up while the unemployment share of the health sector decreased. Starting from 2010, sectoral unemployment and vacancy shares began to regress toward 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.

[33] The average unemployment rate was 4.6 percent in 2006 and 10 percent 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.

Table 1—Changes in Mismatch Unemployment at the Industry, Occupation, and County Levels

	Index	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$ (percent)
Industry	$\mathcal{M}$	0.26	1.01	0.75	13.9
	$\mathcal{M}_x$	0.24	0.84	0.59	11.0
	$\mathcal{M}_x^{AK}$	0.28	0.89	0.61	11.2
	$\mathcal{M}^{\alpha-het}$	0.39	1.10	0.71	13.1
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	0.67	1.90	1.22	22.5
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.35	1.24	0.90	16.6
	$\mathcal{M}_x^{v^*}(\varepsilon = 2.0)$	0.27	0.95	0.69	12.7
2-digit occupation	$\mathcal{M}$	0.85	2.00	1.15	21.3
	$\mathcal{M}_x$	0.42	1.02	0.60	11.1
	$\mathcal{M}_x^{v^*}(\varepsilon = 0.5)$	1.08	2.60	1.52	28.1
	$\mathcal{M}_x^{v^*}(\varepsilon = 1.0)$	0.75	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	0.14	2.5
2-digit × division	$\mathcal{M}$	0.81	1.71	0.90	16.9
2-digit	$\mathcal{M}$	0.68	1.53	0.85	16.0

Notes: All the differences are calculated as the difference between October 2009 and the average of 2006. Note that $\Delta u = 5.4$ percentage points. All calculations are monthly, except for the last two lines which are quarterly.

Table 1 shows, the corresponding index $\mathcal{M}_{xt}^{AK}$ implies a contribution of mismatch unemployment similar to the benchmark.[34]

Table C9 and Figures C8–C11 in online Appendix C contain a sensitivity analysis of industry-level mismatch with respect to values of α ranging from 0.3 to 0.7; alternative estimates of matching efficiency ϕ_ts which are separately estimated for the periods before and after the recession;[35] values of the home-production flow ζ ranging between 0 and 0.25 of aggregate productivity; using hires data from the CPS instead of the JOLTS; and using HWOL vacancy data by industry instead of the JOLTS. The results are very robust: the contribution of (two-digit) industry-level mismatch to the rise in the unemployment rate around the Great Recession varies between 0.5 and 1 percentage points.

C. *Occupation-Level Mismatch*

Figure 4 plots the $\mathcal{M}_t$ and $\mathcal{M}_{xt}$ indexes (left panels) and the resulting mismatch unemployment (right panels) for two- and three-digit SOCs. $\mathcal{M}_t$ index for two-digit occupations rises by almost 4 percentage points. Similar to the pattern observed

[34] Figure C7 in online Appendix C shows the mismatch index and the corresponding mismatch unemployment computed using the benchmark specification and this alternative interpretation.

[35] We denote this index as $\mathcal{M}_{xt}^{break}$.

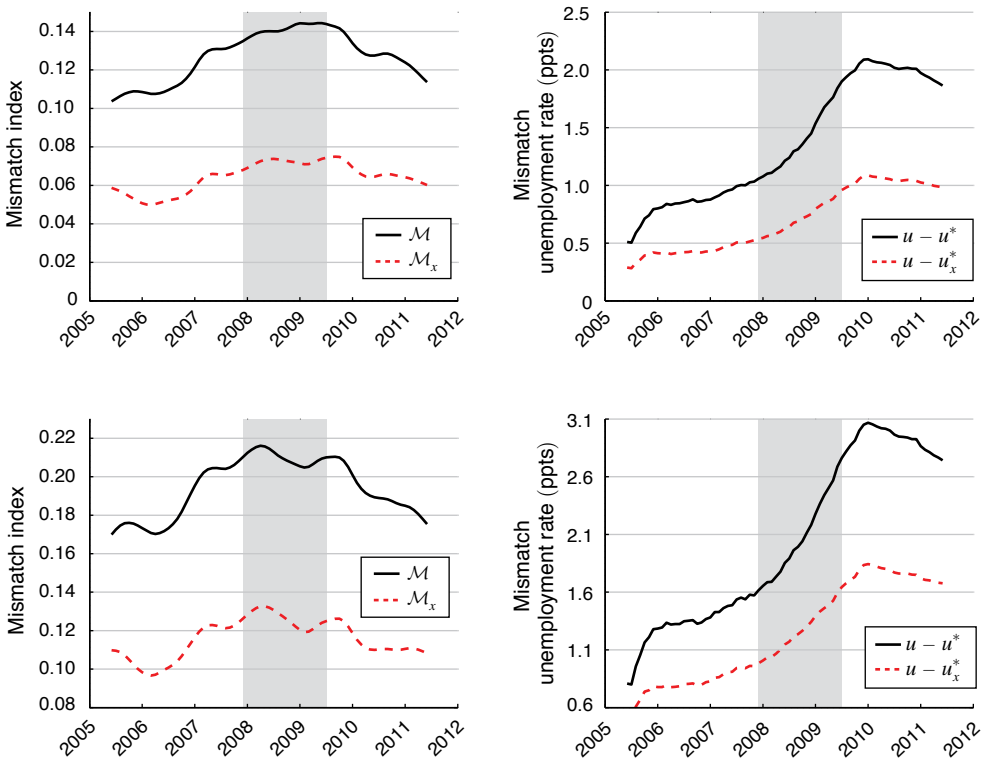

FIGURE 4

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

for industries, the rise in mismatch leads the recession by over a year. As seen in the figure and in Table 1, based on the $\mathcal{M}_t$ index, around 1.1 percentage points (or 21 percent) of the recent surge in US unemployment can be attributed to occupational mismatch measured at the two-digit occupation level. At the three-digit level, the portion of the increase in unemployment attributable to mismatch is around 1.6 percentage points, or roughly 29 percent of the rise in the unemployment rate.[36]

