How Tight is the Labor Market?*

Katharine G. Abraham
University of Maryland

John C. Haltiwanger
University of Maryland

May 2019

*We are grateful to Lea Rendell for excellent research assistance, to Daniel Aaronson, Jason Faberman, Chris Nekarda and Robert Valletta for helpful conversations at an early stage of the project, and to colleagues at the University of Maryland for comments during a brown bag seminar that helped to sharpen our thinking about these issues.

…with the unemployment rate well below estimates of its longer-term normal level, why isn't the FOMC tightening monetary policy more sharply to head off overheating and inflation? …while the unemployment rate is below the Committee's estimate of the longer-run natural rate, estimates of this rate are quite uncertain.

Federal Reserve Chair Jerome Powell, August 2018, Jackson Hole

… factors determining maximum employment "may change over time and may not be directly measurable," and … assessments of the level of maximum employment "are necessarily uncertain and subject to revision……(I)n its 2012 statement,… the FOMC explicitly recognized that our assessments of the degree of slack must be based on a wide range of variables and will require difficult judgments about the cyclical and structural influences in the labor market.

Federal Reserve Chair Janet Yellen, August 2014, Jackson Hole

A significant puzzle for U.S. central bankers has been the discrepancy between what available data seem to be telling us about the tightness of the labor market and the apparent lack of upward pressure on wages and prices. Unemployment is as low as it has been since the 1960s. The ratio of job vacancies to unemployment, a measure of labor market tightness available since 2000 that is displayed in Figure 1, is at a series high. As can be seen in Figure 2, however, both wages and prices have been surprisingly stable. There are a number of possible explanations for why wages and prices are not growing more rapidly. Inflation expectations may be better anchored than in the past (Ball and Mazumder 2014, Blanchard 2018); globalization could have flattened the Phillips curve (Bean 2006; Auer, Borio and Filardo 2017; Jasova, Moessner and Takats 2018); or workers may simply have less bargaining power than in the past (Krueger 2018). Another potential contributing factor, and the focus of our paper, is that existing measures could be doing a poor job of capturing the true state of the labor market.

For a simple summary of labor market conditions, observers and analysts long have turned to the unemployment rate—the share of the labor force that is not employed but wants to work, is available to work and has actively searched for work within the past four weeks. The unemployment rate exhibits clearly cyclical behavior, rising during downturns and falling during recoveries, and it is tempting to view it as a sufficient statistic for understanding the state of the labor market. The standard approach to estimating the natural rate of unemployment—essentially, the rate of unemployment at which the labor market is in a sustainable equilibrium, with demand-induced inflation neither accelerating nor decelerating—is to infer it from an equation in which wage growth or price growth is regressed on variables intended to capture inflation expectations and the unemployment rate. This relationship is the familiar expectations-augmented Phillips curve. The basic model typically is modified to account for structural changes in the labor market and other factors that may affect the relationship between unemployment and inflation. Unfortunately, estimates of the natural rate obtained using the Phillips curve approach are notoriously unstable, creating considerable uncertainty in the assessment of labor market tightness.

A complementary approach is to think about unemployment within the framework of search and matching in the labor market. Rather than being pinned down only by its influence on wage and price inflation, unemployment also is pinned down by the constraint that, in steady state, the rate at which new job openings are created must equal the rate at which people are hired into previously vacant jobs. This constraint provides additional information that can be used to identify the natural rate of unemployment. There are, however, some important complications. For one thing, different groups among the unemployed may be more or less likely to move into employment. Data showing that a higher-than-usual share of the unemployed are long-term unemployed, for example, might lead an analyst to conclude that effective unemployment is lower than suggested by the unemployment rate. Further, the unemployed are not the only people who may be available to fill vacant jobs. Data showing that an unusually large number of those out of the labor force say they would like to work or an unusually large share of workers are part-time but would have preferred full-time work, for example, might lead the same analyst to conclude that effective unemployment is higher than suggested by the unemployment rate.

What has been lacking is a well-accepted framework for incorporating these insights into a meaningful overall assessment of labor market conditions. We build on existing models of search and matching in the labor market (see, e.g., Diamond 1982, Blanchard and Diamond 1992, Mortensen and Pissarides 1994, Pissarides 2000) to provide such a framework. In the standard search and matching approach, a higher ratio of vacancies to unemployment—a larger number of jobs that employers would like to fill relative to the number of unemployed people available to fill them—implies a tighter labor market and thus a labor market that is closer to maximum employment. As emphasized in a number of recent empirical studies, however, most new hires originate from out of the labor force or from another job (job-to-job flows) rather than from unemployment. There is also empirical evidence (see, e.g., Davis, Faberman and Haltiwanger 2013) that the intensity with which firms recruit to fill their vacancies varies cyclically and that this variation in recruiting intensity helps to account for the observed cyclical variation in job-finding and job-filling rates. Our framework builds on the search and matching literature to propose a generalized framework that accounts both for variation in the availability of potential new hires, drawn not only from the unemployed but also from those currently out of the labor force or already working, and for variation in the intensity with which employers seek to fill their jobs. Based on this framework, we define a generalized measure of labor market tightness that is equal to the ratio of effective vacancies (recruiting intensity times measured vacancies) to effective searchers (a weighted sum of the different groups within the working age population with weights based on relative job search intensities).

A considerable body of recent theoretical and empirical research motivates our framework. The challenge is to translate the ideas and findings from this literature into a workable generalized index of labor market tightness. We have taken a first step in this direction by producing a generalized index that offers a proof of concept. Our generalized labor market tightness index undoubtedly can be improved upon, but we show that even this first version dramatically outperforms the standard labor market tightness measure as a predictor of the share of vacant jobs that employers are able to fill. In competing models of the job-filling rate (hires per vacancy) for the period from 2000 to the present, the model based on our prototype generalized index has a root mean squared error that is less than 25 percent as large as that based on the standard measure. We view this as important evidence that a generalized index of the sort we are proposing can provide a useful measure of labor market tightness.

The paper proceeds as follows. Section I develops the organizing framework that guides our analysis. In Section II, we review the recent theoretical and empirical literature motivating our approach. Section III presents our prototype generalized labor market tightness measure and investigates its properties relative to those of the standard measure. Section IV offers some concluding remarks and a discussion of next steps.

I. An Organizing Framework

Maximum sustainable employment often is conceptualized in terms of the non-accelerating inflation rate of unemployment or NAIRU, frequently referred to as U*. The gap between the actual unemployment rate, U, and U* is referred to as the unemployment gap. In this framework, an unemployment rate U in excess of U* implies the existence of labor market slack, which should put downward pressure on wages. In contrast, an unemployment rate U that is less than U* implies a labor market that is operating at an unsustainable pace, creating upward pressure on wages and the risk of accelerating inflation. The concept of an unemployment gap, or more generally an output gap, lies at the heart of New Keynsian models of economic activity (see, for example, Clarida, Gali and Gertler 1999, Ball and Mankiw 2002, and Gali and Gertler 2007).

Forests' worth of paper have been devoted to the topic of identifying U* and the unemployment gap U-U* (or alternatively to identifying the output gap). The standard approach to estimating U* is to fit some variant of an expectations-augmented Phillips curve equation. In its simplest form, this model can be written as:

$$\pi_t = \pi_t^e + \alpha (U_t - U_t^*) + v_t \tag{1}$$

where π represents inflation, π^e is expected inflation, v is an unobserved cost or productivity shock, and α is a parameter to be estimated. Empirical estimates of U* vary widely depending on the choice of inflation measure, the treatment of inflation expectations, the instruments chosen to account for possible correlations between the explanatory variables and the error term, the choice of time period and other modeling decisions. A further complication is the many forces that could lead to changes in U* over time, including changes in the composition of unemployment (e.g., by age or duration of unemployment) and other factors (e.g., the generosity of unemployment benefits). Despite a plethora of studies on the topic, there is considerable uncertainty about the level of the natural rate of unemployment and its evolution over time.

An alternative perspective on the labor market focuses on labor market flows and the drivers of those flows. In the canonical search-and-matching model (Diamond 1982, Blanchard and Diamond 1992, Mortensen and Pissarides 1994, Pissarides 2000), employers create job openings they would like to fill (V) and unemployed individuals (U) search among these job openings for employment. The process of matching unemployed workers to vacant jobs is represented by a production function, often assumed to be Cobb-Douglas in form, with vacancies and unemployment as the inputs and matches (hires) as the output:

$$H_t = m(V_t, U_t) = \mu V_t^{1-\alpha} U_t^{\alpha} \tag{2}$$

where H is hires, V is the number of job openings, U is the number of unemployed people, t is the time period, and μ and α are parameters to be estimated. In this framework, labor market tightness (θ) typically is expressed as:

$$\theta_t = \frac{V_t}{U_t} \tag{3}$$

Rather than the matching function being estimated directly, this relationship may be viewed through the lens of the job-finding rate, expressed as hires relative to the number of unemployed workers:

$$\frac{H_t}{U_t} = \mu \left(\frac{V_t}{U_t} \right)^{1-\alpha} = \mu \left(\theta_t \right)^{1-\alpha} \tag{4}$$

An alternative but equivalent approach is to view it through the lens of the job-filling rate, expressed as hires relative to the number of vacant jobs:

$$\frac{H_t}{V_t} = \mu \left(\frac{U_t}{V_t} \right)^{\alpha} = \mu \left(\frac{1}{\theta_t} \right)^{\alpha} \tag{5}$$

When the labor market is tighter (θ is larger), unemployed individuals have a greater chance of finding employment. Conversely, in a tighter labor market, employers have a smaller chance of recruiting an unemployed person to fill their vacant job.

In the case of a matching function with constant returns to scale, equation (2) can be rewritten as a relationship among the hiring rate *h*, vacancy rate *v* and unemployment rate *u*:

$$h_t = m(v_t, u_t) = \mu v_t^{1-\alpha} u_t^{\alpha} \tag{6}$$

where *h*=H/E, *v*=V/E and *u*=U/E. An additional constraint is that, in steady state, the number of hires must equal the number of job openings created. The latter commonly is expressed in terms of the rate of separations from employment:

$$s = h_t = m(v_t, u_t) = \mu v_t^{1-\alpha} u_t^{\alpha} \tag{7}$$

where s is the separation rate and the other terms are as previously defined.[1] The downward sloping relationship between the unemployment rate and the vacancy rate implied by equation (7) commonly is termed the Beveridge curve. Over the course of a business cycle, unemployment and vacancies will move together along the Beveridge curve. Shifts in *s* or shifts in the matching function (i.e., shifts in μ) will shift the Beveridge curve. Improvements in the matching function (an increase in μ), for example, will shift the Beveridge curve inwards (lowering unemployment), while deterioration in the matching function will shift the Beveridge curve outwards (raising unemployment).

To pin down the economy's position along the Beveridge curve, the wage determination process must be specified. Wages must be consistent both with firms achieving normal profits

[1] Nothing fundamental is changed if this expression is modified to allow for steady state growth at rate *g* in desired employment, in which case the left hand side becomes *s*+*g*.

(i.e., zero economic profits) and with the outcome of bargaining between firms and workers. Wage-setting can be represented as:

$$\overline{w} = w(\frac{v_t}{u_t}, z) = w(\theta_t, z) \tag{8}$$

where $\overline{w}$ is the wage that is consistent with normal profits, z is a vector representing the other factors that may affect the wage bargaining process, and other terms are as previously defined. Changes in labor market tightness θ will be associated with changes in the wage rate through changes in the marginal productivity of labor and thus in the value to the firm of creating an additional job. The vector z can be thought of as including anything that affects workers' bargaining power, such as unionization, minimum wages, unemployment insurance benefits, and globalization, among other factors. To bring dynamics into the picture, this equation can be recast as a Phillips-curve type equation. In this framework, u, v and w depend on s, μ and z.[2]

While the search-and-matching framework has proven to be of enormous value for thinking about the labor market, the simple model just outlined omits many significant features of the real-world labor market. Our focus in this paper will be on rethinking the measurement of labor market tightness that underlies the simple model. As described, in the model as just sketched out, $\theta_t = \frac{V_t}{U_t}$, but unemployment and vacancies are imperfect proxies for the measures of effective searchers and effective vacancies that we will argue should be the objects of interest. First, the simple model ignores heterogeneity among the unemployed. There are reasons to believe, for example, that the long-term unemployed may contribute less to effective labor supply than the short-term unemployed, suggesting that changes over time in the share of the unemployed who are long-term unemployed should be taken into account in the measurement of

[2] This discussion draws on Dickens (2009), Blanchard (2009) and Daly, Hobijn, Sahin and Valletta (2012).

effective searchers. Second, the simple model does not allow for job search among those who are out of the labor force or employed. Given that the majority of those filling jobs each month were out of the labor force in the previous month or are making a job-to-job transition (Sedlacek 2016), this is a material omission. Finally, the simple model does not incorporate the possibility of temporal variation in either search intensity (on the part of those seeking work) or recruiting intensity (on the part of employers seeking to fill jobs).

We can elaborate the simple model to take these features of real-world labor markets into account. Building on the standard hiring function, we can write:

$$H_t = m(\rho_t^v V_t, \sum_i \rho_t^{s_i} S_{it}) = \mu\left(\rho_t^v V_t\right)^{1-\alpha}\left(\sum_i \rho_t^{s_i} S_{it}\right)^{\alpha} \tag{9}$$

where V again represents the number of job openings, S_i represents the number of job searchers of type *i*, ρ_t^v represents the intensity of employer recruiting effort at time *t*, and $\rho_t^{s_i}$ represents the intensity of job search on the part of searchers of type *i* at time *t*. In this expanded framework, labor market tightness can be written as:

$$\tilde{\theta}_t = \frac{\rho_t^v V_t}{\sum_i \rho_t^{s_i} S_{it}} \tag{10}$$

We will refer to the numerator of this expression as effective vacancies and the denominator as effective searchers. This generalized measure of labor market tightness can be substituted into the equation for the job-finding rate (to produce a generalized version of equation (4)) or the equation for the job-filling rate (to produce a generalized version of equation (5)).

Something we have not considered explicitly in this conceptual elaboration is the possibility of mismatch between vacant jobs and effective job seekers. Although commonly cited by business leaders and policy officials as an important contributor to unemployment, especially during periods of rising unemployment (Abraham 2015), there is little hard evidence to suggest that mismatch plays a large role in explaining fluctuations in aggregate unemployment (see, for example, Sahin, Song, Topa and Violante 2014). More fundamentally, the concept of mismatch itself may be elusive. Researchers most often assess occupational mismatch, for example, based on the correspondence between the occupations of the jobs most recently held by unemployed workers and the occupations of the jobs that employers are seeking to fill. In fact, the unemployed may be suited to fill jobs in a number of different occupations, calling this metric into question. Looking only at the unemployed also ignores individuals who are out of the labor force who may be qualified to fill available positions. Further, even if the nonemployed are not qualified to fill some of the vacancies advertised by employers, employers may be able to fill those positions by recruiting people away from other jobs. To the extent that job-to-job transitions tend to represent a movement up the economic job ladder, the positions that are vacated when this occurs may be a better fit for the skills and experience of the nonemployed than the positions higher up the vacancy chain. On the employer side of the equation, there may be some discretion about how work will be organized and what type of person the employer will seek to hire, and thus about the occupations of the jobs that are posted. While all of this certainly merits more explicit exploration, in our framework, we will think of mismatch as captured indirectly in the ρ's that translate numbers of people into effective searchers and numbers of job openings into effective vacancies.

If the number of effective job seekers of each of the different types rose and fell in the same proportions over time, it would not be important to account for them separately, as in this case, any single measure such as the aggregate unemployment rate would capture the mirroring movements in all of the relevant series. We cannot assume, however, that this will be the case.

When labor markets are weak and the number of unemployed job seekers is large, for example, those who are out of the labor force or already have a job may be less inclined to search, meaning that unemployment could rise while search among other groups fell. More generally, if the elasticity of the effective size of different groups of job seekers with respect to overall economic conditions varies, the unemployment rate will give a biased picture of movements in the number of effective job seekers over time (Broersma and van Ours 1999, Sedlacek 2016).

II. A Broader Perspective on Labor Market Tightness

A first step towards a more comprehensive treatment of effective searchers is to consider the potential role of heterogeneity among the unemployed. A broader perspective also should recognize effective searchers who are out of the labor force or already hold a job. Finally with regard to effective searchers, we would like to allow for temporal variation in the intensity of job search. In addition, we would like to incorporate temporal variation in the intensity of employers' recruiting efforts—i.e., for the possibility that effective vacancies may behave differently than the simple count of the number of job openings. As we will show, each of these factors can make a material difference to our understanding of the evolution of labor market conditions over the past two decades.

We are of course far from the first to think about the construction of measures of labor market conditions that are more comprehensive than the official unemployment rate. The Bureau of Labor Statistics (BLS) publishes two extended unemployment rates each month along with the official unemployment rate. The first of these is labeled U5; it includes not only the unemployed but also the marginally attached, individuals who satisfy all of the conditions for being counted as unemployed except for having searched for work within the last four weeks, though they are required to have searched within the last year. The most comprehensive BLS measure is U6, which incorporates both the marginally attached and those who are part time for economic reasons. Researchers have used information from the Current Population Survey (CPS) to construct other expanded measures designed to better capture aggregate job search activity, though as we will describe few of these efforts have incorporated the possibility of on-the-job search or the possibility of time-varying search intensity. Empirical research on job vacancies tends to be of a more recent vintage, reflecting the fact that monthly job openings data for the United States have been available only since 2000.

Heterogeneity among the Unemployed

There is a lengthy literature that has examined how changes in the composition of the unemployed may affect the interpretation of the official unemployment rate. Demographics are one dimension along which it may be informative to disaggregate the unemployed. In a seminal paper, Perry (1970) noted that women's rising labor force participation and the entry of the Baby Boom generation into the labor force could have raised measured unemployment independently of underlying labor market conditions. He computed an alternate unemployment rate that weighted those in different age-sex groups according to their average wages and work hours. Because the women and young workers who accounted for a growing share of the unemployed tended to have lower wages and work fewer hours, this adjusted unemployment rate showed the labor market to be relatively tighter in the late 1960s compared to the mid-1950s than did the official unemployment rate. Subsequent papers that have examined the effects of changing demographics on the unemployment rate include Shimer (2001), Aaronson, Hu, Seifoddini and Sullivan (2015), and Barnichon and Mesters (2018).

More recently, the growth in long-term unemployment following the Great Recession has attracted considerable attention. The number of people unemployed for 27 weeks or more rose from 1.1 million at the start of 2007 to a peak of 6.8 million in April 2010 and did not fall below 5 million until September 2012. The long-term share of total unemployment exceeded 40 percent from December 2009 through November 2012 and even today remains elevated compared to its level in the early 2000s. The fact that the long-term unemployed tend to have lower job-finding rates than the short-term unemployed has been well-documented (see, e.g., Kaitz 1970, Krueger, Cramer and Cho 2014). Possible reasons for this pattern include falling search intensity, loss of human capital, and employer unwillingness to hire the long-term unemployed (see Abraham, Haltiwanger, Sandusky and Spletzer 2016 for a review of potential explanations and citations to the literature). Any of these explanations might imply that the long-term unemployed contribute proportionately less to the pool of effective searchers than the short-term unemployed.

Another dimension along which the unemployed differ is their route of entry into unemployment. As an example, the job-finding pattern among those laid off from a job differs considerably from the pattern for other groups among the unemployed (Katz 1986, Katz and Meyer 1990, Fujita and Moscarini 2017). Relatedly, an unemployed individual's recent labor market history may help to predict how likely it is that she will find a job. In an interesting recent study, Kudlyak and Lange (2019) find significant differences in job-finding rates among nonemployed individuals based on their labor force status during the preceding months. For example, unemployed people who were employed in either or both of the prior two months have substantially higher job-finding rates than unemployed people who were unemployed or out of the labor force in both of those months.

Job Search among Those Who Are Out of the Labor Force

While differentiating among subgroups of the unemployed is undoubtedly important for constructing a more accurate measure of effective job searchers, it also is important to account for the potential labor supply of those who are outside of the labor force. In official U.S. statistics, only someone who wants to work, is available for work and reports having engaged in active job search within the past four weeks is counted as unemployed. Non-employed individuals who do not satisfy these criteria are counted as out of the labor force, though such people may well become job searchers and move into jobs. The job-finding rate among those who are out of the labor force—and even among the subgroup of those who are out of the labor force who say they want a job—is much lower than the job-finding rate among the unemployed. Because there are so many people out of the labor force, however, even a modest job-finding rate translates into a very large number of job fillers. In a typical month, despite the much higher job-finding rate among the unemployed, the number of people who enter employment directly from out of the labor force is much larger than the number who enter employment directly from unemployment (see, for example, Hornstein, Kudlyak and Lange 2014).

Similar to the unemployed, there is considerably heterogeneity among the out of the labor force population. Flinn and Heckman (1983) were among the first to make this point. Jones and Riddell (1999) use data from a supplement to the Canadian Labor Force Survey (LFS) together with information on labor force status from the monthly LFS to explore some of this heterogeneity. They find that those who are out of the labor force but want a job are somewhat less likely than the unemployed to transition to employment in the following month, but much more likely to transition to employment than the rest of those who are out of the labor force. Since 1994, the Current Population Survey (CPS) has collected information on whether those out of the labor force want a job; whether they have searched in the last 12 months; if so, their reasons for not having searched in the past four weeks; and their availability for work. Several recent studies have documented differences in job-finding rates among groups disaggregated based on the answers to some or all of these questions (Hornstein, Kudlyak and Lange 2014, Kudlyak 2017, Hall and Schulhofer-Wohl 2018).

The Richmond Fed's Non-employment Index is an interesting recent effort to incorporate all of the non-employed, rather than just the unemployed, into a measure of effective searchers (Hornstein, Kudlyak and Lange 2014, Kudlyak 2017). The index is constructed using data on two groups of unemployed job seekers (short-term and long-term); three groups of people who are out of the labor force but say they want a job (discouraged workers, other marginally attached, and others who want a job); and four groups of people who are out of the labor force and say they do not want a job (disabled, retired, others in school and others not in school). To create the index, which is constructed using CPS data, the authors weight the number of people in each group by the group's average job-finding rate over the 1994-2016 period. Prior to 2007, this index had a close linear relationship with the unemployment rate. Between 2007 and 2013, the unemployment rate was higher than would have been predicted based on the previous relationship between the two series. Since 2013, however, the former relationship between the two measures appears to have been restored.

On-the-Job Search and Job-to-Job Flows

One important thing to note about the Richmond Fed Non-employment Index is that it does not attempt to account for on-the-job search or job-to-job transitions. Because many jobs are filled by people who are making job-to-job transitions, this is a material omission. In the canonical search-and-matching model, vacancies are created either when a worker leaves an existing position or when a firm wishes to expand. Many of those who leave a job move immediately to a different position. Measured vacancies already include the effects of separations leading to a job-to-job transition, as they include the job openings created when employers must replace departing employees. Symmetrically, the measurement of effective searchers should take into account the contribution of on-the-job searchers to the overall pool of effective searchers.

The basic monthly CPS unfortunately does not provide information on job search among the employed. Other data suggest, however, that on-the-job search is prevalent. Black (1980), for example, finds that in a sample of respondents to the Panel Study of Income Dynamics, 14 percent of white workers and 10 percent of black workers reported on-the-job search in the 1972 interview. Using data from the Employment Opportunity Pilot Projects (EOPP) baseline household survey conducted from April through October 1980, Blau and Robins (1990) also report that a substantial share of the employed engage in on-the-job search. More recently, Faberman, Mueller, Sahin and Topa (2016) have studied job search based on the responses to a module added in 2013, 2014 and 2015 to the Survey of Consumer Expectations. In their sample, nearly a quarter of the employed searched for work over the prior four weeks (including passive search such as reading help wanted advertisements) and 20 percent applied for at least one job during the same period. In addition, they observe that it is relatively common for employed individuals to receive unsolicited job offers.

Consistent with this evidence, administrative data show that a large share of hires are people moving from one job to another. Haltiwanger, Hyatt and McEntarfer (2018) find that, in Longitudinal Employer-Household Dynamics administrative data, job-to-job transitions account for approximately half of gross hires at a quarterly frequency. Haltiwanger, Kyatt, Kahn and McEntarfer (2018) show that these job-to-job transitions are strongly procyclical.

Job Search Intensity

A final factor to consider in constructing a comprehensive index of the volume of effective job search activity is temporal variation in the intensity of job search. In a simple model of job search in which searchers equate the marginal cost of search to the expected marginal return from search, all else the same, less effort should be devoted to searching when the chances of finding a job are lower. This might lead one to expect job search intensity to be procyclical, though whether or not this is the case ultimately is an empirical question.

In the CPS, non-employed individuals who say they want a job and are available to work are asked whether they have searched for work in the last four weeks and, if so, what job search methods they have used. Shimer (2004) uses information on the number of different reported search methods as a proxy for job search intensity.[3] He finds that, controlling for demographics, industry and occupation, this measure of search intensity among the unemployed is countercyclical. One obvious limitation of this approach is that the number of search methods is an imperfect proxy for the intensity of search. The CPS does not collect information on job search by the employed.

In principle, time spent searching may be a better proxy for search intensity than the number of different search methods used. Data from the American Time Use Survey (ATUS),

[3] The methods Shimer considers include 1) contacting an employer directly or having a job interview; 2) contacting a public employment agency; 3) contacting a private employment agency; 4) contacting friends or relatives; 5) contacting a school or university employment center; 6) sending out resumes or filling out applications; 7) placing or answering advertisements; 8) checking union or professional registers; 9) a catchall other active search category; 10) attending a job training program or course; 11) reading help-wanted advertisements; and 12) a catchall other passive search category.

fielded each year since 2003, have been used in several papers to estimate time devoted to job search. Deloach and Kurt (2013) find that weak labor markers are associated with lower levels of search intensity, though declines in house prices during and following the Great Recession had an offsetting effect, leading job search intensity to be acylical on net over the period studied in their paper. Also using ATUS data, Gomme and Lkagvasuren (2015) find search intensity among the unemployed to be procyclical, whereas Mukoyama, Patterson and Sahin (2018) conclude that it is countercyclical. Part of the reason for the differences in findings across these studies may be the relatively small ATUS sample size and resulting sensitivity to details of model specification. In addition, to the extent that intervals of job search are short, occur simultaneously with other activities (e.g., looking through online job postings while watching television) or take place at work, they are likely not to be well captured in the ATUS.[4]

An interesting study by Faberman and Kudlyak (2016) takes a different approach to measuring job search intensity. They make use of information on the job application behavior of the users of Snag-A-Job, an online job site. While their interest lies primarily with the relationship between search intensity and search duration, they also report that search intensity is higher in weaker local labor markets, consistent with job search intensity being countercyclical. Because applications on Snag-A-Job represent only one among many possible search channels a job seeker might use, however, it is hard to know exactly what to make of these results.

As an alternative to measuring job search intensity directly, some recent studies have attempted to infer its behavior from changes in job-finding rates. In essence, these studies fit a

[4]From 2003 through 2017, ATUS respondents reported an average of 19.4 activities on the diary day (Bureau of Labor Statistics 2019), meaning that the average duration of reported activities was in excess of an hour. ATUS respondents engaged in multiple activities simultaneously are asked to report their primary activity. Ahn and Shao (2017) used ATUS data to study the cyclicality of job search among the employed. Because the ATUS does not ask what respondents are doing while they are at work, ATUS measures of job search among the employed seem especially likely to miss at least some job search activity.

matching function with vacancies relative to a generalized measure of effective job searchers on the right hand side. The papers differ in important ways with respect to how the different groups of job searchers are defined. In each case, however, the objective is to infer what is happening to group-specific search intensities based on how having more or fewer people in any given group affects the number of matches. If adding people to a group makes a larger-than-expected contribution to the number of matches realized when the labor market is tight, for example, procyclicality in search intensity is a plausible explanation.

As recognized in the literature that has taken this approach, common variation in search intensities across groups cannot be distinguished empirically from the elasticity of matching with respect to the (properly measured) ratio of vacancies to searchers in the standard matching function. In practice, however, there is a good deal of variation in the estimated elasticities of the contributions to realized matches with respect to aggregate conditions made by different groups of searchers. It is natural to interpret these differences as resulting from differences in the cyclicality of search intensity. Taking only the variation in search intensity inferred from cross-group differences in the cyclicality of contributions to the matching function thus seems to us to be a conservative approach.[5]

An early example of research in this vein is Veracierto (2011), who develops a model in which both the unemployed and nonparticipants may be effective searchers. Hornstein and Kudlyak (2016) consider three different job searcher groupings, two consisting of different breakouts among the unemployed (by duration and by reason) and the third consisting of all nonemployed persons broken out into four groups (unemployed or out of the labor force by

[5] Alternatively, the cross-group differences that are the basis for the suggested inference about job search intensity could be attributable to differences in the pattern of the shocks experienced by different groups of searchers. This is a less parsimonious explanation and it is not entirely apparent what the source of such shocks might be, but we cannot rule it out.

gender). They measure the size of these groups in CPS data, which also are used to measure transitions from unemployment or (in the case of the third grouping) out of the labor force to employment. Job vacancies are measured using either a composite series based on Barnichon (2010) that makes use of Help Wanted Index data together with more recent data from the Job Openings and Labor Turnover (JOLTS) survey or, in a separate analysis for a shorter period, just the JOLTS data. This analysis does not take into account the possibility of on-the-job search or job-to-job transitions.

Sedlacek (2016) considers three groups—unemployed, out of the labor force and employed—as sources of potential hires. He uses CPS data to measure transitions to a new job for each of the three groups and JOLTS data to measure job vacancies. While this analysis allows for the possibility of on-the-job search, it does not consider heterogeneity among the unemployed or among those out of the labor force.

Finally, Hall and Schulhofer-Wohl (2018) consider sixteen groups of job seekers—thirteen groups among the unemployed, two groups among those out of the labor force, and the employed. They disaggregate the unemployed by duration and reason for unemployment and those out of the labor force by whether they say they want a job. In Hall and Schulhofer-Whol's analysis, hires are measured using JOLTS data. As will be discussed further below, their estimation allows for group-specific base levels, group-specific elasticities with respect to average vacancy duration and group-specific trends in the contribution to matching. Appealing features of the HSW analysis are that it allows for job search among the employed and for heterogeneity both among the unemployed and among those who are out of the labor force. Without suggesting that the Hall and Schulhofer-Wohl estimates are necessarily the final answer, we have adopted them for use in a proof-of-concept exercise to show how a more comprehensive measure of labor market tightness can be developed. We discuss this further in the next section of the paper.

Employer Recruiting Intensity

A final factor missing from the standard search-and-matching model is employer recruiting intensity. Empirical implementations of the standard model use data on job openings, which provide an estimate of the number of jobs that employers say they would like to fill. The intensity with which employers recruit to fill their vacant jobs can vary considerably, however, depending both on the company's own circumstances and on aggregate labor market conditions.