The $\mathcal{M}_{xt}$ index is lower than the $\mathcal{M}_t$ index and features a smaller rise, implying around 2 percent 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 percent of the increase) was due to mismatch at the two-digit and three-digit SOC levels, respectively. Therefore, similar to what we found for

[36] Figure C12 in online Appendix C shows the individual components of the index, the unemployment and vacancy shares of selected two-digit SOCs. 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 while the corresponding unemployment shares declined. Starting from 2010, unemployment and vacancy shares began to normalize, similar to the JOLTS data.

industries, the index that accounts for heterogeneity in matching and productive efficiency across occupations, implies a smaller role for mismatch unemployment.[37]

Acemoglu and Autor (2011) have argued that job polarization—the increasing concentration of employment in the highest-wage (non-routine) and lowest-wage (routine cognitive) occupations, with job opportunities in middle-skill (routine manual) occupations disappearing—is useful to interpret the long-run aggregate employment dynamics in the United States. Jaimovich and Siu (2012) extended this analysis to business cycle frequencies. We ask whether classifying all our two-digit occupations into these four categories (routine cognitive, routine manual, non-routine cognitive, and non-routine manual) captures most of the dynamics of mismatch or whether something is lost. We call this classification "Routine/Cognitive" and denote the corresponding mismatch index with $\mathcal{M}_t^{RC}$.[38]

Our findings are summarized in Table 1. Consistent with the existing literature, we do find that the vacancy (unemployment) share dropped (rose) faster for routine manual occupations relative to the other groups, but this classification can only account for about half of the increase in mismatch unemployment across the 21 two-digit occupations, suggesting a residual rise in mismatch within these four broad categories.[39]

Table C10 and Figures C14 and C15 in online Appendix C contain a sensitivity analysis on occupational-level mismatch at the two-digit level with respect to (i) the value of α; (ii) alternative estimates of matching efficiency ϕ_is separately estimated for the periods before and after the recession; and (iii) values of the home-production flow ζ ranging between 0 and 0.25 of aggregate productivity. Our findings remain robust to these alternative specifications.

Occupational Mismatch within Education Groups and within Regions.—Is occupational mismatch a more relevant source of unemployment dynamics for less skilled or for more skilled workers? A priori, the answer is ambiguous: more education means more adaptability, but also more specialized knowledge. To address this question, we define less than high school diploma, high school diploma or equivalent, some college or associate's degree, bachelor's degree or higher. Within each of these four groups, we analyze mismatch by two-digit occupation *within* each of these four education groups.

The CPS provides information on the education level of the unemployed. Recall that each job listing recorded in HWOL reports its six-digit occupation. The BLS provides information on the distribution of workers employed in each six-digit occupation broken down by their educational attainment.[40] We allocate the total

[37] Figure C13 in online Appendix C shows mismatch indexes with one source of heterogeneity at a time, $\mathcal{M}_{\phi t}$, $\mathcal{M}_{zt}$, $\mathcal{M}_{\delta t}$. The corresponding mismatch unemployment rates at the two-digit occupation level are reported in Table C10.

[38] We classify occupations at the two-digit level instead of directly using Acemoglu and Autor's 2011 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 C2 in online Appendix C for our classification of occupations into these four groups.

[39] Figure C16 in online Appendix C contrasts the unadjusted mismatch index across these four occupation groups against the index calculated at the two-digit level, and reports the implied path for mismatch unemployment.

[40] This information comes from the American Community Survey microdata from 2006–2008. 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.

Table 2—Changes in Mismatch Unemployment across Two-Digit Occupations for Different Education Groups Using $\mathcal{M}_t$

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

Notes: 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.

count of vacancies from HWOL in a given month for a given six-digit occupation to each of the four education groups we consider, proportionally to the educational attainment distributions from the BLS.[41] Finally, we aggregate up to the two-digit level to obtain vacancy counts for each occupation by education cell. The implicit assumption we make in using the BLS information is that the educational requirement of newly created vacancies, for each occupation, is equal to the educational content in the existing jobs for that same occupation.

The counterfactual exercises summarized in Table 2 reveal a 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 group with less than a high school education, mismatch explains a little less than 1 percentage point (12 percent) of the 8.5 percentage point increase in the unemployment rate of that group. For high school graduates, mismatch explains 0.89 (13 percent) out of the 6.9 percentage point increase in unemployment. For those with some college, mismatch explains about 1.0 (18 percent) out of a 5.3 percentage point rise in unemployment, and for college graduates 0.65 (24 percent) 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.[42]

In Figure 5 looking at occupational mismatch separately for each of the four US census regions reveals that the only region where our index is still significantly above its pre-recession level is the West, the region where the fall in house prices and the rise in unemployment were the sharpest.

D. *Geographical Mismatch*

We perform our geographical analysis on mismatch across US counties using the HWOL data on online job ads coupled with LAUS data on the unemployed.

Figure 6 shows the indexes $\mathcal{M}_t$ and $\mathcal{M}_{zt}$ and the corresponding mismatch unemployment rates. We find that geographic mismatch is very low (about one-tenth

[41] For robustness, we have experimented with other allocation rules, such as not imputing vacancies of a given six-digit SOC to an education level that accounts for less than 15 percent of the workers in that occupation. The results are very similar.

[42] Figures C17 in online Appendix C plots mismatch indexes within each broad education category. The index for college graduates is the only one which is still significantly above its 2006 level.

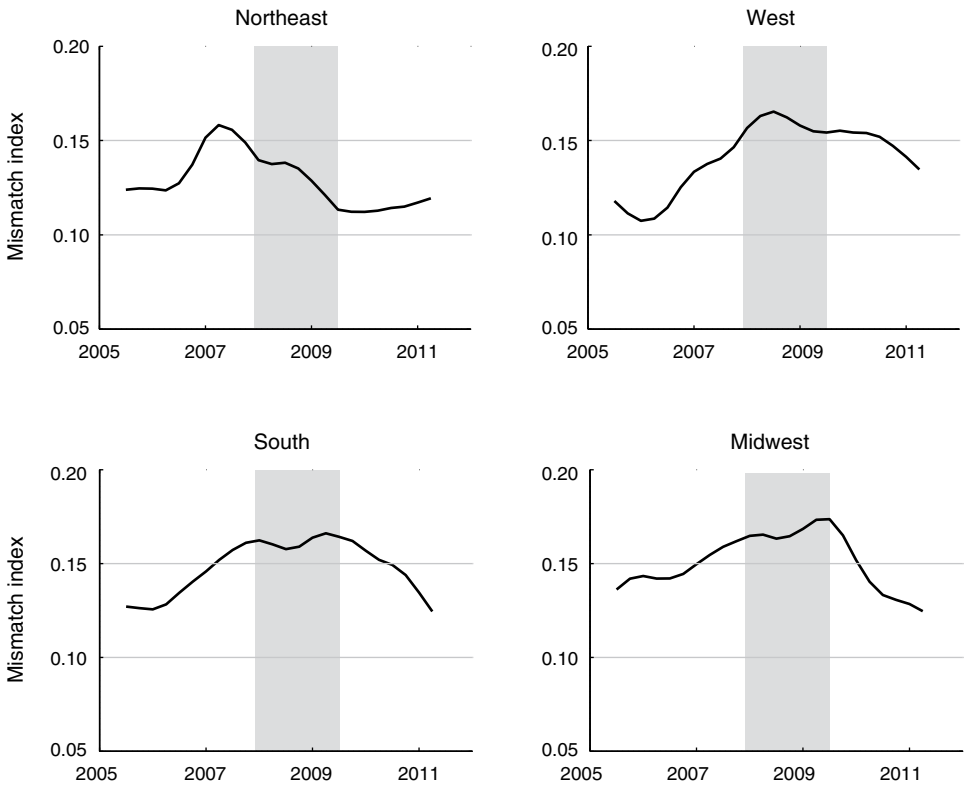

FIGURE 5. TWO-DIGIT OCCUPATIONAL MISMATCH INDEXES $\mathcal{M}_t$ IN THE FOUR US CENSUS REGIONS

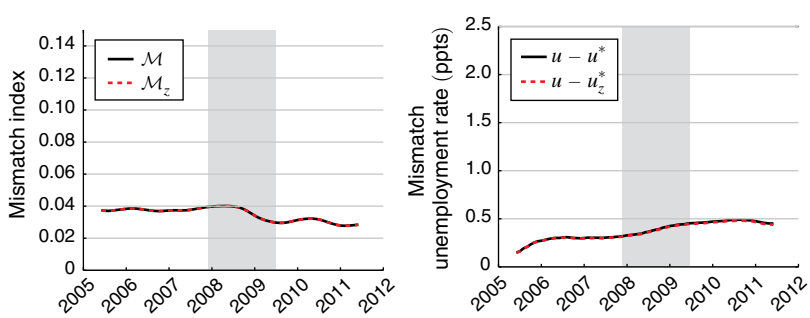

FIGURE 6. GEOGRAPHICAL MISMATCH INDEXES $\mathcal{M}_t$ AND $\mathcal{M}_{zt}$ BY COUNTY (*Left panel*) AND CORRESPONDING MISMATCH UNEMPLOYMENT RATES (*Right panel*)

of the two-digit occupation index, even though the number of sectors is ten times higher) and is essentially flat over the sample period. These two results are interesting because they indicate that the rise of the index with the number of sectors, as well as its countercyclicality, are not mechanical features of our methodology, but they depend on how the equilibrium distribution of unemployment and vacancies (a) varies across labor markets and (b) evolves over the cycle.

Unsurprisingly, the rise in mismatch unemployment implied by this index is around one-tenth of a percentage point, implying that geographical mismatch—

across US counties and MSAs—played a negligible role in the recent dynamics of US unemployment. This finding is consistent with other recent work that investigated the link between housing market and labor market using different methods. Examples include Schulhofer-Wohl (2010); Farber (2012); Karahan and Rhee (2012); Kothari, Saporta-Eksten, and Yu (2013).[43]

We also examine mismatch across labor markets jointly defined by occupation and location. Because of the small sample size of the CPS, we define sectors as the combination of two-digit occupations and the nine census divisions, and perform our analysis at the quarterly frequency. Both mismatch index and mismatch unemployment are very similar to those computed at the two-digit occupation level.[44]

E. *Is the Great Recession Different from the 2001 Recession?*

At the industry-level, the sample is long enough to allow a comparison of mismatch unemployment in the Great Recession to that of the 2001 recession. Figures 2 and 3 show that the fall in the cross-sectoral unemployment-vacancy correlation and the rise in our mismatch index is common to the last two downturns. In Table C11 in online Appendix C we report our calculations on the role of mismatch unemployment in 2001. We find that worsening mismatch accounted for a larger portion of the (smaller) rise in unemployment in the 2001 recession (23 percent instead of 11 to 14 percent). This finding echoes the fact that the employment dynamics for different occupational groups were much more asymmetric in 2001 than in 2008 (Jaimovich and Siu 2012).