Recruiting intensity can take a number of different forms. The most literal interpretation of recruiting intensity is the time and effort devoted to advertising the firm's job openings, processing applications and so on, but other aspects of firms' recruiting behavior may be even more important. One step a firm that is eager to hire may take is to expand the pool of candidates considered. As an illustration, employers who previously ruled out job candidates with criminal records may change their policies when the labor market tightens (see, for example, Casselman 2018, Smialek 2019). Similarly, employers may lower the levels of education and experience they require of job candidates. Other steps might include offering better working conditions or raising wages. We view all of these as changes in recruiting intensity, in the sense that employers who take such steps are trying harder to fill their vacant jobs.

Hard direct evidence on employer recruiting behavior and its temporal variation is in relatively short supply. An interesting recent study by Modestino, Shoag and Balance (2019) sheds light on one of the ways in which employer recruiting behavior may respond to changes in aggregate labor market conditions. They show that, controlling for occupation, the shares of online job advertisements stating a requirement for a college degree or for four-plus years of experience rose during the recession. These changes were larger in states and occupations that experienced a larger increase in the supply of workers. The findings are robust to controlling for firm-by-job-title fixed effects and to restricting attention to the exogenous variation in labor supply created by the return of large numbers of veterans from Iraq and Afghanistan between 2009 and 2012.

Davis, Faberman and Haltiwanger (2013) report evidence consistent with cyclical variation in aggregate employer search intensity. In an analysis of establishment-level JOLTS data, they show that employers with a larger number of vacancies to fill experience considerably larger hiring rates than employers with fewer openings, holding constant the state of the aggregate labor market. They interpret this finding through the lens of recruiting intensity—that is, they infer that recruiting intensity is positively associated with the gross hiring rate. Applying the relationship between these two variables in the cross sectional data to changes in gross hiring over time allows them to construct an index of how employer recruiting intensity has changed.

III. Creating a Measure of Labor Market Tightness Based on Effective Searchers and Effective Vacancies

Measures of effective searchers and effective vacancies are needed to produce a generalized measure of labor market tightness. We would expect such a measure to better capture the state of the labor market than either the unemployment rate or (in the framework we have adopted) the unadjusted ratio of vacancies to unemployment. Our objective, then, is to implement equation (10), the generalized measure of labor market tightness discussed earlier in the paper, and then to assess its performance. We use as our performance metric how well the generalized measure does in explaining changes in the job-filling rate over time compared to the standard measure of labor market tightness.

In order to carry out this plan of work, we need first to define a set of job searcher categories that do a good of capturing the heterogeneity in search behavior across the population. Then, we need to construct measures of search intensity for each of these groups, allowing both for differences in the base level of search intensity across groups and for possible heterogeneity across groups in how search intensity evolves time. Finally, we need to construct a measure of employer recruiting intensity that we can use to translate the number of job vacancies into effective vacancies. In this paper, rather than estimating all of the necessary parameters ourselves, we have built on estimates already existing in the literature in order to construct these measures. We view what we have accomplished thus far as a proof of concept exercise. As will become clear, our findings suggest that the approach we have outlined merits further development.

For our measures of search intensity, we build on the analysis of Hall and Schulhofer-Wohl (2018) (hereafter HSW). Using CPS microdata that allow them to track flows across labor market states and from job to job, they quantify systematic variation in job-finding rates across sixteen groups. The groups include thirteen groups among the unemployed, two groups among those who are out of the labor force, and the employed. Among the unemployed, those unemployed less than 4 weeks and those unemployed 4-26 weeks are disaggregated by reason for unemployment (job leaver, permanent layoff, temporary layoff, temporary job ended, entrant, or re-entrant). Those unemployed 27 or more weeks constitute a thirteenth category. Among those out of the labor force, HSW distinguish between those who say they want a job and those who say they do not want a job. The employed are their sixteenth and final category. After controlling for demographic composition (including age, gender, and education), HSW estimate job-finding rates for each of their sixteen groups.[6] We interpret the cross-group variation in the job-finding rates they identify as variation in search intensity and use their estimates to measure the ρ_t^i in equation (10).

Intuitively, we are using the relative variation in job-finding rates implied by the HSW estimates to provide relative weights for the sixteen groups. Base period differences in job-finding rates across groups are a core component of this approach, but HSW also allow for variation in job-finding rates related to changes in vacancy duration and for time trend effects. Our simplest generalized estimates incorporate only base period variation; the most general incorporate variation from all three sources to construct relative weighting factors that vary across time.

To be more specific, following HSW, we assume that, after adjusting for search intensity, all groups have a common job-finding rate:

$$\frac{H_t}{ES_t} = \frac{H_{it}}{ES_{it}} = \frac{H_{it}}{\rho_t^i S_{it}} = \tilde{f}_t = \tilde{f}_{it} = A_t T_t^{\eta} \tag{11}$$

where $T_t = \dfrac{V_t}{H_t}$ is average vacancy duration and the A_t are any common time effects in job-finding rates not captured by vacancy duration. It is easy to show that this characterization of the job-finding rate is consistent with equation (5). Define $A_t = \tilde{A}_t^{1+\eta} (\rho_t^v)^{\eta}$. Then with appropriate substitution we have:

[6] HSW estimate job-finding rates for the unemployed and those who are out of the labor force based on transitions to employment. Job-finding rates for the employed are estimated using information on changes of employer. In recent years, the BLS has changed how this information is collected in ways that likely have somewhat depressed the estimated job-to-job transition rate. The effects of this change should be captured in the time trends in the matching function estimated by HSW. As we show, it makes little difference to our conclusions whether we allow for these time trends or not.

$$H_t = \tilde{A}_t(\rho_t^v V_t)^{\eta/(1+\eta)}(\sum_i \rho_t^i S_i^t)^{1/(1+\eta)} \tag{12}$$

where $\alpha = 1/(1+\eta)$. Returning to the job-finding rate for group i, we can write:

$$\frac{H_{it}}{S_{it}} = f_{it} = \rho_t^i A_t T_t^\eta \tag{13}$$

Specifying $\rho_i^t = \gamma_{it} T_t^{\eta_i}$ implies a relationship that is isomorphic to HSW's main estimating equation for each group i:

$$f_{it} = \gamma_{it} A_t (T_t)^{\eta+\eta_i} \tag{14}$$

In practice, HSW estimate the following relationship:

$$\log(f_{it}) = \log(\gamma_i) + \tilde{\eta}_i \log(T_t) + \tilde{\delta}_i t + \varepsilon_{it} \tag{15}$$

This basic estimating equation includes a linear time trend. As discussed further below, HSW also permit a break in the trend in 2008. We use the notation $\tilde{\eta}_i = \eta + \eta_i$ and $\tilde{\delta}_i = \delta + \delta_i$ to distinguish between common and idiosyncratic components of the elasticity of job-finding rates with respect to vacancy duration and the time trend effect. The idiosyncratic components are assumed to have mean zero (on a base-period-population-weighted basis). The search intensities we construct—the ρ_t^i's—incorporate only the idiosyncratic components of these effects. Both the common component of the elasticity with respect to vacancy duration (η) and the common component of the time trend (δ) capture factors in addition variation in search intensities. To be more specific, the former also reflects the procyclical job-finding rate that is implicit in the matching function, while the latter also reflects any common time-varying factors that may shift the matching function, including but not limited to trends in recruiting intensity.

Given that we are exploiting only the relative differences in elasticities across groups with respect to vacancy duration and time trends, our most general estimate of job search intensity for the members of group i is $\rho_t^i = \gamma_i T_t^{\eta_i} e^{\delta_i t}$. We implement this measure as follows. First, we use the estimates of average 2007 job-finding rates reported in Table 5 of HSW to generate our measures of γ_i. We normalize the reported job-finding rates so that, for the recently laid off, $\gamma_i = 1$ on average over the 12 months of 2007. The values of γ_i for all of the other groups then are defined based on the ratio of their average job-finding rate to that for the recently laid off. We implement the other components of search intensity to ensure that the same relative average values of the measures for the different groups continue to hold exactly for 2007. To accomplish this, we normalize so that both T_t and $e^{\delta_i t}$ equal one on average over the 12 months of 2007. We use the estimated (short span) elasticities with respect to vacancy duration from HSW's Table 6 to construct our measure of η_i. The elasticities reported in the table are estimates of $\tilde{\eta}_i$; based on those values, we compute $\eta_i = \tilde{\eta}_i - \eta$ where η is the (base period) population weighted average of the estimates from Table 6. Similar remarks apply to δ_i.[7]

In our analysis, we report results based on generalized effective searchers using just the constant γ_i; results that also incorporate the idiosyncratic vacancy elasticity effects (the η_i); and results that further incorporate the idiosyncratic time trend effects (e.g., the δ_i). Selected relative search intensity estimates are depicted in Figures 3A, 3B and 3C.[8] The relative search intensities using only the constant γ_i's can be detected in these figures by focusing on the values in 2007; the normalizations just described ensure that the average values for the different series all equal the γ_i's in that year. The series labeled simply with the name of a group refer to the estimates that incorporate idiosyncratic vacancy elasticity effects and the series labeled with the

[7] We follow for the same procedures for the supplemental time trend that commences in 2008:1 from Table 6.
[8] Relative search intensities for the remaining groups are reported in Figure A.1.

name of a group followed by "Tr" (for trend) also incorporate the idiosyncratic time trend effects.

As can be seen in Figure 3A, average relative search intensity, as inferred from the job-finding rate, is smaller for those who have been permanently laid off than for the baseline group of people on temporary layoff (who by construction have a search intensity that is normalized to equal one in 2007).[9] From Figure 3B, the relative search intensities for the long-term unemployed and those who want a job are lower, but interestingly very similar to each other on average. The employed and those out of the labor force who do not want a job have even lower relative search intensities.

Several groups exhibit evident procyclicality in their search intensities compared to the average for other groups. These groups include those who have been permanently laid off, the long term unemployed and the want-a-job group. Relative trends also differ across groups. In some cases, the supplemental trend effect that commences in 2008 dampens the procyclicality of the relative search intensity that otherwise would be more evident. This is especially the case for the long term unemployed, who have a relatively high elasticity of job-finding with respect to vacancy duration (apparent in the job search intensity line in Figure 3B that does not account for trends) but superimposed on a downward post-2008 trend that dampens the effect once taken into account. Figure 3C shows that the relative search intensity of the employed and those out of the labor force who do not want a job exhibit only modest cyclical variation.

[9] We chose those on temporary layoff as the baseline group because they have the highest average job-finding rate. Although that high rate is primarily a reflection of the high likelihood of returning to a former job, we adopt the verbal shorthand of describing them as searching more intensively than other groups. Although in this particular case those specific words may not be precisely accurate, it seems reasonable to view members of this group as representing more in the way of effective labor supply than those in other groups. It is perhaps also worth noting that this group represents less than 0.2 percent of the population age 16 and older, so that how we treat them makes little difference to the measures we construct.

The shares of effective searchers accounted for by different groups are displayed in Figure 4A and Figure 4B.[10] Figure 4A shows shares constructed using only the γ_i (i.e., assuming constant relative search intensities); Figure 4B shows shares based on calculations that allow for variation in relative search intensities over time. In these figures, for illustrative purposes, we collapse the thirteen groups into which the unemployed are broken into just two groups, the short-term unemployed and the long-term unemployed. The patterns in the two panels are quite similar not only in the average levels for each of the different groups but also with respect to the variation in those levels over time. This implies that much of what we see in the more encompassing calculation derives from the changing shares of the different groups within the working age population, rather than from variation in the weighting of the different groups over time. That said, as can be seen in Figure 4B, allowing the weights to vary somewhat dampens the temporal variation in shares. This reflects the fact that, as illustrated in Figure 3, search intensity among the unemployed fell during the years when unemployment as a share of the population was rising.

Strikingly, in both panels of Figure 4, the unemployed account for less than 30 percent of effective searchers. The employed and those out of the labor force who do not want a job account for the largest shares of effective searchers. From Figure 3C, we know that both of these groups have low relative search intensities, but both also represent a very large share of the

[10] Calculation of these shares and subsequently of our generalized labor market tightness measures requires not only relative search intensities but also the number of people in each of the sixteen HSW groups. We derive the latter from estimates based on CPS data published by the BLS. The HWS unemployment duration groups and the unemployment duration groups the BLS uses for its published estimates are slightly different. The HSW unemployment duration groupings are less than 4 weeks, 4-26 weeks and 27 or more weeks; BLS publishes data broken out for those with unemployment durations of less than 5 weeks, 5-26 weeks and 27 or more weeks. We use estimates reported by HSW to construct relative search intensities, then apply these relative search intensities to the slightly different groups for which the BLS publishes estimates. Addressing this minor discrepancy is on the longer and more substantive agenda for future research related to development of the generalized index that we discuss in the paper’s conclusion.

working age population. Figure 4 also illustrates the substantial changes in the relative shares of effective searchers accounted for by different groups over time. The short-term unemployment share rises substantially in the Great Recession, but then declines. In contrast, the long-term unemployment share rises with a lag in the Great Recession, but then stays persistently high for many years, recovering to its pre-Great-Recession level only in 2018. The share of effective searchers who are employed declines sharply in the Great Recession and also is slow to recover. The share for those out of the labor force who say they do not want a job fell modestly in the Great Recession, but has risen since that time.

Changes in the mix of effective searchers play a critical role in accounting for the cyclical movements in aggregate search activity. Figure 5 illustrates the standard measure of searchers (the unemployed) versus three generalized measures. The first generalized measure is constructed using constant relative group-specific job search intensities; the second incorporates time-varying relative search intensities due to elasticities with respect to vacancy duration; and the third additionally incorporates the effects of group-specific relative time trends. All of the measures in Figure 5 are ratios of searchers to the population age 16 and older.[11] The generalized measures are much less procyclical than the standard measure that counts only the unemployed as searchers and weights all unemployed searchers equally. The countercyclical increase in effective searchers in the generalized measure with constant relative search intensities reflects the shift away from the employed (who have low relative search intensity) toward the unemployed (who have high relative search intensity). This simpler generalized measure captures much of the cyclical variation that is present in the measures that also incorporate time variation in the relative search intensities. The latter are slightly less procyclical, reflecting the

[11] That is, for the purpose of comparability, the standard measure of job searchers is reported in this figure as the ratio of the number of people unemployed to the population age 16 years and older.

fact that, in contractions, the unemployed are a rising share of effective searchers, but their relative search intensity is declining. There is not much difference between the time varying effective searcher measures constructed allowing and not allowing for relative trends. Thus, even though Figure 3 shows some notable impacts of trends on relative search intensities, accounting for that variation has little effect on the aggregate effective searcher measure. Figure 3 demonstrates that both the employed and those out of the labor force who do not want a job exhibit relatively modest time trends in relative search intensities. As was shown in Figure 4, most effective searchers belong to one of these two groups.

To provide some further perspective, Figure 6 displays the standard measure of labor market tightness (unemployment), the generalized measure with constant relative search intensities, an index based on the U6 measure of slackness (with the number of searchers in the U6 numerator normalized by the population age 16 years and older) and the Richmond Fed Non-employment Index. As discussed above, U6 adds the marginally attached and those who are part-time for economic reasons to what we would call the effective searcher count, but weights them equally with the unemployed. The U6-based index has about the same volatility as the standard measure. The Richmond Fed Non-employment index focuses on the unemployed and those who are out of the labor force, weighting different groups using their average relative job-finding rates. It is very similar in spirit to our index using constant relative search intensities, though it disaggregates both the unemployed and those who are out of the labor force somewhat differently than our index does, and also does not incorporate search among the employed. The cyclical variation in the Richmond Fed index lies somewhere between that for the standard measure and that for our generalized index of effective searchers.

We now turn to our generalized measure of effective vacancies, which rests on the analysis of Davis, Faberman and Haltiwanger (2013) (hereafter DFH). Figure 7 depicts the DFH index of recruiting intensity, which we also normalize to one in 2007. This measure is highly procylical. The implications for effective vacancies can be seen in Figure 8. Effective vacancies decline more in the Great Recession than actual vacancies and increase more than effective vacancies in the recovery.

We are now ready to put the pieces together. Figure 9 compares the standard measure of labor market tightness (the vacancy to unemployment ratio) to the three different versions of our generalized measure using the ratio of effective vacancies to effective searchers. The first version uses only the differences in the γ_i's to construct the effective searcher series; the second also incorporates the idiosyncratic vacancy elasticity effects (the η_i); and the third incorporates in addition the idiosyncratic time trend effects (e.g., the δ_i). All three tightness measures incorporate our adjustment for recruiting intensity. For ease of comparison, all of the measures in Figure 9 have been normalized to equal one on average in 2007. The generalized measures all declined substantially less during the Great Recession than the standard measure. All also are substantially lower in September 2018, the last month included in our analysis, than the standard measure, implying that the labor market was not nearly as tight at that point as implied by the standard measure. To put this into context, the most recent value of the standard labor market tightness measure is about 30 percent higher than it was in early 2001. In contrast, the generalized measure is about the same as it was in early 2001. In short, our generalized measure suggests a significantly different evolution of labor market tightness than the standard measure.

We believe the generalized measure is preferable on conceptual grounds, but we also would like to have evidence that it actually does a better job of explaining labor market behavior.

To evaluate the alternative measures, we return to the standard matching function in (2) and the generalized matching function (9). Both the standard and the generalized matching function have predictions about the evolution of the job-filling rate (H/V).[12] The standard matching function yields a job-filling rate given by equation (5), repeated here for reference:

$$\frac{H_t}{V_t} = \mu\left(\frac{U_t}{V_t}\right)^{\alpha} = \mu\left(\frac{1}{\theta_t}\right)^{\alpha} \tag{5}$$

The generalized matching function (9) implies a job-filling rate (H/V) that is given by:

$$\frac{H_t}{V_t} = \mu\left(\frac{ES_t}{EV_t}\right)^{\alpha} \rho_t^{v} \tag{16}$$

Because the LHS of (5) and (16) are the same and based on readily-available data, we can compare the performance of the predictions obtained using the standard and the generalized matching functions, respectively. For the elasticity in those expressions, we use our empirical estimate of $\alpha = 1/(1+\eta)$, which using the value of η obtained above, gives us an estimate of α close to 0.7. This is within the range of estimates in the literature (Petrongolo and Pissarides 2001), but a little on the high side.[13]

Figure 10 presents the actual and predicted job-filling rates from (5) and (16). All series displayed in Figure 10 have been normalized to average one in 2007. We report job-filling rates for the generalized tightness measure constructed assuming constant search intensities and for

[12] In recognition of some time-aggregation issues related to the flow of hires over the month relative to initial vacancies, Davis, Faberman and Haltiwanger (2013) refer to the ratio H/V as the vacancy yield rather than the job-filling rate. They provide a method for adjusting the H/V measure so that it is a true job-filling rate. The exercise DFH conduct to evaluate their recruiting intensity measure as an input into the measurement of labor market tightness is similar in spirit to the exercises we report below for evaluating our more fully generalized labor market tightness measures. The two approaches are closely aligned in that both examine the relationship between H/V and predicted H/V.

[13] In Appendix Figure A.2, we show the actual job-filling rate and the predicted rate using $\alpha = 0.5$. Using this lower elasticity reduces the RMSE for the gap between the actual and predicted rates using the standard labor market tightness measure substantially, but the resulting RMSE is still twice that obtained with the same 0.5 elasticity using the generalized measure.

the generalized tightness measure incorporating both cyclical and trend effects on relative search intensities. The standard matching function performs reasonably well prior to the Great Recession, but predicts a much larger increase in job-filling rates during and after the Great Recession than actually observed. In contrast, the generalized matching function closely tracks the actual job-filling rate. This pattern holds whether we use the generalized labor market tightness measure constructed using constant relative search intensities or the generalized measure that incorporates time-varying relative search intensities. The improvement in performance obtained by using the generalized matching function rather than the standard matching function is dramatic. The root mean-squared error (RMSE) in the predicted hiring rate is slightly lower for the generalized measure with time varying relative search intensities, but even with constant relative search intensities the RMSE is less than 25 percent as large as that obtained using the standard matching function.[14]

Figures 11 and 12 repeat this exercise using the U6 index and the Richmond Fed Non-employment Index, respectively. The U6 index performs no better than the standard measure in predicting job-filling rates. The Richmond Fed Non-employment Index performs substantially better than the standard labor market tightness measure—the RMSE is about 50 percent of that using the standard measure—but not nearly as well as our generalized measure.

To explore the relative contributions of the different components of the generalized measure to its behavior relative to the standard measure, we have computed alternative measures that shut down certain groups of effective searchers. For this purpose, we work with the

[14] The RMSE in the matching function based on the generalized tightness measure using constant relative search intensities is 24 percent of that in the matching function based on the standard tightness measure, versus 22 percent when we allow for time varying relative search intensities. Figure A.3 shows results using a matching function that adjusts only for effective searchers while keeping the standard measure of vacancies. Most of the improvement in the RMSE from using the generalized measure comes from substituting effective searchers for the unemployed. The RMSE using effective searchers together with actual vacancies is about 30 percent of that using the standard measure, compared to 22 percent when we also replace actual vacancies with effective vacancies.

constant relative search intensity version of the generalized measure, as the interpretation of these results is more transparent. Two restricted measures are considered. First, we exclude the employed as effective searchers by setting the relative search intensity for the employed equal to zero. Second, we further exclude everyone who is out of the labor force as effective searchers, in this case setting relative search intensities for both the employed and those who are out of the labor force to zero. These restricted measures are shown in Figure 13. Excluding the employed yields a labor tightness measure that declines more in the Great Recession but by 2018 is at about the same level as the generalized measure. Further excluding those who are out of the labor force but keeping our preferred weighting for the different groups among the unemployed yields a labor tightness measure that closely tracks the standard measure.

To evaluate these more restrictive alternatives, Figures 14 and 15 illustrate the corresponding predicted job-filling rates. The predictions in Figure 14 are based on a generalized job searcher measure that excludes the employed; the predictions in Figure 15 are based on a generalized searcher measure that also excludes those who are out of the labor force. Excluding the employed yields a predicted job-filling rate that tracks the actual job-filling rate rather less well than the fully generalized measure that incorporates all potential searchers. The RMSE of the predictions displayed in Figure 14 are 39 percent as large as when using the standard measure, compared to a RMSE for the generalized measure including employed job searchers that is 24 percent as large. Figure 15 shows that further excluding those who are out of the labor force has an even larger adverse impact, with the pattern of predicted job-filling rates in this case looking quite similar to the pattern of predictions obtained using the standard measure. Even in this case, however, the gap between the actual and predicted job-filling rate is not quite as large during the Great Recession as is the case for the standard measure.

IV. Conclusions and Next Steps

The generalized measure of labor market tightness we have constructed based on the ratio of effective vacancies to effective searchers suggests that the U.S. labor market was considerably less tight at the end of 2018 than implied by the standard ratio of vacancies to unemployment. The differing behavior of the two measures reflects the fact that the standard tightness measure does not account for important variation in search behavior on the part of both firms and workers. The best available evidence suggests that employer recruiting intensity was considerably lower at the end of 2018 than it had been in early 2001, implying a relatively lower level of labor market tightness during the later period than would have been estimated without making that adjustment. Job searchers include not only the unemployed but also the employed and those who are out of the labor force. In downturns, a more general index of effective searchers rises less than unemployment, as effective search among the employed and those out of the labor force decreases. Likewise, in booms the more general index of effective searchers does not decline as much as implied by the decline in unemployment, as there are offsetting increases in effective search among the employed and those out of the labor force. Even among the unemployed, there are differences in job search intensities across groups defined by reason and duration, implying that just counting up their numbers will not adequately capture effective search among the unemployed. The generalized measure of labor market tightness we have constructed dramatically outperforms the standard measure via the lens of the matching function for hires. Specifically, the predicted job-filling rate (hires per vacancy) using the generalized measure tracks the actual job-filling rate much more closely than the job-filling rate predicted using the standard measure of labor market tightness.

The prototype measure we construct in this paper builds on a number of recent papers that have advocated for a broader measure of labor market tightness. The closest antecedent to the measure we have constructed is the Non-employment Index produced by the Richmond Federal Reserve Bank. The Richmond Fed index uses a different grouping of effective searchers but is very much in the same spirit as our prototype index. The most significant difference between the two indexes is that we have taken into account search and job-finding activity among the employed, whereas the Richmond Fed index makes use of information only for the non-employed. An important reason that vacancies rise in booms is that more job openings are created by job-to-job flows. To understand what is happening to labor market tightness, the job search behavior of potential job changers also needs to be considered.

The prototype measure of labor market tightness we have constructed is intended as a proof of concept. The strong performance of this prototype relative to the alternatives argues for its further development. We have several thoughts about next steps for this research agenda. One practical step that we suggest be taken sooner rather than later is to begin regular production of an index of effective searchers that incorporates fixed weighting factors constructed to capture differences in search intensity across groups. This index ideally would capture not only unemployed searchers and searchers who are out of the labor force, but also employed searchers. A necessary first step would be to agree on the best way to disaggregate the data to capture the relevant cross-group variation in search intensity. The existing literature suggests several options for consideration. If a consensus can be reached about how to do this, however, producing such a measure on a regular basis should be relatively straightforward. It would require only weighting factors constructed using base period job-finding rates, which can be estimated using linked CPS microdata, and estimates of the number of people in each of the groups from the monthly CPS.

A generalized index of labor market tightness constructed assuming constant within-group relative search intensity likely will miss some important variation in effective search activity but is a conservative and transparent improvement over using either the standard measure of tightness based on unemployment or a measure such as the U6 index described earlier in the paper. Our finding that temporal variation in relative job search intensities contributes only modestly to the performance of the prototype generalized tightness measure leads us to believe that the first step we are suggesting would be not only practical but also informative.

That said, we readily acknowledge that, beyond agreeing on the best disaggregation of job searchers to use for the construction of a generalized measure of labor market tightness, considerable further research and development still is needed. First, the indirect approach used in our prototype uses observed job-finding rates to develop weighting factors for the different groups of searchers. As discussed in section II, there is a growing literature on the measurement and analysis of direct measures of job search behavior. Reconciling the indirect and direct approaches to the measurement of search intensity should be an active area of research. The same comment applies to the measurement of employer recruiting intensity. Second, the prototype we develop abstracts from the impact of changing demographics on labor market tightness. Exploring how changing demographics may have affected effective search and thus the type of generalized measure we advocate is another area for future research.

Another important area for further research is to explore the implications of the generalized labor market tightness approach we have outlined for defining and measuring the natural rate of unemployment. The standard labor market tightness approach yields a natural rate of unemployment based on a flow equilibrium that equates inflows into and outflows from unemployment. With multiple groups of searchers who may transition across states, the dynamics of the generalized approach are considerably richer. In principle, however, it should be possible to use these richer dynamics to characterize a more general flow-based steady state. This in turn should yield a generalized steady state labor market tightness measure $\tilde{\theta}^*$ and a steady state "natural" rate of unemployment. A challenge for implementing this approach will be to develop a method for quantifying the long-run transition rates across labor market states for the different relevant groups, which will reflect a range of frictional and structural factors. This is analogous to the challenge of quantifying the long-run transition rates to and from unemployment that are part of the standard labor market tightness approach, albeit a considerably more difficult task.

A related area of inquiry is to consider the implications of generalized labor market tightness for wage and price pressures. It would be interesting to explore the estimation of Phillips-curve-type relationships using labor market tightness rather than the unemployment rate gap as the central explanatory variable. Even if it is true that labor market tightness is a better predictor of wage and price changes than the unemployment rate, however, there are other sources of instability in the Phillips curve relationship that seem likely to pose problems for the estimation of such relationships.

We do not in any way mean to suggest that the Bureau of Labor Statistics should stop producing statistics on unemployment. Unemployment can be devastating for those who experience it and that in itself is an important reason to monitor the unemployed population. Moreover, even purely from the perspective of assessing the tightness of the labor market, the unemployed are quite different in their search behavior from the employed and those out of the labor force. To implement our generalized approach, information will be needed not only on the size of the total pool of unemployment but also on unemployment decomposed by duration, reason for unemployment and perhaps other factors as well. Similar to other papers in the recent literature, however, we are arguing that the unemployment rate and the unemployment gap are not sufficient statistics for assessing the state of the labor market.

References

Aaronson, Daniel, Luojia Hu, Arian Seifoddini, and Daniel G. Sullivan. 2015. "Changing Labor Force Composition and the Natural Rate of Unemployment," Chicago Fed Letter No. 338.

Abraham, Katharine G. 2015. "Is Skill Mismatch Impeding U.S. Economic Recovery?" *ILR Review*, 68(2), 291–313. https://doi.org/10.1177/0019793914564962

Abraham, Katharine G., John C. Haltiwanger, Kristin Sandusky, and James R. Spletzer. 2019. "The Consequences of Long-Term Unemployment: Evidence from Linked Survey and Administrative Data, *ILR Review*, 72(2), 266–299. https://doi.org/10.1177/0019793918797624

Ahn, Hie Joo and Ling Shao. 2017. "Precautionary On-the-Job Search over the Business Cycle," Finance and Economics Discussion Series 2017-025. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2017.025.

Auer, Raphael, Claudio Borio and Andrew Filardo. 2017. "The globalisation of inflation: the growing importance of global value chains," BIS Working Paper No. 602. January.

Ball, Laurence and N. Gregory Mankiw. 2002. "The NAIRU in Theory and Practice," *Journal of Economic Perspectives*, 16(4): 115-136.

Ball, Laurence and Sandeep Mazumder. 2014. "A Phillips Curve with Anchored Expectations and Short-term Unemployment," NBER Working Paper No. 20715.

Barnichon, Regis. 2010. "Building a Composite Help-Wanted Index," *Economics Letters*, 109, 175-178.

Barnichon, Regis and Geert Mesters. 2018. "On the Demographic Adjustment of Unemployment," *Review of Economics and Statistics*, 100(2): 219-231.

Bean, Charles. 2006. "Globalisation and Inflation," speech delivered to the LSE Economics Society, October 24.

Black, Matthew, 1980. "Pecuniary Implications of On-The-Job Search and Quit Activity," *Review of Economics and Statistics* 62(2): 222-229.

Blanchard, Olivier. 2009. "Comment on William Dickens, 'A New Method for Estimating Time Variation in the NAIRU,'" in Jeff Fuhrer, Yolanda K. Kodrzycki, Jane Sneddon Little, and Giovanni P. Olivei, eds., *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective,* Cambridge, MA: MIT Press, 229-234.

Blanchard, Olivier. 2018. "Should We Reject the Natural Rate Hypothesis?" *Journal of Economic Perspectives*, 32(1): 97-120.

Blanchard, Olivier and Peter A. Diamond. 1992. "The Flow Approach to Labor Markets," *American Economic Review Papers and Proceedings*, 82(2): 354-359.