V. 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 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 required to identify the shocks to the vacancy creation cost. These cost-shocks are needed to compute the planner's counterfactual vacancy distribution. We then proceed to formally explain this additional feedback effect of mismatch. Finally, we present our findings. Online Appendix A.A6 contains more details on all the derivations.

[43] We also compute geographic mismatch for the 50 US 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-based analyses are fully aligned with the county-based study.

[44] See Figure C18 in online Appendix C and Table 1.

A. *Measurement of the Vacancy Creation Cost*

Let the cost, in terms of final good, of creating v_{it} vacancies in sector i at date t be

$$K_{it}(v_{it}) = \kappa_{it}^{\varepsilon} \cdot \frac{v_{it}^{1+\varepsilon}}{1+\varepsilon}, \quad \text{with} \quad \varepsilon \in (0, \infty). \tag{14}$$

With this isoelastic specification, ε measures the elasticity of the vacancy creation cost, i.e., how the (log of the) marginal cost increases with the (log of the) number of vacancies.[45] The random variable κ_{it} shifts the cost of vacancy creation across sectors and over time. We let κ_{it} be independent of the other idiosyncratic shocks, and denote its conditional distribution as Γ_{κ}. The choice of how many vacancies to post takes place after observing sectoral and aggregate states, but before the allocation of unemployment across sectors.

Up to this point, we could conduct our analysis without modeling the behavior and choices of firms and workers in equilibrium. However, the measurement of $\{\kappa_{it}\}$ requires imposing a minimal amount of structure on the equilibrium data generating process. Three assumptions suffice: (i) free entry of vacancies in each sector; (ii) 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); and (iii) no within-market congestion externality, in the spirit of Hosios (1990).[46]

Free entry is the standard condition determining vacancies in this class of matching models. The choice of bargaining protocol is convenient because it enables us to remain agnostic about the equilibrium value of unemployment for a worker—therefore reducing to a bare minimum the structure needed on the equilibrium model. The Hosios condition isolates mismatch unemployment as the unique source of discrepancy between the efficient and equilibrium distributions of vacancies.

Under assumptions (i) and (ii), the equilibrium condition in the economy of Section IB with heterogeneity in $\{\phi_{it}, z_{it}, \delta_{it}, \kappa_{it}\}$ is

$$\kappa_{it}^{\varepsilon}(v_{it})^{\varepsilon} = \Phi_t \phi_{it} \left(\frac{u_{it}}{v_{it}}\right)^{1-\alpha} \lambda \frac{Z_t z_{it}}{1-\beta(1-\Delta_t)(1-\delta_{it})}, \tag{15}$$

stating that the marginal cost of a vacancy in sector i (the left-hand side), also heterogeneous 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 also that, as $\varepsilon \to \infty$, $v_{it} = 1/\kappa_{it}$, i.e., vacancies are exogenously determined. This special case corresponds to the economy of Section I.

[45] 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.

[46] 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.

All variables in condition (15) are observable, except for κ_{it} and ε. For a given value of the elasticity ε, we derive the sequence for κ_{it} that makes that condition hold exactly at every date t in each sector i. 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 (both observable) have been accounted for.[47] Then, we can use this cost sequence in the planner's vacancy creation condition to compute the planner's distribution of vacancies.

B. *Comparison between Equilibrium and Planner FOCs*

In online Appendix A.A6, we show that the planner problem of Section IB, augmented with a vacancy creation decision where the planner faces the cost function (14), yields the first-order condition

$$\kappa_{it}^{\varepsilon}(v_{it}^{*})^{\varepsilon} = \Phi_t \phi_{it} \left(\frac{u_{it}^{*}}{v_{it}^{*}}\right)^{1-\alpha} \alpha \frac{Z_t z_{it}}{1-\beta(1-\Delta_t)(1-\delta_{it})}, \tag{16}$$

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 effect of an additional vacancy on the probability of meeting an unemployed worker allocated to sector i.[48]

A comparison of equations (15) and (16) is instructive. Imposing the Hosios condition $\lambda = \alpha$ in (15), 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 searches for jobs in declining sectors, firms would create more vacancies than the planner in those sectors, amplifying the initial source of misallocation. Combining equations (15) and (16), we therefore arrive at the relationship

$$\frac{v_{it}}{v_{it}^{*}} = \left(\frac{u_{it}}{u_{it}^{*}}\right)^{\frac{1-\alpha}{1-\alpha+\varepsilon}},$$

which demonstrates that the extent to which mismatch unemployment (i.e., deviations of u_{it} from u_{it}^{*}), translate into misallocation of vacancies in equilibrium (i.e., deviation of v_{it} from v_{it}^{*}) depends on the value of the elasticity ε. If the marginal cost function is steep (ε high), large differences in the ratio (u_{it}/u_{it}^{*}) and, therefore,

[47] 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 2014) 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_{it}. A planner subject to the same asymmetric information would face the same fluctuations in κ_{it}.

[48] For ease of exposition, in equation (16) we have already set the flow output from nonemployment ζ to zero, since this is the value we use in the quantitative analysis (to facilitate the comparison with the baseline model). Recall that in the model with exogenous vacancies we used $\zeta = 0$ because we found that it is the value that maximizes the role of mismatch. All the derivations in online Appendix A.A6 are obtained for the general case $\zeta \geq 0$.

in meeting probabilities and expected output gains, translate into small differences in the ratio (v_{it}/v_{it}^*). In this case, the planner's vacancies are close to equilibrium vacancies, as assumed in our benchmark analysis. If, instead, ε is close to zero, the misallocation of unemployed workers across sectors translates "one-for-one" into the distribution of vacancies.