Blau, David M. and Philip K. Robins, 1990. "Job Search Outcomes for the Employed and Unemployed," *Journal of Political Economy* 98(3): 637-655.

Broersma, Lourens and Jan C. van Ours. 1999. "Job Searchers, Job Matching and the Elasticity of Matching," *Labour Economics*, 6:77-93.

Bureau of Labor Statistics. 2019. American Time Use Survey User's Guide. February. Accessed May 18, 2019 at https://www.bls.gov/tus/atususersguide.pdf.

Casselman, Ben. 2018. "As Labor Pool Shrinks, Prison Time Is less of a Hurdle." *New York Times*. January 13.

Clarida, Richard, Jordi Galí, and Mark Gertler. 1999. "The Science of Monetary Policy: A New Keynesian Perspective," *Journal of Economic Literature*, 37: 1661–1707.

Daly, Mary C., Bart Hobijn, Aysegul Sahin and Robert G. Valletta. 2012. "A Search and Matching Approach to Labor Markets: Did the Natural Rate of Unemployment Rise?" *Journal of Economic Perspectives,* 26(3): 3-26.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger. 2013. "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics*, 128(2): 581-622.

Deloach, Stephen B. and Mark Kurt. 2013. "Discouraging Workers: Estimating the Impacts of Macroeconomic Shocks on the Search Intensity of the Unemployed," *Journal of Labor Research*, 34:433–454. DOI 10.1007/s12122-013-9166-0

Diamond, Peter A. 1982. "Wage Determination and Efficiency in Search Equilibrium," *Review of Economic Studies,* 49(2): 217-227.

Dickens, William. 2009. "A New Method for Estimating Time Variation in the NAIRU,'" in Jeff Fuhrer, Yolanda K. Kodrzycki, Jane Sneddon Little, and Giovanni P. Olivei, eds., *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective,* Cambridge, MA: MIT Press, 205-228.

Faberman, R. Jason and Marianna Kudlyak. 2016. "The Intensity of Job Search and Search Duration." Federal Reserve Bank of San Francisco Working Paper 2016-13. http://www.frbsf.org/economic-research/publications/working-papers/wp2016-13.pdf

Faberman, R. Jason, Andreas I. Mueller, Ayşegül Şahin and Giorgio Topa. 2017. "Job Search Behavior among the Employed and the Non-Employed," NBER Working Paper No. 23731.

Flinn, Christopher J. and James J. Heckman. 1983. “Are Unemployment and Out of the Labor Force Behaviorally Distinct Labor Force States?” *Journal of Labor Economics*, 1(1): 28-42.

Fujita, Shigeru and Guiseppe Moscarini. 2017. “Recall and Unemployment,” *American Economic Review*, 107(12): 3875-3916.

Gali, Jordi and Mark Gertler. 2007. “Macroeconomic Modeling for Monetary Policy Evaluatoin,” *Journal of Economic Perspectives*, 21(4): 25-45.

Gomme, Paul and Damba Lkhagvasuren. 2015. “Worker Search Effort as an Amplification Mechanism,” *Journal of Monetary Economics*, 75: 106-122.

Hall, Robert and Sam Schulhofer-Wohl. 2018. ”Measuring Job Finding Rates and Matching Efficiency with Heterogeneous Job-Seekers,” *American Economic Journal: Macroeconomics*, 10(1): 1-32.

Haltiwanger, John C., Henry R. Hyatt and Erica McEntarfer. 2018. “Who Moves Up the Job Ladder?” *Journal of Labor Economics*, 36(S1): S301-S336.

Haltiwanger, John C., Henry R. Hyatt, Lisa B. Kahn, and Erica McEntarfer. 2018. “Cyclical Job Ladders by Firm Size and Firm Wage,” *American Economic Journal: Macroeconomics*, 10(2): 52–85.

Hornstein, Andreas and Marianna Kudlyak. 2016. “Estimating Matching Efficiency with Variable Search Effort,” Federal Reserve Bank of San Francisco Working Paper No. 2016-24.

Hornstein, Andreas, Marianna Kudlyak, and Fabian Lange. 2014. “Measuring Resource Utilization in the Labor Market,” *Federal Reserve Bank of Richmond Economic Quarterly*, 100(1): 1-21.

Martina Jašová, Richhild Moessner and Előd Takáts. 2018. “Domestic and global output gaps as inflation drivers: what does the Phillips curve tell?” BIS Working Paper No. 748. September.

Jones, Stephen R.G. and W. Craig Riddell. 1999. “The Measurement of Unemployment: An Empirical Approach,” *Econometrica*, 67(1): 147-162.

Kaitz, Hyman. 1970. “Analyzing the Length of Spells of Unemployment,” *Monthly Labor Review*, 93(11), 11-20.

Katz, Lawrence F. 1986. “Layoffs, Recalls and the Duration of Unemployment,” NBER Working Paper No. 1825.

Katz, Lawrence F. and Bruce D. Meyer. 1990. “The impact of the potential duration of unemployment benefits on the duration of unemployment,” *Journal of Public Economics*, 41(1): 45-72.

Krueger, Alan B. 2018. “Reflections on Dwindling Worker Bargaining Power and Monetary Policy,” Federal Reserve Bank of Kansas City Economic Symposium, Jackson Hole, Wyoming. August 24.

Krueger, Alan B., Judd Cramer, and David Cho. 2014. “Are the Long-Term Unemployed on the Margins of the Labor Market?” *Brookings Papers on Economic Activity*, Spring, 229-280.

Kudlyak, Marianna. 2017. “Measuring Labor Utilization: The Non-Employment Index,” *Federal Reserve Bank of San Francisco Economic Letter*, 2017-08. March 17.

Kudlyak, Marianna and Fabian Lange. 2018. “Measuring Heterogeneity in Job Finding Rates among the Non-Employed Using Labor Force Status Histories,” Federal Reserve Bank of San Francisco Working Paper 2017-20.

Modestino, Alicia Sasser, Danial Shoag and Joshua Balance. 2019. “Upskilling: Do Employers Demand Greater Skill when Workers are Plentiful?” Unpublished working paper, Northeastern University.

Mortensen, Dale T. and Christopher A. Pissarides. 1994. “Job Creation and Job Destruction in the Theory of Unemployment,” *Review of Economic Studies*, 61(3): 397-415.

Mukoyama, Toshihiko, Christina Patterson and Aysegul Sahin. 2018. “Job Search Behavior over the Business Cycle,” *American Economic Journal: Macroeconomics*, 10(1): 190-215.

Perry, George L. 1970. "Changing Labor Markets and Inflation," *Brookings Papers on Economic Activity*, 1(3): 411-448.

Petrongolo, Barbara, and Christopher A. Pissarides. 2001. “Looking into the Black Box: A Survey of the Matching Function,” *Journal of Economic Literature*, 39(2): 390-431.

Pissarides, Christopher. 2000. *Equilibrium Unemployment Theory, 2nd ed.* Cambridge: MIT Press.

Powell, Jerome H. 2018. “Monetary Policy in a Changing Economy,” Federal Reserve Bank of Kansas City Economic Symposium, Jackson Hole, Wyoming. August 24.

Şahin, Ayşegül, Joseph Song, Giorgio Topa and Giovanni L. Violante. 2014. “Mismatch Unemployment,” *American Economic Review*, 104(11): 3529-64.

Sedlacek, Petr. 2016. “The Aggregate Matching Function and Job Search from Employment and Out of the Labor Force,” *Review of Economic Dynamics*, 21: 16-28.

Shimer, Robert. 2001. “The Impact of Young Workers on the Aggregate Labor Market,” *Quarterly Journal of Economics,* 116(3), 969–1008.

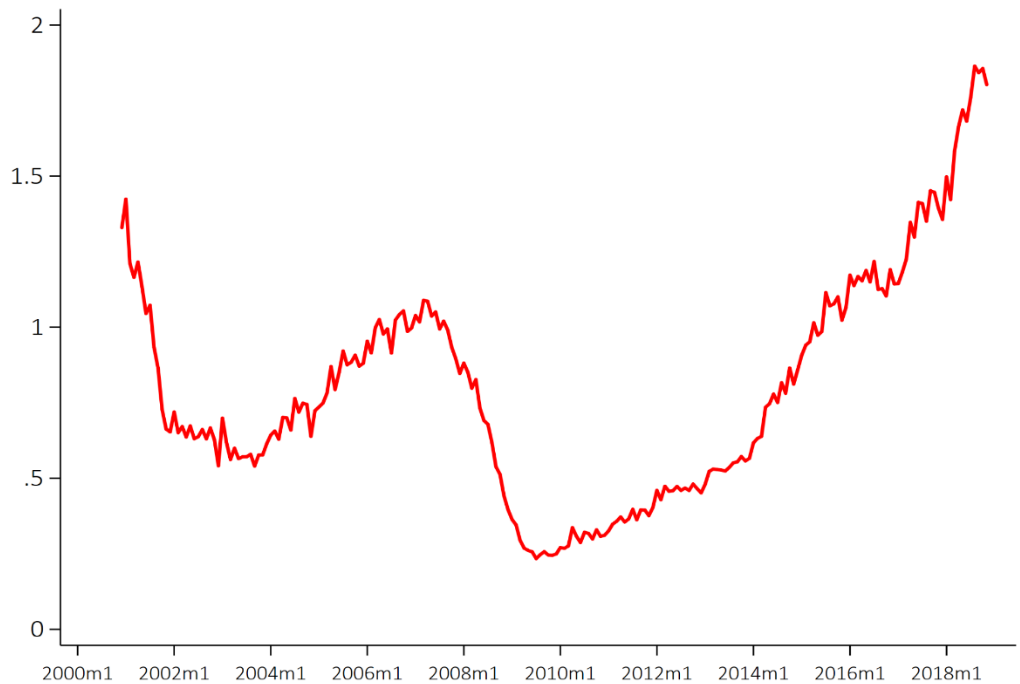
Shimer, Robert. 2004. “Search Intensity.” Unpublished working paper. University of Chicago. April.

Smialek, Jeanna. 2019. “The Economy Is Strong and Inflation Is Low. That’s What Worries the Fed,” *New York Times*. May 21.

Veracierto, Marcelo. 2011. “Worker Flows and Matching Efficiency,” *Federal Reserve Bank of Chicago Economic Perspectives*, 35(4): 147-169.

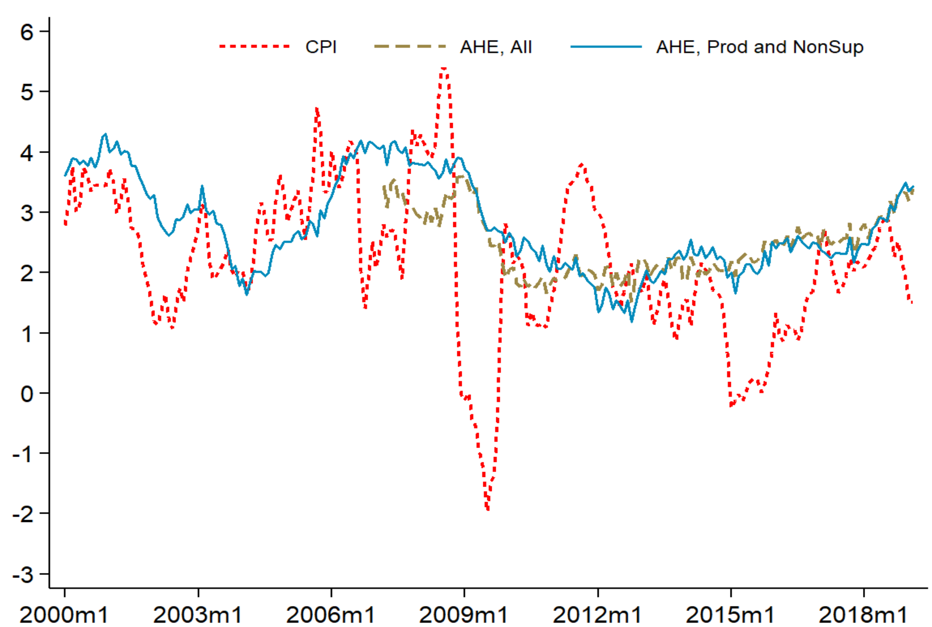
Yellen, Janet L. 2014. “Labor Market Dynamics and Monetary Policy,” Federal Reserve Bank of Kansas City Economic Symposium, Jackson Hole, Wyoming. August 22.

Figure 1. Standard Measure of Labor Market Tightness (V/U)



NOTE: Normalized to one in 2007

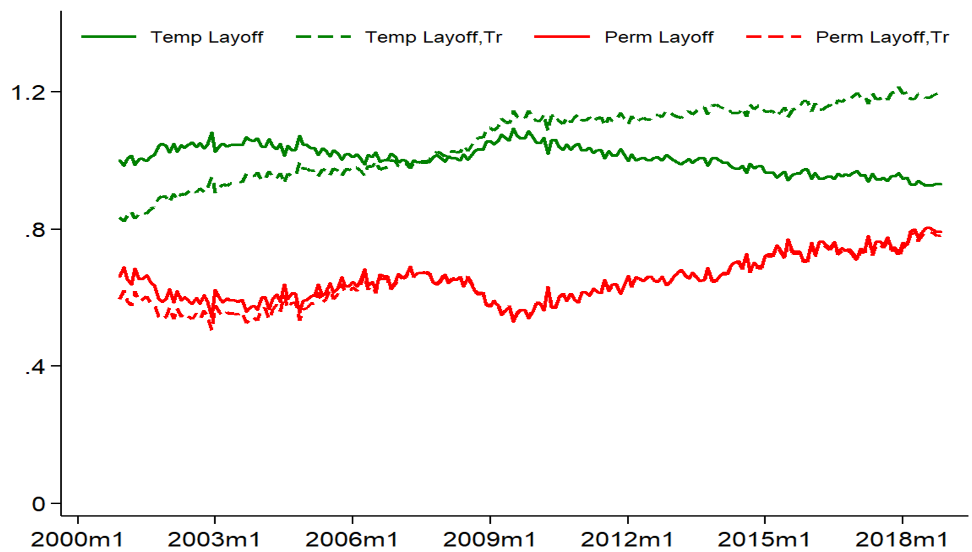
Figure 2. Nominal Growth in Wages and Prices



NOTE: Reported series are percent changes from same month one year earlier. CPI= Consumer Price Index for All Urban Consumers. AHE=Average Hourly Earnings, either for all (All) or production and non-supervisory (Prod and NonSup) private sector workers.