In online Appendix A.A6, 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:

$$f_t^* = f_t \cdot \underbrace{\frac{1}{(1-\mathcal{M}_{xt})}}_{\text{Direct Effect}} \cdot \underbrace{\left(\frac{u_t}{u_t^*}\right)^{\alpha}}_{\substack{\text{Feedback}\\ \text{through } u}} \cdot \underbrace{\left[\left(\frac{\overline{\phi}_{xt}^*}{\overline{\phi}_{xt}}\right) \cdot \left(\frac{v_t^*}{v_t}\right)^{\alpha}\right]}_{\substack{\text{Feedback}\\ \text{through } v}}, \tag{17}$$

where $\overline{\phi}_{xt}$ is given by equation (11) and $\overline{\phi}_{xt}^*$ 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 mismatch feedback effect that operates through vacancies and has two components. Mismatch reduces the aggregate job-finding rate, one, by distorting the distribution of vacancy shares across sectors (the first term in the square brackets), and, two, lowering total vacancies (the second term).

C. *Results*

The first challenge we face is to choose a value for the marginal cost elasticity ε. Here, we rely on the existing literature. Merz and Yashiv (2007) specify a cost function where the argument is hires, and estimate an elasticity of 2.40 on aggregate US time series. Given a Cobb-Douglas specification for the matching function and a value for $\alpha = 0.5$, their estimate translates into an elasticity with respect to vacancies of 1.20. Coşar, Guner, and Tybout (2010) use establishment-level data for Colombia and estimate ε to be 1.085. Lise and Robin (2013) report an estimate of ε of 1.12 based on aggregate US time series. In all these papers, the identification of ε comes from the response of vacancies and employment changes to productivity shocks, and ε is precisely estimated. We conclude that existing estimates of ε, at various levels of disaggregation, are quite tightly centered around one.

Given ε, we can estimate the sector-specific vacancy cost creation vector $\{\kappa_{it}\}$. Our estimates of vacancy costs κ_{it} increase for almost all industries and occupations during the recession, therefore contributing to the observed vacancy drop. Figure C19 in online Appendix C plots the estimated sequences of κ_{it} in selected industries and occupations for the case $\varepsilon = 1$. Next, we compute the distribution of the planner's vacancies and the implied planner's aggregate job-finding rate with endogenous vacancies (17), which we then feed into the law of motion for the unemployment rate to perform our counterfactual exercise.

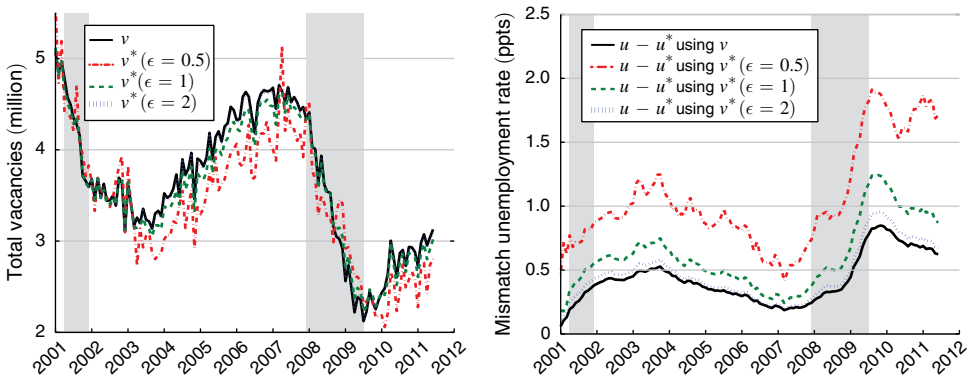

FIGURE 7. AGGREGATE VACANCIES (*Left panel*) AND CORRESPONDING MISMATCH UNEMPLOYMENT RATES (*Right panel*) AT THE INDUSTRY LEVEL USING ENDOGENOUS VACANCIES SPECIFICATION WITH JOLTS

Table 1 summarizes the results.[49] We first present our analysis by industry. Figure 7 (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) only occur for low values of the cost elasticity ε. For $\varepsilon \geq 1$, planner and equilibrium vacancies line up closely. This finding is reflected in the calculation of mismatch unemployment (right panel). For $\varepsilon = 1$, with endogenous vacancy creation, mismatch unemployment rises by 0.9 percentage points between 2006 and October 2009, that is only an additional 0.3 percentage points relative to the exogenous vacancy calculation. 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 8 indicates, the contribution of mismatch unemployment to the rise in the US unemployment rate between 2006 and October 2009 is 1.1 percentage points. For $\varepsilon = 0.5$, it increases up to 1.5 percent, or 28 percent 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 IV 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 specification 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 below $1/2$. While our current knowledge suggests that such a range is not too plausible, the number of available empirical estimates of this parameter is still small, so more research is needed to firmly establish this inference.

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

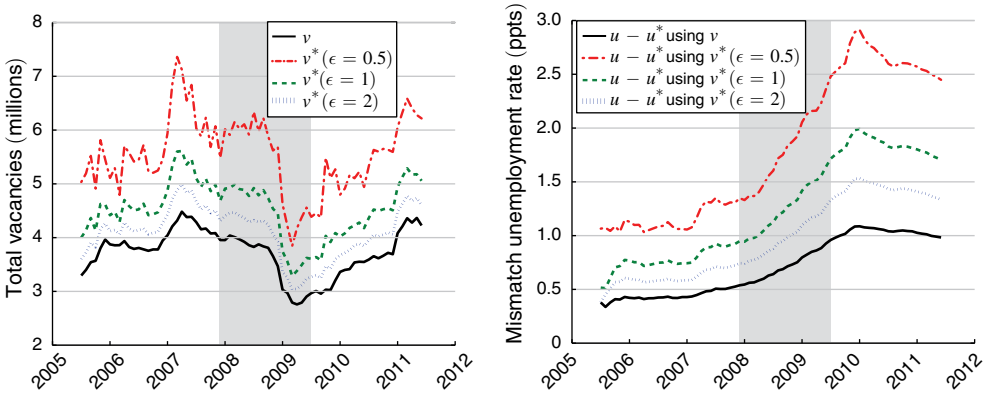

FIGURE 8. AGGREGATE VACANCIES (*Left panel*) AND CORRESPONDING MISMATCH UNEMPLOYMENT RATES (*Right panel*) AT THE OCCUPATION LEVEL USING ENDOGENOUS VACANCIES SPECIFICATION WITH THE HWOL

VI. Robustness on Inputs and Specification of the Matching Function

The matching function is a key ingredient of our analysis. In this section we investigate a number of potential concerns that relate to the measurement of its inputs (job seekers and job vacancies) and to its specification.

Our unemployment counts for industry and occupation are calculated from the CPS samples. We explore whether this random sampling can generate a bias in our mismatch index. With respect to job seekers, we have assumed that each unemployed worker is searching in the same industry or occupation as the one where she was last employed. Here, we correct our index for the direction of search based on observed unemployment-employment transitions. Since the focus of our study is on mismatch *unemployment*, so far we have only included unemployed workers among job seekers in all our calculations. It is useful to ask whether our findings are robust to broader definitions of job seekers which includes (i) discouraged workers, and (ii) employed workers searching on the job. The HWOL data on aggregate vacancies show a stronger upward trend than their JOLTS counterpart. If this trend is uneven across sectors, it may bias our mismatch measures. Here we assess the magnitude of this bias. Finally, we have assumed that the input shares of vacancies and unemployment $(\alpha, 1 - \alpha)$ are constant across sectors. This assumption is crucial for maintaining tractability, but the model can be solved numerically with heterogeneous shares to confirm this restriction does not drive our findings.

Since the endogenous vacancy creation margin did not substantially affect our results section, we use the baseline model with an exogenous distribution of vacancies. In this section, with the exception of the industry and occupation level adjustment for the direction of search and heterogeneity in input shares—which requires a long time series and is therefore done at the industry level—we perform our sensitivity analysis for two-digit occupations. Finally, we use $\mathcal{M}_t$ (the index unadjusted for heterogeneity) since, as is clear from Table 1, it leads to the largest role for mismatch. All the results of the robustness checks in this section are summarized in Table 3.

Table 3—Changes in Mismatch Unemployment across Two-Digit Occupations Using the Baseline Index $\mathcal{M}_t$ with Different Adjustments

	$u_{06} - u^*_{06}$	$u_{10.09} - u^*_{10.09}$	$\Delta(u - u^*)$	$\Delta(u - u^*)/\Delta u$ (percent)
$\mathcal{M}$	0.85	2.00	1.14	21.3
$\mathcal{M}^{u-adj}$	0.84	2.00	1.16	21.4
$\mathcal{M}^D$ (all D in U)	0.92	2.03	1.11	20.6
$\mathcal{M}^D$ (D from constr. and prod. in U)	1.06	2.33	1.27	23.4
$\mathcal{M}^E$ (E: weighted by search time)	0.78	1.90	1.13	20.9
$\mathcal{M}^E$ (E: fraction searching)	0.79	1.97	1.18	21.8
$\mathcal{M}^{v-adj}$	0.92	2.12	1.19	22.1

Notes: The second row displays the adjustment for the direction of search. The first adjustment for discouraged (D) workers (third row) counts all discouraged workers as unemployed (U) while the second one (fourth row) only counts discouraged workers from construction and production as unemployed. The first adjustment for employed (E) job seekers (fifth row) is done by using the time used for job search by the employed relative to the unemployed while the second adjustment (sixth row) assumes that all employed who report positive search time are counted as unemployed. The seventh row reweighs vacancies from HWOL. All the changes are calculated as the difference between October 2009 and the average of 2006.

A. *Sampling Error as a Potential Source of Bias*

In Section IV we documented a positive correlation between unemployment and vacancy shares across industries and occupations. Under this scenario, classic measurement error in sectoral unemployment counts may lead to an upward bias in our mismatch index because it artificially lowers the cross-sectoral correlation between vacancy and unemployment shares toward zero (an example of "division bias").

To assess the size of the bias, we draw 5,000 independent samples, with replacement, from our CPS data at the two-digit occupation and industry level. Each bootstrapped sample is of the same size as the original CPS sample.[50] For each sample, we compute the mismatch index. The mean index computed from the resulting sampling distribution is virtually identical to our point estimate, suggesting that this potential source of bias is quantitatively negligible. With the sampling distribution in hand, we are also able to compute confidence intervals for the mismatch index and for mismatch unemployment. The 95 percent confidence band for mismatch unemployment is around 0.2 percentage points in both cases, thereby confirming that our estimates are quite precise. See Figure C20 in online Appendix C.

B. *Adjustment for Direction of Search*

We now relax the assumption that unemployed workers search in their last sector of employment, and propose an alternative calculation of the number of job seekers in each industry or occupation by exploiting the semi-panel dimension of the CPS. Respondents in the CPS are interviewed for several consecutive months and we can track unemployed workers who find new employment from one month to the next and record: (i) industry/occupation of the job prior to the worker's unemployment spell; (ii) industry/occupation of the new job. We then create annual transition matrices

[50] We did it in two ways: (i) using the unweighted microdata from the CPS, and (ii) using the population weights in the CPS. Results are almost identical.