Figure 3. Selected Relative Search Intensities

A. Recent Temporary Layoffs and Recent Permanent Layoffs



B. Long Term Unemployed and Want a Job

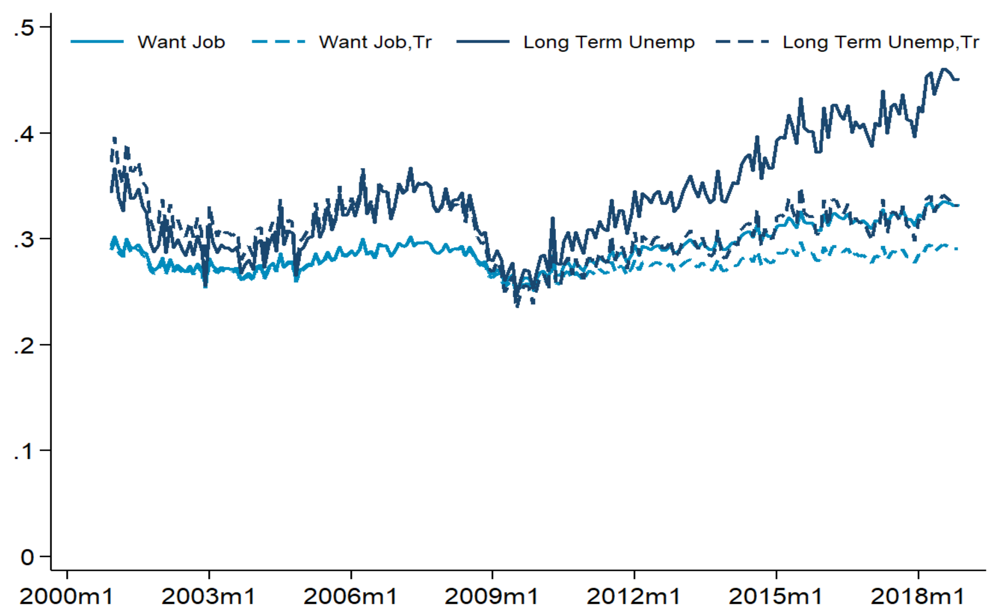
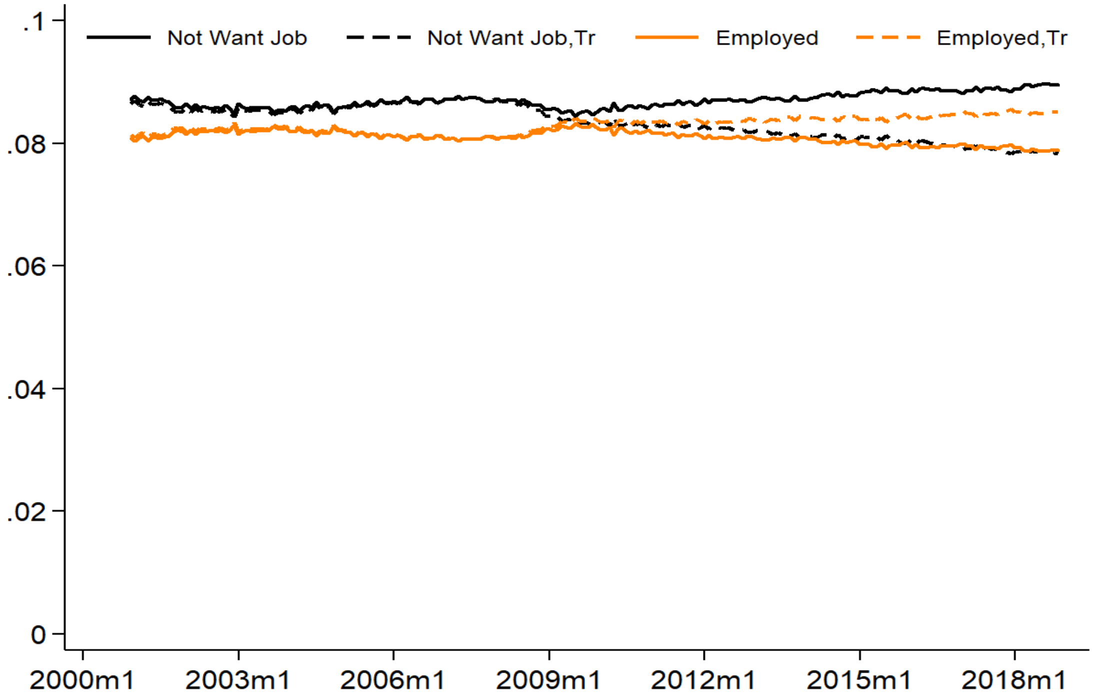


Figure 3. Selected Relative Search Intensities (continued)

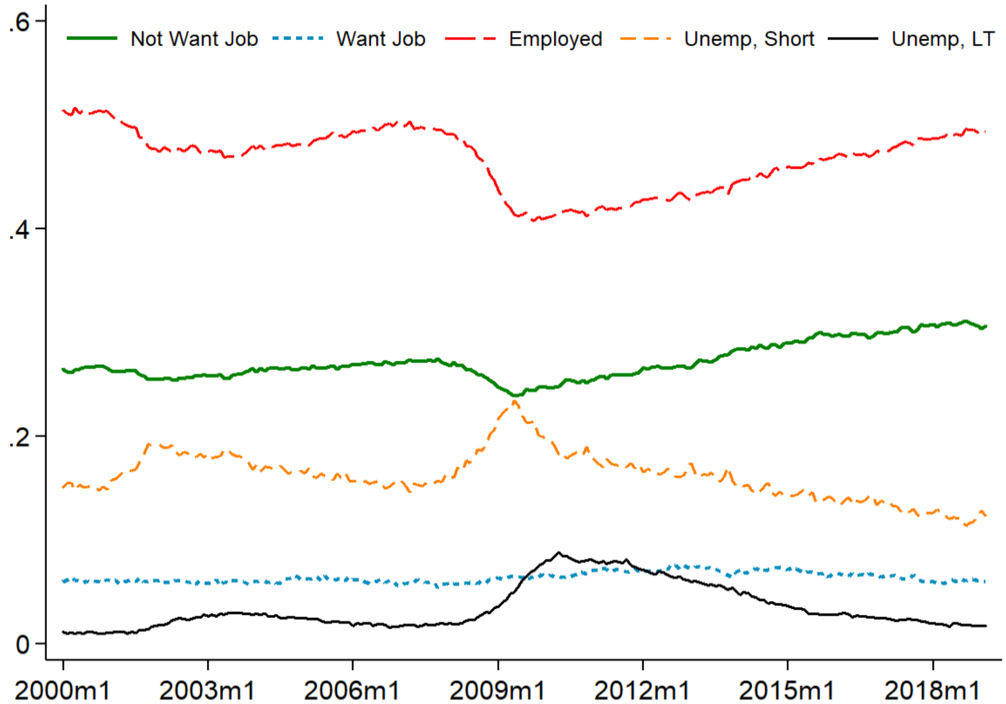
C. Not Want Job and Employed



NOTE: All series include the effects of group-specific elasticities of the relative job-finding rate with respect to vacancy duration. Series denoted Tr (trend) also include the effects of group-specific trends in relative job-finding rates.

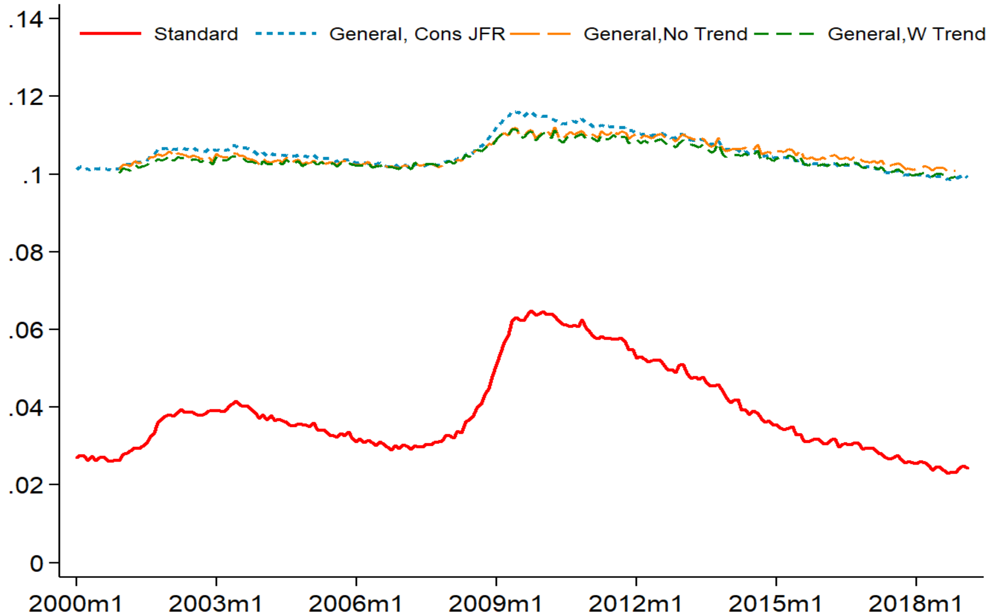
Figure 4. Shares of Effective Searchers

A. Constant relative search intensities



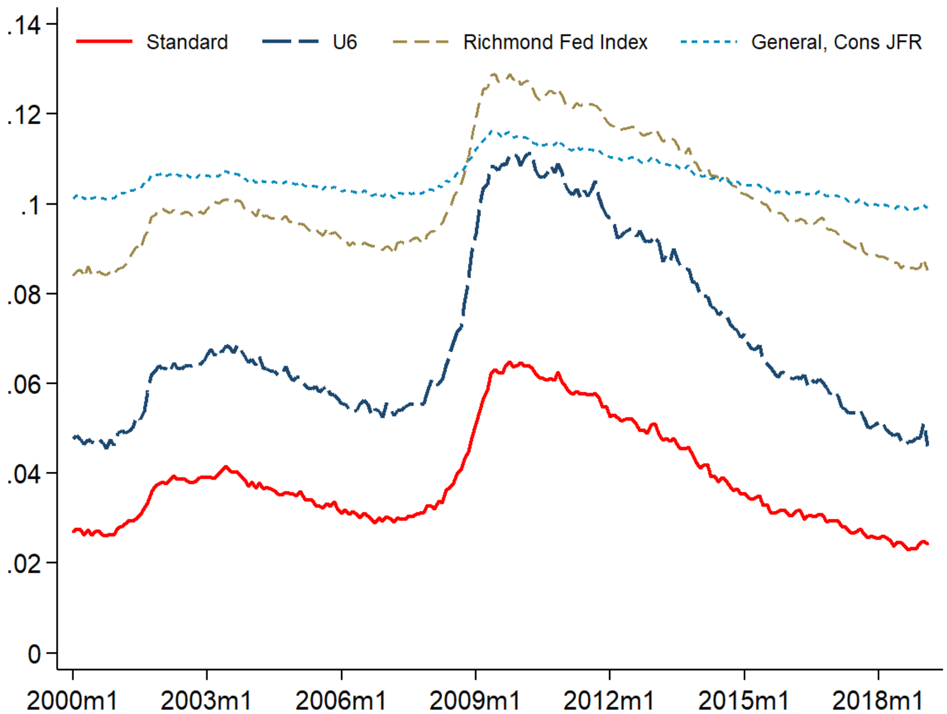
B. Time varying relative search intensities

Figure 5. Standard vs. Generalized Measures of Searchers



NOTE: All measures ratios to the population age 16 plus. Numerator for Standard is number unemployed. General, Cons JFR assumes constant search intensities. General, No Trend and General, W Trend allow search intensities to vary.

Figure 6. Standard, U6, Richmond Fed, and Generalized Effective Searcher Measures



NOTE: All measures ratios to the population age 16 plus. Numerators are unemployed for Standard; unemployed, marginally attached and part-time for economic reasons for U6; and weighted sums as described in the text for the Richmond Fed Index and General, Cons JFR measures.

Figure 7. Index of Recruiting Intensity Per Vacancy

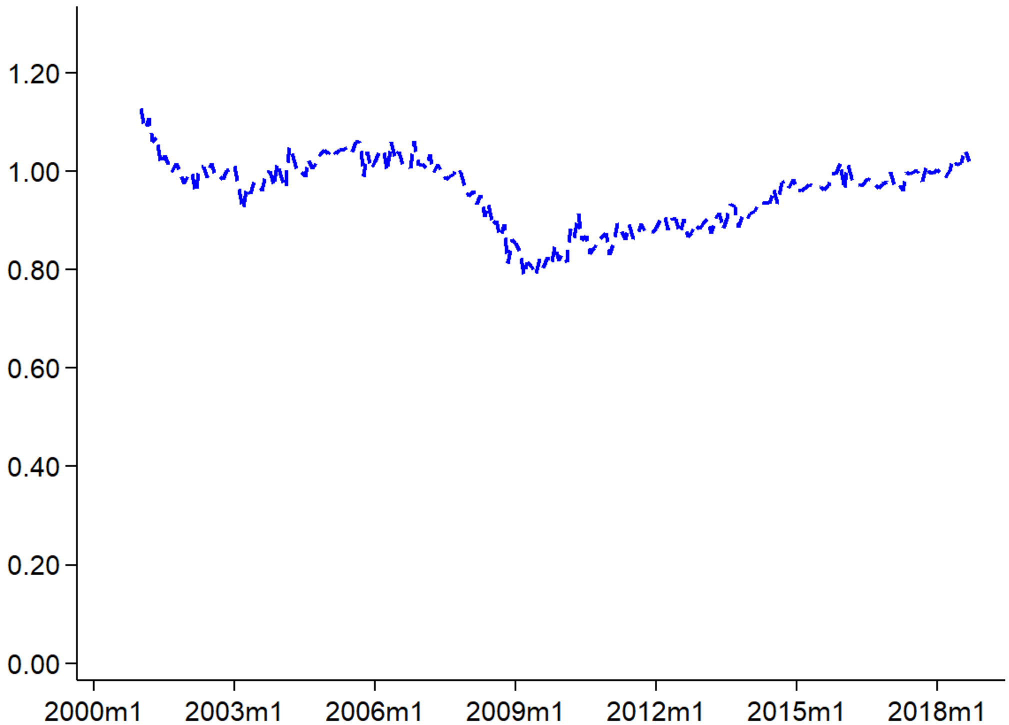


Figure 8. Vacancies vs. Effective Vacancies

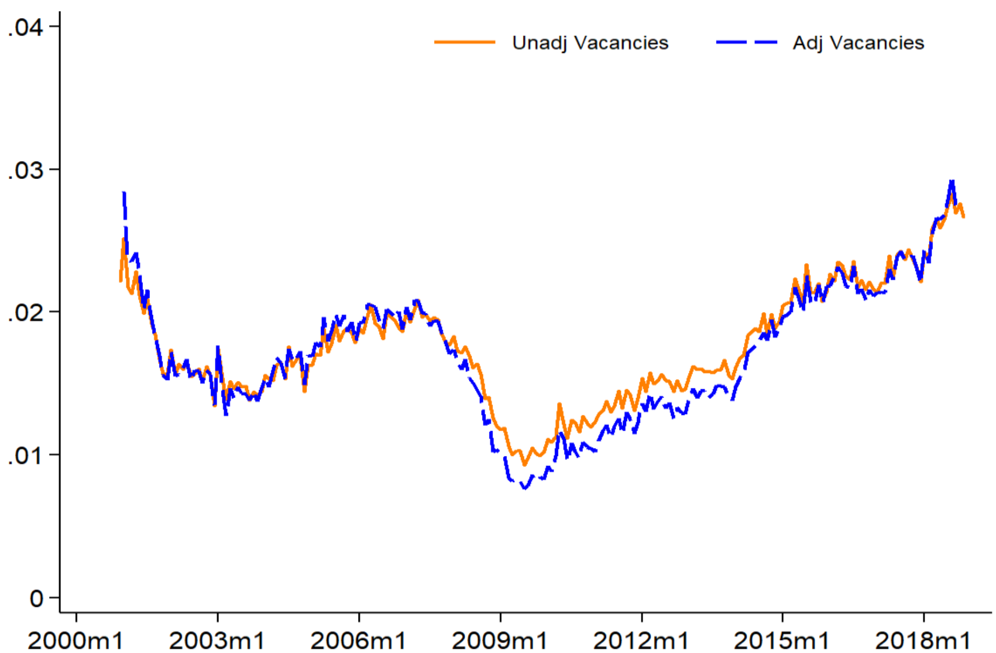
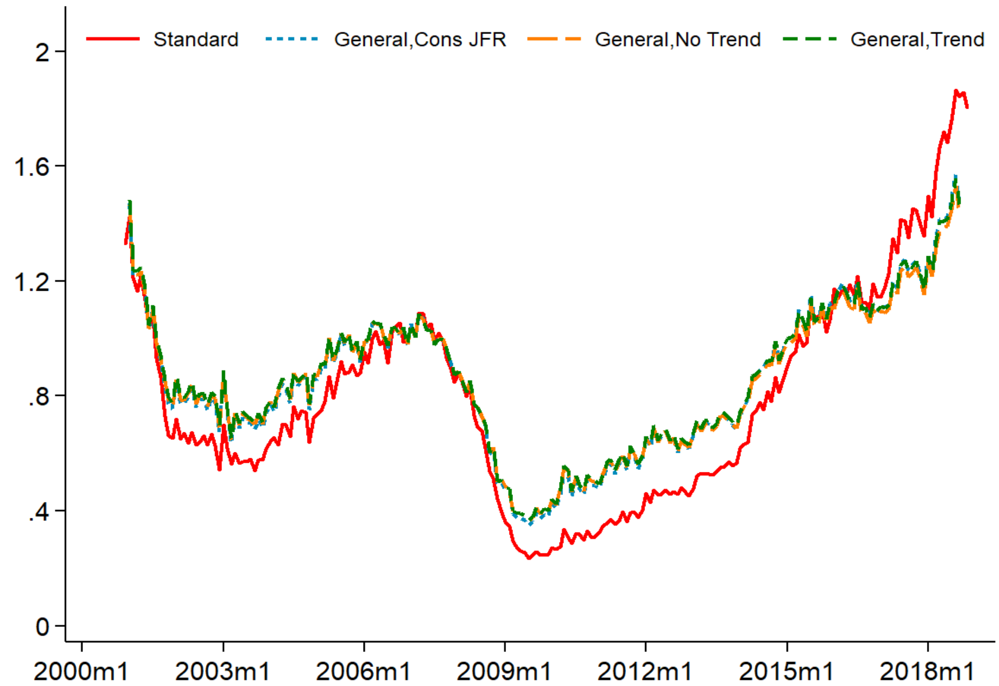


Figure 9. Standard vs. Generalized Measures of Labor Market Tightness



NOTE: All series normalized to one in 2007.

Figure 10. Actual vs. Predicted Job Filling Rates from Matching Function

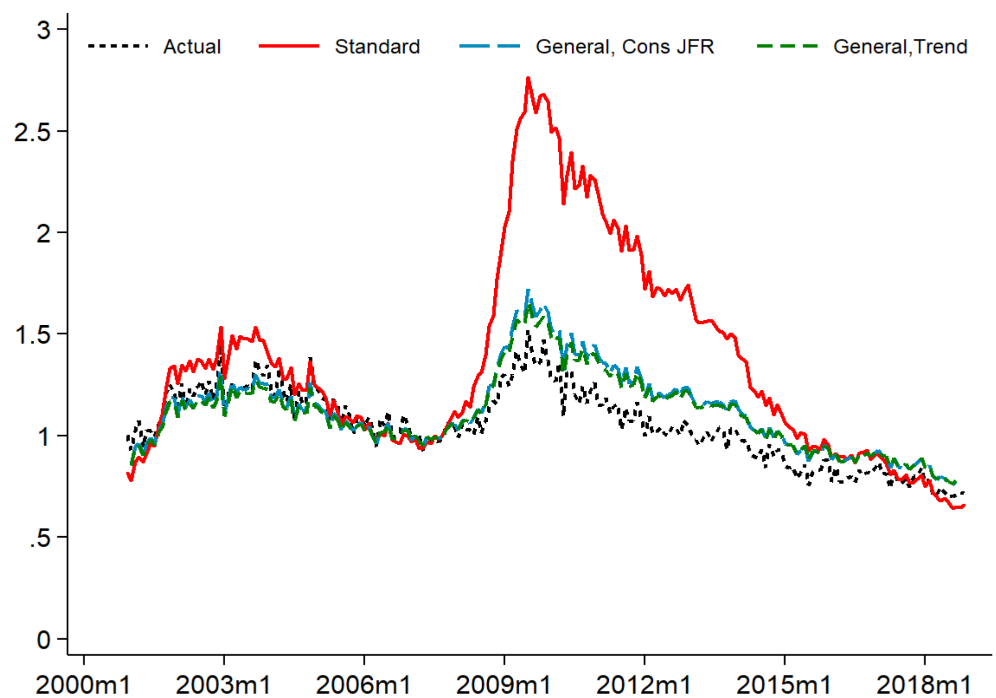


Figure 11. Actual vs. Predicted Job Filling Rates, Generalized vs. U6 Based Index

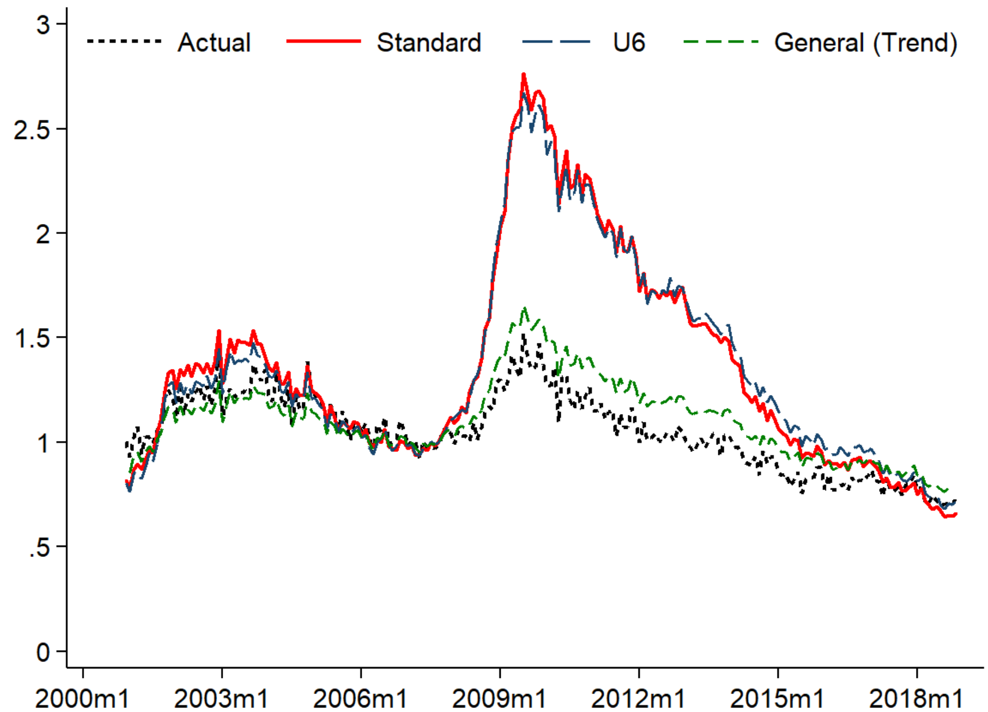


Figure 12. Actual vs. Predicted Job Filling Rates, Generalized vs. Richmond Fed Index

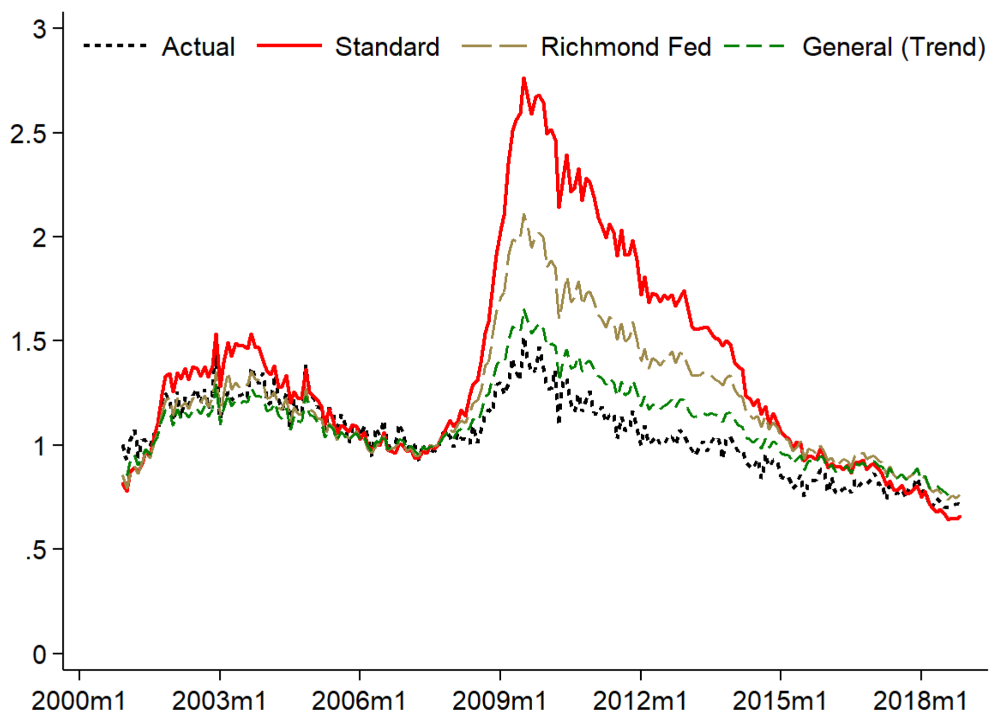
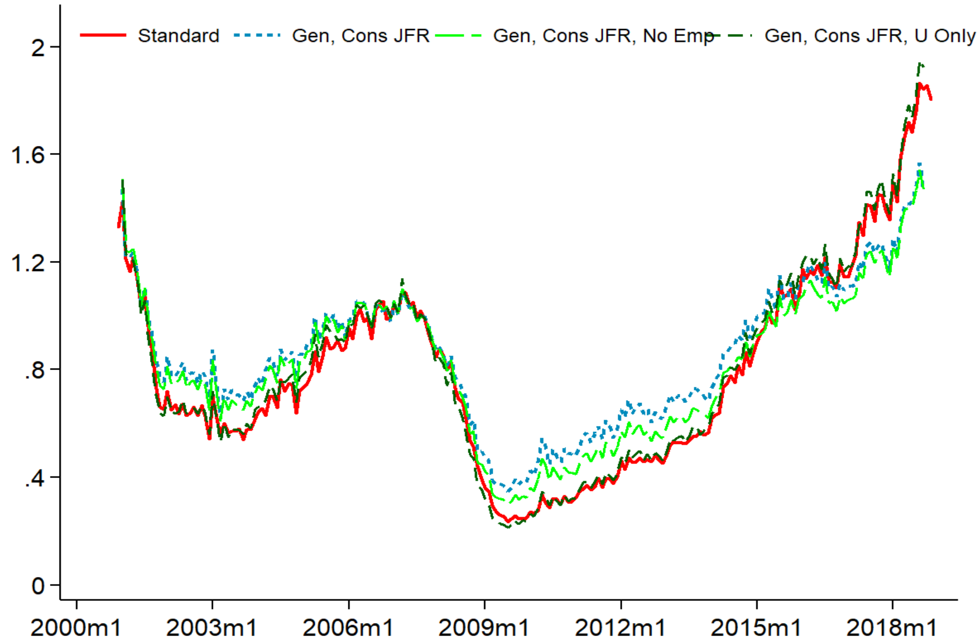
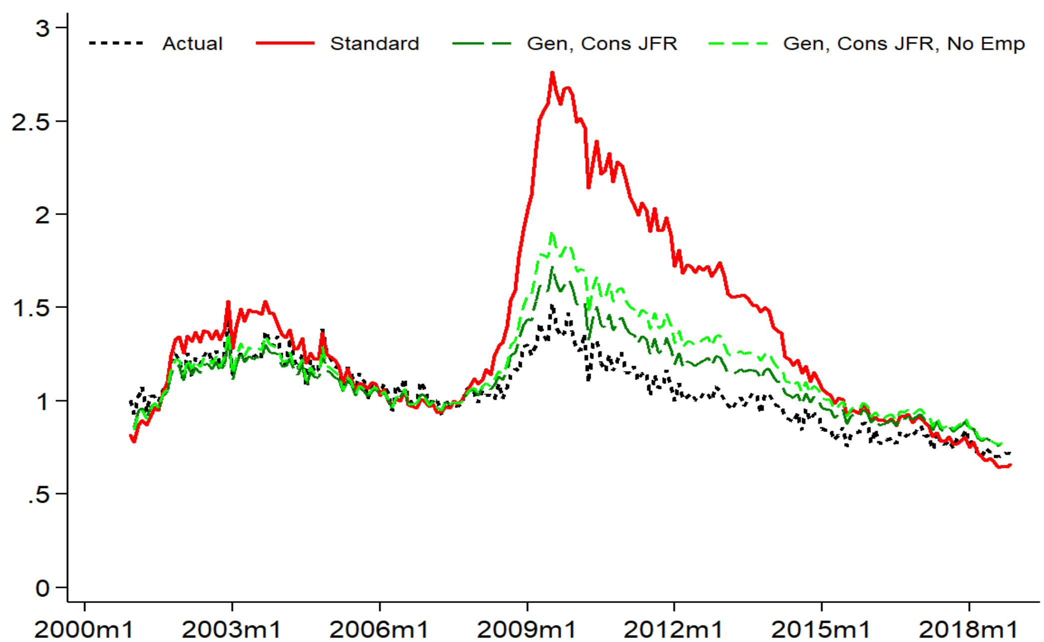


Figure 13. Alternative More Restricted Measures of Tightness



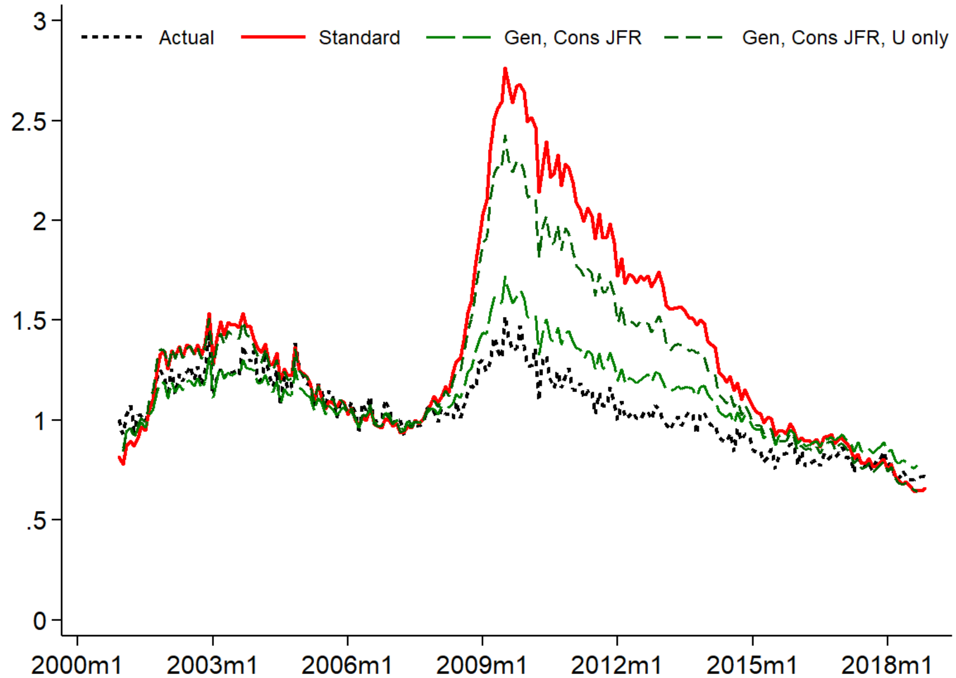
NOTE: All Generalized measures use constant relative search intensities. No Emp sets relative search intensity for employed to zero. U Only sets relative search intensity for employed and out of labor force to zero.