(from sector i to sector j) by aggregating monthly flows, as in Hobijn (2012). 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. We call this index $\mathcal{M}_t^{u-adj}$. The method is outlined in detail in online Appendix B.B3.[51]

The second row of Table 3 shows that, when using adjusted unemployment counts by occupation, the contribution of mismatch to the rise in the US unemployment rate is virtually the same as in the baseline (first row).[52] The estimated transition matrices by industry and occupation reveal that the bulk of unemployed workers keep searching in their previous employment sector. This is the key reason our findings are robust to this adjustment.

C. *Adjustment for Discouraged Workers*

According to the CPS, an individual is unemployed if 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 become discouraged by unsuccessful job searching and reduce their search intensity enough to be classified as out of the labor force in the official statistics. This grey area between unemployment and nonparticipation is occupied by "discouraged workers."[53]

If workers from certain occupations are more likely than others to become discouraged (and exit from unemployment) or remain discouraged (and delay re-entry into the unemployment ranks), our mismatch measures—based on the official unemployment counts—may be biased. For example, if most of the discouraged workers who dropped out of the labor force during the last recession originate from the construction sector, then the number of unemployed would be an underestimate of the true number of potential job seekers in the construction sector. In this example, actual mismatch would be larger than what we measure when including only the unemployed among the job seekers. However, if the number of discouraged workers across sectors is roughly proportional to that of the unemployed, then the effect of this adjustment would be minor.

To correct for this potential source of bias, we count workers in the CPS classified as "discouraged not in the labor force" (D), record their previous occupation, and add them to the corresponding unemployment stock, month by month, for the entire sample period.[54] Table C12 in online Appendix C reveals that, on average,

[51] Figures C21 and C22 in online Appendix C 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.

[52] Figure C23 in online Appendix C plots both the mismatch index $\mathcal{M}_t^{u-adj}$ and the corresponding mismatch unemployment by two-digit occupation and by two-digit industry.

[53] The CPS 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."

[54] The information about previous occupation of discouraged workers is incomplete. We therefore compute the distribution of previous occupations and we impute it (as if that was a random subsample) to the entire sample from the subsample of discouraged workers for which we have this information (around 10 percent of the total). We

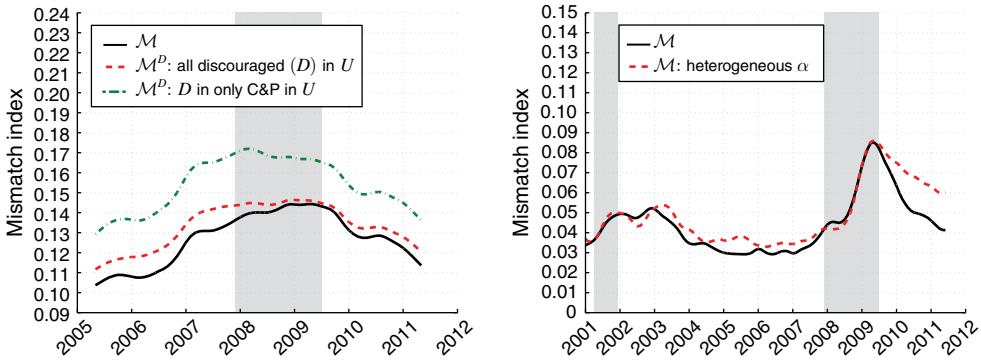

FIGURE 9

Notes: Mismatch index $\mathcal{M}_t^D$ by occupation including all discouraged (D) workers and only discouraged workers in construction and production (C&P) in unemployment (U) (left panel). Industry-level mismatch index $\mathcal{M}^{\alpha-het}$ computed with vacancy share parameter α estimated separately by industry (right panel).

the distributions of discouraged and unemployed workers are strikingly similar across occupations—the correlation is around 0.95. As a consequence, including discouraged workers only marginally affects the job seeker shares of different occupations. As Table 3 and Figure 9 show, the difference between the modified mismatch index, which we call $\mathcal{M}_t^D$, and the original index is quantitatively insignificant.

Next, to maximize the potential impact of such a correction, we only count discouraged workers in construction and production related occupations (mostly manufacturing) as unemployed, the occupation groups with the largest increase (decrease) in their unemployment (vacancy) share. Once again, the adjustment has small effects: the contribution of mismatch to the rise in the unemployment rate is 23.4 percent as opposed to 21.3 percent in the baseline case. All these results are reported in Table 3, and Figure C24 in online Appendix C shows the plot of mismatch unemployment.

D. *Adjustment for Employed Job Seekers*

Since the CPS does not have any information on employed workers' job search behavior, we use the American Time Use Survey (ATUS) to impute the number of employed job seekers in each sector. The ATUS reports the amount of time respondents devoted to various activities on the day preceding the day of the interview, including time spent on job search activities. In addition, it reports the individual's occupation (two-digit SOC) and her employment status. These data allow us to make an adjustment for on-the-job search. The correction is in the same spirit as the one for discouraged workers, i.e., broadening the notion of job seekers. This modified index is called $\mathcal{M}_t^E$.

have also tried an alternative strategy where we identified those workers who flowed from unemployment to discouragement between month t and $t+1$ and we added them back to the unemployment pool in the occupation of origin at month t. Results are similar with both methods, but the effect of this adjustment is larger for the first strategy and, hence, in what follows we only report results for that case.

We implement two versions of this adjustment. First, we compute the ratio between the average time spent searching by employed workers in occupation i and that spent by the unemployed, and augment the job seeker count in occupation i in month t with a number equal to that ratio times the CPS employment stock in this same occupation-month.[55] This method's shortcoming is that, if employed workers allocate less time to job search because they are more effective, we underestimate the contribution of employed job seekers. In our second version, we compute the number of all the workers employed in occupation i who report any positive amount of time spent searching for another job and add this to the unemployment stock in occupation i.[56]

These modifications do not result in major changes in the distribution of job seekers across occupations and thus have very small effects on our mismatch measures.[57] The plot of the modified mismatch index is shown in Figure C25 in online Appendix C.