Figure 14. Actual vs. Predicted Job Filling Rates Using More Restricted Measures: No Effective Searchers from Employed



NOTE: All Generalized measures use constant relative search intensities. No Emp sets relative search intensity for employed to zero.

Figure 15. Actual vs. Predicted Job Filling Rates Using More Restricted Measures: Only Unemployed Included in Effective Searchers

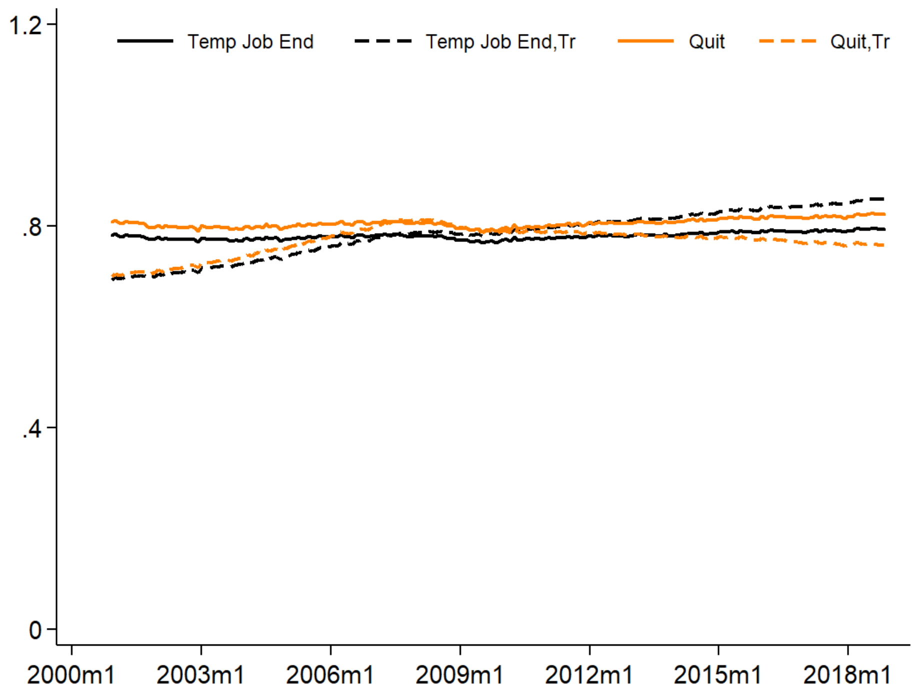


NOTE: All Generalized measures use constant relative search intensities. U Only sets relative search intensity for employed and out of labor force to zero.

Appendix Figures

Figure A.1. Remaining Relative Search Intensities

A. Recent Temporary Job End and Recent Quits



B. Recent Entrants and Recent ReEntrants

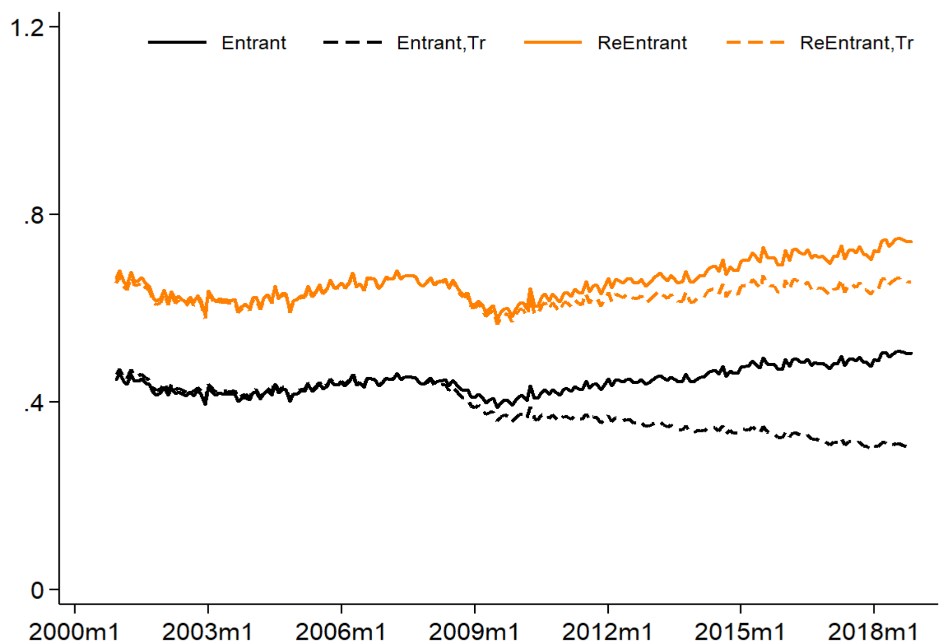
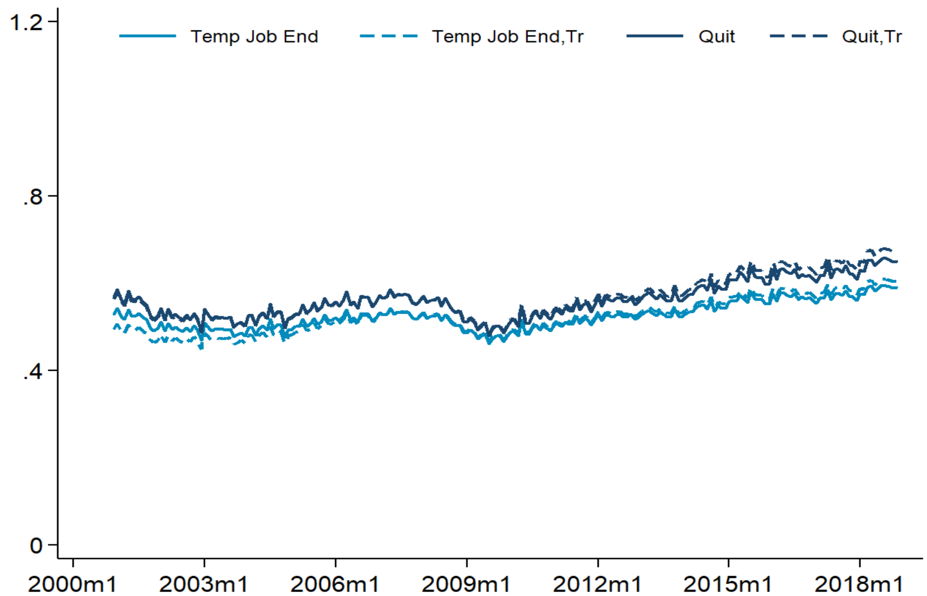


Figure A.1. Remaining Relative Search Intensities (continued)

C. **Medium Term (4-26 weeks) Temporary Job End and Quits**



D. **Medium Term (4-26 weeks) Entrants and Re-Entrants**

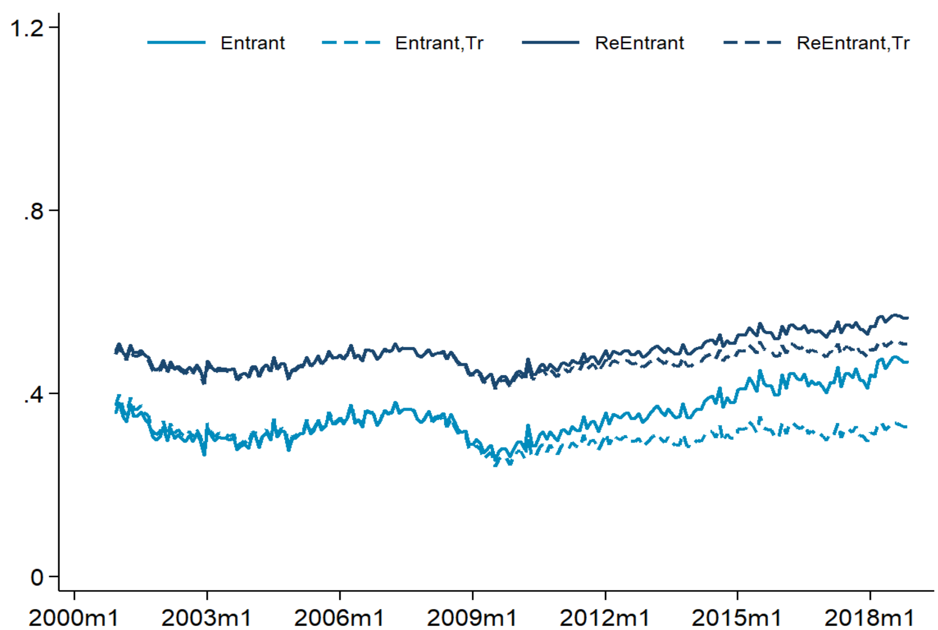


Figure A.1. Remaining Relative Search Intensities (continued)

E. Medium Term (5-26 weeks) Temporary Layoff and Permanent Layoff

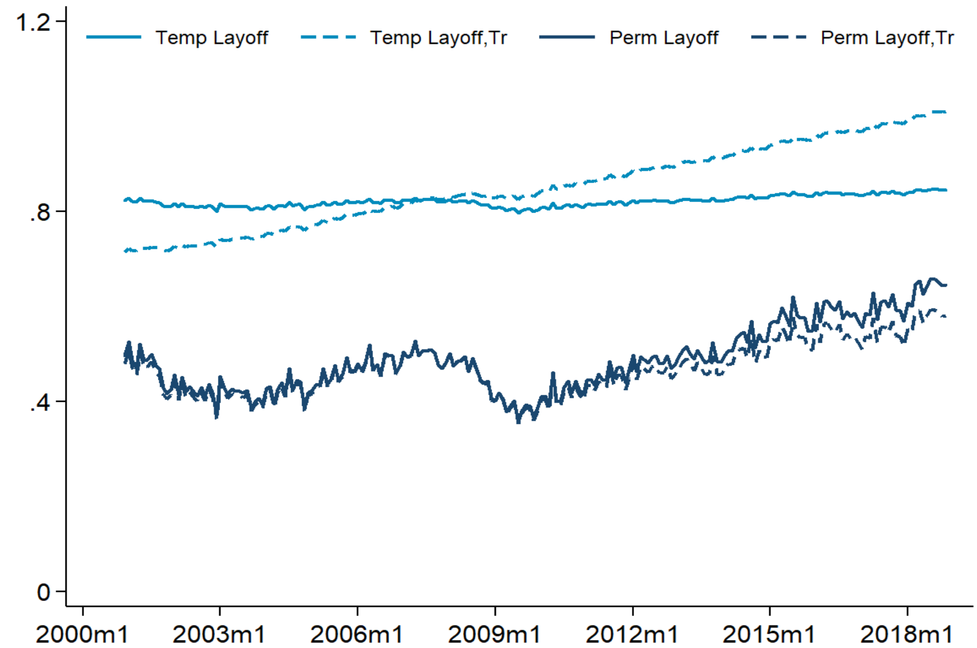
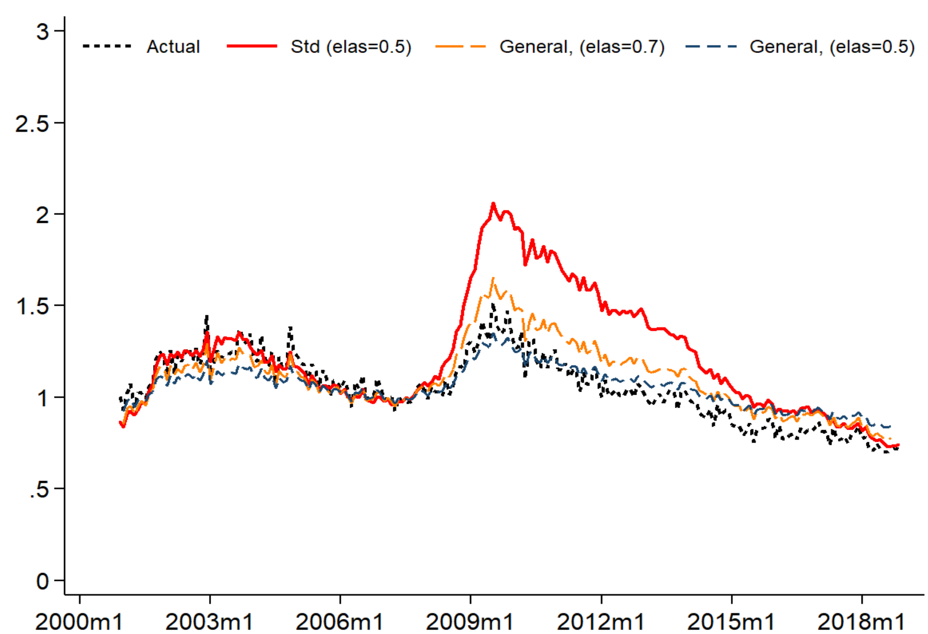
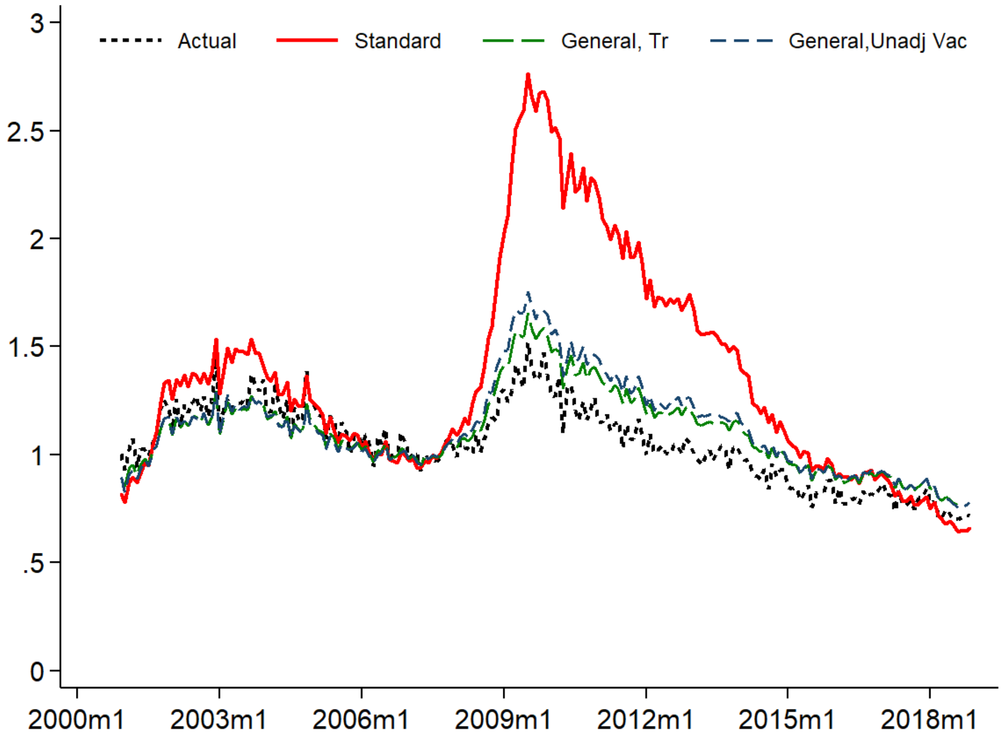


Figure A.2. Robustness of Predicted Job Filling Rate to Alternative Elasticities



NOTE: Elasticity of matching function is permitted to vary from 0.5 to 0.7 for Generalized matching function. Standard considers elasticity equal to 0.5.

Figure A.3. Actual vs. Job Filling Rate, Without Recruiting Intensity



NOTE: General, Unadj Vac uses generalized measure of searchers with trends but does not adjust for changes in recruiting intensity.