E. *Reweighting of HWOL Vacancies*

The two main concerns with the HWOL data are that some sectors may systematically over- or under-use online recruitment tools compared to the aggregate and that some sectors may have faster or slower upward trends in the penetration of online advertisement. To address these concerns, we reweight HWOL vacancy counts by occupation to match the total JOLTS vacancy counts month by month by industry and region. Online Appendix B.B4 describes our approach in detail.

Table C13 in online Appendix C reports the estimated weights by industry and region. A low (high) weight means that sector or region makes use of online recruitment boards more (less) than the aggregate economy. Our findings are quite intuitive. Finance, real estate, and professional services are among the most overrepresented industries in online recruitment, while accommodation, government, and construction are among the most underrepresented. Weights can change over time. However, the correlation between the 2005–2006 and the 2010–2011 weights is 0.90, indicating that the upward trend is quite common across sectors.

When we recompute the mismatch index using these reweighted vacancy counts by two-digit occupation ($\mathcal{M}_t^{v-adj}$) we do find a slightly higher increase in occupational mismatch (see Figure C26 in the online Appendix), but as can be seen in Table 3, the counterfactual exercise yields results similar to our baseline calculation with the raw HWOL data. Overall, these findings are encouraging and, over time, more will be learned about the virtues and limitations of this new dataset. For the

[55] The ATUS has a considerably smaller sample size relative to the CPS, so we can only make this adjustment for each occupation by pooling all the years (2003–2011) together.

[56] For this extension, we do not perform a correction for the direction of search, as we did for unemployed job seekers. A recent paper by Hyatt and McEntarfer (2013) uses Longitudinal Employer-Household Dynamics (LEHD) data to calculate the industries of origin and destination of employment-to-employment flows. We calculated the correlation between the entries of their transition matrix and the entries of the one we estimated for unemployed workers in Section VIB. This correlation is very high (0.96), suggesting that our correction for on-the-job search would be robust to a further correction for the direction of search, as the one proposed for the unemployed job seekers.

[57] Over time, the correlation between the modified and original unemployment shares of occupations is between 0.987 and 0.997 with the first method; it is above 0.999 with the second method. The average absolute difference between the modified and the original index is 0.01 when we use the first method while the second method yields 0.007.

moment, one should bear in mind that results based on HWOL may be not as definitive as those based on JOLTS.[58]

F. *Sectoral Heterogeneity in* α

So far, we have assumed that the elasticity of hires to vacancies (α) in the matching function is the same for all sectors. Here we relax this assumption and follow the derivation in online Appendix A.A7 to numerically solve for the sectoral mismatch index and for mismatch unemployment, when α varies across sectors. We perform this analysis by industry because we need a long time series to precisely estimate α_i sector by sector, and JOLTS has over 50 data points more than HWOL. Table C14 in online Appendix C reports the estimates of α_i and the implied new estimates of ϕ_i by industry. There is some variation in α_i across industries and, while most of these differences are statistically insignificant, there are sectors with large elasticities (e.g., Health and Government, where α_i is between 0.7–0.8) and others with elasticities half as large (e.g., Construction and Real Estate, where α_i is between 0.35–0.4).

How much does this heterogeneity affect our estimates of mismatch unemployment at the industry level, relative to the homogeneous α case? Figure 9 shows that the two mismatch indexes track each other closely until the end of the recession, but the index calculated allowing for heterogeneity in α $(\mathcal{M}_t^{\alpha-het})$ declines more gradually afterwards. As a result, mismatch unemployment (displayed in Figure C27 in online Appendix C) remains higher than its homogeneous α counterpart throughout 2010, but only by 0.2 percentage points.

VII. Conclusion

In this paper, we developed a framework to coherently define and measure mismatch unemployment. We use this framework to ask how much sectoral mismatch contributed to the dynamics of US unemployment around the Great Recession. Our findings indicate that mismatch across counties, two-digit industries, and three-digit occupations explains around $1/3$ of the recent rise in the US 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 for each level of disaggregation we analyzed.

While our approach admittedly does not put us in the best position to separately identify the many potential causes of mismatch, we argue that analyzing different layers of disaggregation (e.g., occupation, industry, education, geography), as we do, is informative. The absence of an increase in geographical mismatch casts doubts on the house-lock hypothesis, a conclusion in line with existing research (e.g., Schulhofer-Wohl 2010; Farber 2012; Karahan and Rhee 2012; Kothari,

[58] In a previous version of the paper (Şahin et al. 2012) we also address the issue that vacancies may be measured with error (in both JOLTS and HWOL), since not all hires occur through formal advertisement (see, e.g., Galenianos 2012, for an analysis of hiring through referrals). We show that markets where vacancies are severely underreported look like markets with higher matching efficiency, and argue that our calculations are still appropriate. Intuitively, it makes no difference to the planner whether ϕ_{it} is high in a sector because pure matching efficiency is high or because actual vacancies are larger than those formally advertised: in both cases, the planner would like to allocate many job seekers to that sector.

Saporta-Eksten, and Yu 2013). Occupational mismatch plays a nonnegligible role, especially for higher-skill workers. This leaves room for explanations based combinations of labor demand shifts with human capital specialization, relative wage rigidity, and government policies. Kambourov and Manovskii (2009); Alvarez and Shimer (2011); Carrillo-Tudela and Visscher (2013); and Wiczer (2013), among others, have proposed equilibrium models where unemployed workers accumulate specific human capital and, in equilibrium, make explicit mobility decisions across distinct labor markets. Going forward, these frameworks should be potentially well-suited to investigate the structural causes of mismatch unemployment, to uncover why job seekers search for work in the wrong sectors.

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